Footfall and the Territorialisation of Urban Places measured through the Rhythms of Social Activity

E D W Dargan

PhD 2021

Footfall and the Territorialisation of Urban Places measured through the Rhythms of Social Activity

Edmund D.W. Dargan

A thesis submitted in partial fulfilment of the requirements of the Manchester Metropolitan University for the degree of Doctor of Philosophy

Department of Marketing, Retail and Tourism
Manchester Metropolitan University

2021

Abstract

The UK high street is constantly changing and evolving in response to, for example, online sales, out-of-town developments, and economic crises. With over 10 years of hourly footfall counts from sensors across the UK, this study was an opportunity to perform a longitudinal and quantitative investigation to diagnose how these changes are reflected in the changing patterns of pedestrian activity.
Footfall provides a recognised performance measure of place vitality. However, through a lack of data availability due to historic manual counting methods, few opportunities to contextualise the temporal patterns longitudinally have existed. This study therefore investigates daily, weekly, and annual footfall patterns, to diagnose the similarities and differences between places as social activity patterns from UK high streets evolve over time.

Theoretically, footfall is conceptualised within the framework of Territorology and Assemblage Theory, conceptually underpinning a quantitative approach to represent the collective meso-level (street and town-centre) patterns of footfall (social) activity. To explore the data, the periodic signatures of daily, weekly, and annual footfall are extracted using STL (seasonal trend decomposition using Loess) algorithms and the outputs are then analysed using fuzzy clustering techniques. The analyses successfully identify daily, weekly, and annual periodic patterns and diagnose the varying social activity patterns for different urban place types and how places, both individually and collectively are changing.

Footfall is demonstrated to be a performance measure of meso-scale changes in collective social activity. For place management, the fuzzy analysis provides an analytical tool to monitor the annual, weekly, and daily footfall signatures providing an evidence-based diagnostic of how places are changing over time. The place manager is therefore better able to identify place specific interventions that correspond to the usage patterns of visitors and adapt these interventions as behaviours change.

Acknowledgments

This study is a consequence of being inspired by Cathy Parker to become involved in the academic world of place management and its challenges. Without Cathy's enthusiasm and encouragement, this study would never have happened, and the opportunity to take a very different path to my working life (hesitate to say career) would have been missed.

My thanks to my Principal Supervisor, Gary Warnaby who challenged, supported, and helped me navigate through the research process. I am incredibly grateful and feel extremely privileged to have had his guidance and support. Thanks also to Christine Mumford, who provided ideas and options for the data analysis as well as guidance how to report the results of the data analysis.

To Springboard, for providing access to the data – this was a unique opportunity for which I am very grateful.

To everyone at the Institute of Place Management, thanks for making me feel welcome and for all your advice and help. Many of the ideas explored in the thesis arose following discussions with you all. Additionally, thanks to Chloe Steadman, you probably do not appreciate how much the annual review process provided hope and encouragement.

Over the period of this study, friends and family have supported and helped me along the way – my thanks to all of you. Thanks go to Ángela Carrasco Garcia from the Universidad de Castilla-La Mancha who found me a place to study with internet access during the time I was living in Almáden, Spain. Thank you Ángela so much for it was during this time the theoretical framework for this thesis really began to take shape.

Finally, to Ted, Max, and Pistachio - and of course, most importantly, Debbie, my wife.

Table of Contents

List of Tables

List of Figures

List of Equations

1 Introduction

If 2019 was described as the ‘worst year for 25 years’ for the UK retail industry (Centre for Retail Research, 2021) then the impact of COVID-19 has accelerated the changes that are reshaping the high street (High Street Task Force, 2021). By April 2021, of the medium to large stores that have gone into administration, 53% had closed and 43.7% of staff were made redundant. The equivalent figures from 2019 were 36.9% and 20.6% respectively (Centre for Retail Research, 2021). Individual retailers such as Debenhams, Laura Ashley, Topshop, Harveys Furniture, Go Outdoors and T M Lewin and in addition, shopping centres such as Grosvenor Shopping Centre (Chester) and St George’s Shopping Centre (Preston), were either in administration and/or being restructured (Centre for Retail Research, 2021). The UK high street therefore continues to go through disruptive change and arguably, the future cannot be one focused on retail alone (Wrigley and Lambiri, 2014; Delage et al., 2020; Mumford et al., 2021). This is highlighted by Grimsey (2018) with the following recommendation:

> *“There is already too much retail space in the UK and that bricks and mortar retailing can no longer be the anchor for thriving high streets and town centres. They need to be repopulated and re-fashioned as community hubs, including housing, health and leisure, entertainment, education, arts, business/office space and some shops” (Grimsey, 2018:4)*

The need to rethink the nature of towns centres and to consider them as places to meet for activities other than retail, is not unique to the U.K. and additionally, is not limited to town or city centre locations alone. For example, as part of a plan to enter the U.S. market, IKEA’s shopping mall business also report the need for multi-functional locations where activities other than retail are considered equally important:

> *“We plan to build mixed-use facilities that we call meeting places and that have a wide range of facilities and services,”. Where activities could range from healthcare and education to festivals and events, besides retail and food (Reuters, 2020).*

In recent years, the growth of mobile communications (Wang et al., 2015) and Internet retailing has changed customer behaviours (Verhoef et al., 2015; British Retail Consortium, 2019), as has the use of out-of-town shopping destinations by consumers (Bloch et al., 1994; Teller, 2008). This, coupled with dwindling disposable incomes and increasing business rates for businesses, have seriously threatened the vitality and viability of town centres (BIS, 2011; Wrigley and Lambiri, 2015; Grimsey, 2018; Mumford et al., 2021). As Mumford et al. (2021) note, retail planning policy has failed to account for the rise of the Internet as a major alternative channel, the signs of which were documented more than 25 years ago (Batty, 1997). For example, Hallsworth and Coca-Stefaniak (2018:138) comment that the Internet broke down the traditional understanding that dictates that 'goods and services are locally supplied in line with local demand', and thus led to substitution effects between Internet and bricks-and- mortar retailers, that were especially significant for non-food (comparison) retail categories and bigger centres (Weltevreden and van Rietbergen, 2009; Mumford et al., 2021). The impact of the growth of Internet shopping is however, just one of many influential forces such as car ownership (Latham and McCormack, 2004), the introduction of fridges (Shove and Southerton, 2000) and department stores (Wrigley and Lowe, 1996) that over time have shaped the high street (Parker and Ntounis, 2015).

The economic downturn of 2008 resulted in wide geographical differences in the UK with, for instance, substantially higher levels of store vacancies reported in northern UK regions (Deloitte, 2013; Wrigley and Lambiri, 2015) and, because this was not a problem limited to the UK, shop diversity in smaller cities of France also suffered (Delage et al., 2020). The visual impact of high street decline and the effect upon communities provided the impetus for several reports to be commissioned, some by the UK Government, that identified issues and potential solutions. Such reports included the Portas Review (Portas, 2011), 'Understanding of High Street Performance' (BIS, 2011, 2012), and The Grimsey Reviews (Grimsey, 2013, 2018). In addition, the impact of digital technology, was discussed in a report written by the Digital High Street Advisory Board (2015). It should be noted however that these reports could be viewed as a continuation of concerns for town centres that started with the development of regional-shopping centres (Bennison and Daves, 1980; URBED, 1994), which arguably provided the catalyst for the formation of town centre management (TCM) schemes and the Business Improvement District (BID) concept.

Partly in response to the Portas and Grimsey reports (Wrigley and Lambiri, 2015), in 2013 the UK Government formed the Future High Streets Forum (FHSF, 2013). Instigated by the FHSF, the report, ‘British High Streets: from Crisis to Recovery’ by Wrigley and Lambiri (2015) provided a comprehensive view of the current evidence assessing high street performance and identified opportunities for further research. This report found that the most influential forces found to be impacting the performance of town centres and high streets, to be:

- The rise of online shopping
- Competition from out-of-town one stop retail development
- The rise of a convenience shopping culture
- The burden of business rates and in particular, the imbalance between physical and internet only retailers
- Too much retail space of the wrong type

Beyond looking at the retail elements of the high street, as suggested by Wrigley and Lambiri (2015), aspects of community, everyday experiences, urban design, and liveability of places also need to be considered to enhance the vitality of town centres and cities (Jacobs, 1961; Gehl, 2010, 2011; Coca-Stefaniak and Carroll, 2015). Thus, improving community cohesion, liveability, wellbeing, and sustainability (Mumford et al., 2021) are central to high street reports such as Grimsey (2018) and ‘High Streets and Town Centres in 2030’ by the UK Government Housing, Communities and Local Government Committee (HCLGC, 2019). As Mumford et al. (2021) note, the aspiration for a ‘multifunctional’ high street is not new and was identified by the Urban and Economic Development Group (URBED, 1994, 1997). However, the continuing need for reports such as Grimsey (2018) suggest that despite numerous regulation and policies, the ‘multifunctional’ high street remains elusive (Mumford et al., 2021).

One part of the reason for this elusiveness, is a lack of performance evidence for assessing the success of high street strategies (Hart et al., 2014; Wrigley and

Lambiri, 2015) and the need to recognise the constant evolutionary nature of towns and cities (Parker et al., 2016). Over 20 years after the URBED (1994) report which included recommendations for measuring place performance, Millington and Ntounis (2017) identified that the main challenge that the towns (that participated in their research project) were facing was one of effectively understanding and addressing their current situation. The research found that usually, identification of local variations and the problems and challenges associated with the town centre was based on anecdotal evidence. This was also highlighted by Wrigley and Lambiri (2015) where little in-depth analysis was found to have occurred that could account for the differential performance of different high streets geographically and at different levels of the urban hierarchy.

There is, therefore, a need to develop measures that can reflect the 'multifunctional' nature of the high street, towns, and cities, where 'success' does not solely equate to retail success (Mumford et al., 2021). One such measure is footfall, which historically, has been considered a key criterion for performance measurement within place management (Hogg et al., 2007; BIS, 2011; Digital High Street Advisory Board, 2015), and for measuring the vitality and viability of towns and cities by URBED (1994). Footfall has been defined as:

> *"An indicator that refers to the number of people walking up and down a given town centre (or single street) regardless of their reasons for doing so. Typical reasons may include shopping, a pleasant stroll, going to work or college, to the cinema or for a meal, accessing public services, visiting friends, or simply passing through. " (Coca-Stefaniak, 2013:24)*

As a performance measure, footfall and was found to be used by 87% of TCM schemes by Hogg et al. (2007). Yet, the number of academic studies that investigate the utilisation of footfall data are limited. This was due (historically) to the need for footfall to be counted manually causing issues with data availability, difficulties of count standardisation and the cost and resources needed for acquiring the measures (Monheim, 1998).

In recent years, remote sensors counting footfall have been installed in UK towns and cities by companies such as Springboard and the Local Data Company. This provides researchers the opportunity to explore pedestrian activity over much longer time periods than was previously possible and to start discovering the periodic patterns made by pedestrian movements in urban space. This constitutes an opportunity that enriches the use of footfall data from merely being a guide to rental values (Thornton et al., 1991; Yim Yiu, 2011), time-limited case studies (Gehl, 2011), retailer insights (Kirkup, 1999; Graham et al., 2019), to something that can provide insight into differences and similarities between towns and cities based upon discovered common patterns, or signatures, of pedestrian movement (Mumford et al., 2021). This exploration of footfall is discussed briefly below with reference to previous research.

1.1 Previous Research

Using manually collected footfall data, Monheim (1998) reviewed methodological techniques to identify daily and weekly visitor patterns in German cities. Gehl (2011) monitored changing social activity patterns using manually collected footfall data following the pedestrianisation of a specific street in Elsinore, Denmark. Wunderlich (2014) adopted a diary-based approach, plus photographs, audio, and video records for limited periods over a year to map the urban place rhythms of individuals. Likewise, Hart et al. (2014) used online diaries of shopping activity and questionnaires for several UK cities over a period of a year to map out movements of shoppers and their behaviours. In all these cases, manual collection of the data was required.

Using footfall remote sensor data collected over more than a 10-year period, annual patterns have been identified by Mumford et al. (2021). Mumford et al. (2021) found is that footfall signatures, the distinct clusters of annual patterns, can be used to assign individual places to a classification type and that changes to the assignment and the classifications can be tracked over time. As a methodological approach, although criticised for being too static, it does point to how footfall might be used to capture the dynamic nature of centres (Dolega et al., 2021).

Other studies have used alternative secondary data sources. For example, Sulis and Manley (2018) and Sulis et al. (2018) combine travel smart card data, social media geo-tagging information and points of interest using OpenStreet Map to assess place vitality. This study was, however, limited to London and had only 3 months of data. Traunmueller et al. (2018) used Wi-Fi data from Lower Manhattan to model street usage intensity and paths of travel, although the analysis was based upon only one month of data. Lugomer and Longley (2018) also used Wi-Fi and, additionally, Bluetooth data from the UK for weekdays Monday to Thursday over two years to generate a temporal classification of footfall patterns and finally Nemeškal et al. (2020) used a single day of phone location data to track movements of people in and out of Czech city of Prague.

Except for Mumford et al. (2021), one thing common to all the above studies (whether data was collected manually or made available through from a commercially based secondary data source) was the limitation of the data sample because of budget and/or time constraints. For example, in the case of Nemeškal et al. (2020), only one day of data was used due to budget constraints. Evident in all these studies however are the patterns and rhythms in the daily movements of pedestrians. For this study, there is no such limitation on which days of the week are selected, nor is there a constraint of geographical area within the UK. In contrast, this study is limited only by the availability of locations where footfall sensors (which can also be referred to as cameras) exist – although admittedly, this raises the question of overall representation of the results. This study is, consequently, based upon a continuum of hourly footfall counts with some of the locations recording footfall for over 10 years. Footfall counts are inclusive (Mumford et al., 2021), in that they do not exclude those that do not have mobile devices nor is there the added complication of positioning individuals based upon the need to triangulate multiple signals from mobile communication devices (whether Bluetooth, mobile signal or Wi-Fi based) (Traunmueller et al., 2018).

1.2 Footfall Considerations

Therefore, as a measure of activity within place, counting pedestrians is a well-established (URBED, 1994; Monheim, 1998; Hogg et al., 2007; BIS, 2011; Wrigley and Lambiri, 2015; Mumford et al., 2021) means to measure the vibrancy of city and town life (Gehl, 2010; Sulis et al., 2018). The ability to answer the question, *how many* or *how few,* provides the ability to evaluate and compare activity across different days, weeks, years etc (Gehl and Svarre, 2013). However, an assumption of this study is that simply reporting year-on-year, week-on-week or day-to-day scalar values of footfall counts fails to explore footfall's added capacity to measure the heartbeat, the rhythms of towns and cities (Monheim, 1998; Sulis and Manley, 2018; Mumford et al., 2021). With such insights, the suggestion is that these rhythms can support place managers understand the differences and similarities between places and why pedestrian movements change. For example, using a data-driven approach (Kitchin, 2014a) to identify annual footfall patterns, Mumford et al. (2021) identified cluster-based signatures that differentiate towns and cities based upon monthly time-series of pedestrian activity (see Figure 1.1).

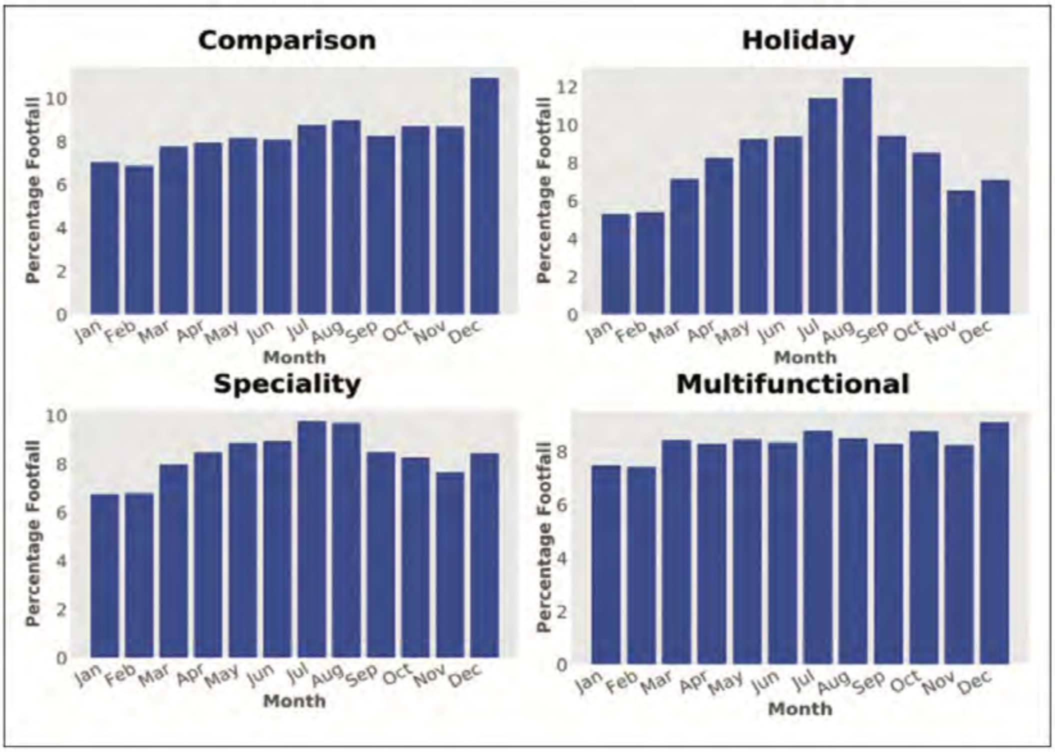


Figure 1.1. Four distinct monthly footfall cluster analysis derived centroids (Source:Mumford et al., 2021:6)

Developing further the footfall patterns discovered by Parker et al. (2016), Mumford et al. (2021) were able to distinguish four principal town signature types based upon the monthly footfall totals (see Figure 1.1). Each signature type is listed below, and offers town managers possible insights as to why pedestrian movements differ between different towns and cities:

- Comparison – driven by a shopper economy with a busy Christmas period
- Holiday – driven by holiday and ‘day-out’ visitors
- Speciality – a mixture of attracting visitors and the local population
- Multifunctional – economy driven and serving regional (larger population size locations) as well as local populations.

This study, as was the case for the study by Mumford et al. (2021), has access to over ten years of footfall data provided by Springboard (www.spring-board.info). Springboard regularly provide reports to the press and subscribing organisations of overall performance around the UK and a common theme in recent years is the decline in footfall numbers. However, rather than use footfall to report statistics such as daily mean changes, year on year change (Springboard, 2020) and benchmark comparisons (https://www.spring-board.info/benchmarks), this study is a continuation of the work done by Mumford et al. (2021). With access to hourly footfall counts, the opportunity exists to identify additional periodic *rhythms*, adding to the insights available to place managers how and why visitors occupy urban space and time.

Places are rhythmic (Brighenti, 2010a; Kärrholm, 2012) as people gather and disperse and so complex patterns are formed from the superimposed set of individual rhythms (Lefebvre, 2004). Places change over time as user behaviour adjusts to macro and micro influences (Parker et al., 2016) and so the rhythms of a place, formed by the processes of territorialisation (Deleuze and Guattari, 1988; Brighenti, 2010a) also evolve over time. Yet, there is little evidence in the literature of footfall data being used to help diagnose and monitor these patterns of change and differentiation over daily, weekly, and annual time periods; thus, a key objective of this study is to determine how footfall can aid the detection of changes in the footfall patterns that reflect how places change over time. As a result, enabling footfall to be a performance measure that can identify external influences on a place as well as internal forces e.g., weekly markets etc. (De Nisco et al., 2008). This study therefore continues the work of Mumford et al. (2021), breaking the data down further into daily and weekly patterns, and not just annual signatures. The expectation is that by analysing different time periods, the more dynamic nature of places can be captured and those signatures that change slowly over time and those that are more transient can be identified (Dolega et al., 2021).

1.3 Research Questions

Therefore, thinking of places in terms of social activity rhythms incorporating the daily, weekly, and annual patterns of pedestrian movement, the analysis of the data should allow the following questions to be answered:

1. As a performance measure, what insights can footfall offer to identify how collectively, places change over time?

2. What can footfall offer as a measurement of how change occurs over time in a particular place?

3. What use might place managers make of such footfall information to facilitate and improve decision making?

1.4 Research Objectives

Consequently, the research objectives for this study are:

1. To review and synthesise the existing literature within areas relating to place and place management (i.e., human geography, economics, marketing, retail, town management and urban planning), the everyday experience of place (i.e., phenomenology, lifeworlds and assemblage theory) and performance measurement and management (PMM).

2. Create an analytical framework for exploring the hourly footfall data supplied by Springboard (www.spring-board.info) at 500+ footfall remote sensor locations throughout the UK.

3. Identify the assemblages of everyday rhythms and periodic (annual, weekly, and daily) processes of territorialisation evident within the footfall data. This objective answers the first two research questions.

4. Evaluate how this information can provide insights for town centre managers for ongoing performance evaluation and assess the implications for strategic decision-making processes in a place context. This objective answers the third research question.

At this point, it should be noted that this study is subject to the following limitations:

1. The location of the footfall sensors and data processes needed to generate the hourly footfall totals were all outside the control of this study.

2. This is not a study of statistical and mathematical methods, rather it employs freely available resources for the analysis phase. No underlying change to the code base of each function is made.

3. The impact of COVID-19 upon city and town centres has become a recent focus (High Street Task Force, 2021; Institute of Place Management, 2021) but this study predates the pandemic period. However, the means of evaluating the footfall data used by this study is considered to be suitable for the assessment of the pre, during and (hopefully) post COVID-19 period to determine how rhythms have changed and places evolved after the period of the pandemic.

1.5 Thesis Structure

This study was an opportunity to explore the Springboard footfall data to find additional town signatures at different periodicities, and thus is a logical progression of the previous research of Mumford et al. (2021). Additionally, there was also the opportunity to contribute to place management decision making and explore how footfall can be more effectively used as a performance measure. Hence, the initial objective for the study was to identify a theoretical framework that could further guide the analysis phase of this study and subsequently help influence place management decision-making.

Place management is multi-faceted, as the identification of two hundred and more factors that influence the management of towns and places by Ntounis and Parker (2017) suggests. Similarly, Ntounis (2018) finds that place management knowledge is derived from a plurality of disciplines (Tomalin, 1997; Jackson, 2001; Otsuka and Reeve, 2007; De Nisco et al., 2008; Peel et al., 2009; Warnaby, 2009; Coca-Stefaniak et al., 2010; Friedmann, 2010; Parker et al., 2014; Thrift, 2014; Cresswell, 2015; Håkansson et al., 2017) and is characterised by a complex relation between theory and practice. Ntounis (2018) argues that no single paradigm or research programme is capable of fully addressing the relational complexity of place management and that multiple theoretical lenses can be used to inform research, theory, and practice.

Recognising these complexities, the literature review that follows is a synthesis of different disciplinary approaches to find a suitable theoretical lens through which the aims of this study can be achieved. Overall, the perspectives highlighted below are mostly based upon human geography but also incorporate economics, marketing, and sociology. At the start of this study, despite access to the footfall data, no a priori theoretical position existed so the subsequent chapters (2 and 3) represent a logical way of framing the theory discovery (retroductive) phase. A starting point for this study was an early view of the 201 factors, eventually published in Ntounis and Parker (2017) that can impact town centre vitality and viability and their levels of influence, either at the macro level (political and economic), meso level (a high street) and micro-level (the customer). This notion of levels of influence is used as a structural framework for this literature review.

The literature review comprises two chapters. Chapter 2 begins by exploring a broad view of different theoretical perspectives of place in terms of how they relate to footfall. The chapter sections are structured to provide macro and micro theoretical perspectives and as such, constitute what could be termed a ‘’traditional’ way of considering footfall. That is, looking at macro influences such as regional retail centre attractiveness (Dolega et al., 2016) or micro influences such as market day rhythms of people activities (Seamon and Nordin, 1980) and the consequential impact upon footfall. The first section thus considers the spatial and macro influences of economics, politics, and culture. The second reviews the temporal and micro influences upon the individual from the perspectives of time-geography, phenomenology and everyday life, non-representative theory, and time-space. The final section looks to synthesise the macro and micro views, focusing on the concepts of rhythmanalysis, territorology and assemblage theory to form a meso-level perspective that better matches the nature of the footfall data. Chapter 3 reviews place classification schemes as a means of understanding place before assessing the performance measurement and management literature at a general level and more specifically for town management. Related research is discussed and the performance measurement and theoretical considerations from Chapter 2 are drawn together. Finally, a conceptual model for footfall analysis is proposed. By considering how footfall data is gathered and analysed, with no means to index individuals, this suggests footfall presents a meso-level view of collective individual movements. This contribution provides a new perspective of using territorialisation (Brighenti, 2010a) and assemblage theory (DeLanda, 2016) for analysing the footfall data.

The subsequent chapters of the thesis, follow a more traditional form of scientific reporting and are:

- **Research Design** (Chapter 4) – where the thinking behind the research design for this study is discussed and the processes identified that were required for operationalisation.

- **Results – combined sensor rhythms** based upon annual, daily, and weekly signatures extracted from the footfall data. These results are reported as individual chapters (Chapters 5 to 7) and aim to provide answers to research questions 1 and 3.

- **Results – exemplar location rhythms** where two specific locations, Manchester (Chapter 8) and Rotherham (Chapter 9) are selected to answer research questions 2 and 3.

- **Discussion** (Chapter 10) – where the results are discussed in relation to the overall objectives of the study.

- **Conclusion** (Chapter 11) – the findings of the study are summarised, study limitations identified, the contribution of the study outlined and possible avenues for further research are suggested.

Due to the technical nature of this study, the Appendices that follow the Discussion provide additional technical details that are important but not considered an essential part of the narrative of the study.

1.6 Motivations behind the research

The nascent stage of this research happened by chance whilst attending an MSc internet marketing course at Manchester Metropolitan University (Dargan, 2015). Professor Cathy Parker was delivering a series of lectures about strategy in business, the last module of courses before the final dissertation. Her enthusiasm for places and place management was contagious and whilst thinking of dissertation topics, I approached her to see if there was anything feasible that could be researched in the timescales of a MSc dissertation. My luck was that Professor Parker had a spreadsheet of monthly footfall data provided by Springboard for several locations around the UK and needed someone to investigate. Instinctively, after several years of validating meteorological data at the UK Met Office (Bromley et al., 1994), the first step to this investigation was to visualise the data and plot out the time-series - as is common practice (Chatfield, 2003; McLeod et al., 2012). The resulting annual patterns identified led to this opportunity to study for a PhD using the footfall data. Eventually, from this initial discovery came the idea that town classifications could be based upon annual footfall signatures (Mumford et al., 2021).

Following on from the initial investigation, the opportunity to study further the footfall data was offered and accepted. At the time, ‘fortunately’, it was thought (by myself) that the study would be a quantitative study mapping to the footfall data, some of the 200+ factors that influence the high street identified by Parker and Ntounis (2015) to create a conceptualised model predicting footfall traffic. So, with this naivety, the opportunity to pursue the PhD was accepted. Thoughts of theory regarding rhythmanalysis, assemblages, territorology etc, did not exist. At least, not in identifiable terms. An unpinning reason why this opportunity was accepted was the desire to remain in the world of research and academia (having just completed a MSc), and the sense that something worthwhile for the place management of towns and cities was achievable.

2 Literature Review

The literature review comprises three sections. Sections 2.1 and 2.2 explore a broad range of different theoretical perspectives of urban places in terms of how they relate to footfall. The sections are structured to provide macro and micro theoretical perspectives and as such, constitute what could be termed a 'traditional' way of considering footfall; that is, looking at macro influences such as regional retail centre attractiveness (Dolega et al., 2016) or micro influences such as market day rhythms of people's activities (Seamon and Nordin, 1980) and the consequential impact upon footfall. Section 2.3 aims to synthesise the macro and micro views to form a meso-level perspective that arguably better reflects the nature of the footfall data.

2.1 Economics, Politics and Culture – a Macro View

Section 2.1 considers the differential and interwoven influences of economics, politics and culture upon town centres as presented conceptually in Figure 2.1. The purpose is to review the different theoretical macro, or top-down, perspectives and how they relate to town and city centres, to build a theoretical perspective that supports the analysis of the footfall data.

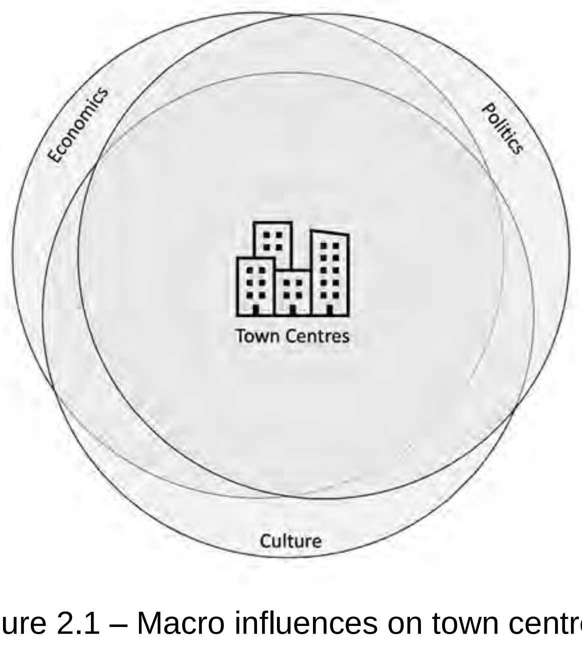


Figure 2.1 – Macro influences on town centres

2.1.1 Economics

Town centres form the core of many urban areas and are characterised by the agglomeration of various socio-economic activities, with retail and related services often being pivotal. Town centres are constantly evolving complex economic systems (Thurstain-Goodwin and Unwin, 2000) and their composition and spatial extent can expand or contract over time. This evolution is linked to land and property values, the distribution of shops, shopping centres and retailers, changing levels of accessibility, technology changes, customer shopping behaviours and other forces of change such as economic shock(s) (Clarke et al., 1997; Singleton et al., 2016; Pavlis et al., 2018).

Historically, an early perspective comes from economics and the spatial economic forces that at the macro level, were posited to explain urban form (Fujita et al., 2001; Dawson, 2013). The quantitatively oriented studies underpinning this perspective were based on neo-classical economic theory following assumptions of equilibrium based modelling and rational choice theory, such as the of supply of production, land-values (von Thünen, 1826), and distance (Christaller, 1933), to produce normative models of urban form (Fujita et al., 2001). Such models, for example, Weber (1909), looked at the location of industry with respect to urban agglomerations, whereas Burgess (1925) and Hoyt (1939) assessed the impact of transport infrastructure and how this distorted urban zoning radiating out from the city (Parker et al., 2016). These early macro theories attempted to conceptualise space and the identification of land-use patterns in geometric space (Merriman, 2012).

Central Place Theory (Christaller, 1933) is a deductive economic model of the spatial distribution and size of places (Merriman, 2012). The Christaller (1933) model assumed the rational behaviour of individuals and assigned thresholds of cost to the purchase of goods. Thus, for any particular good, the distance shoppers were willing to travel to obtain it defined the outer limit of its catchment area. Beyond a certain distance, the shopper might not purchase from the same location or not purchase at all. Consequently, ‘high order’ centres provided all the goods and services to a particular catchment area, whereas ‘lower order’ centres provided what is needed locally (Berry, 1967). Dennis et al. (2002) note that economic modelling based on these assumptions results in catchment hinterlands of interlocking and overlapping areas creating a scalar hierarchy of city, towns, and villages (see Figure 2.2).

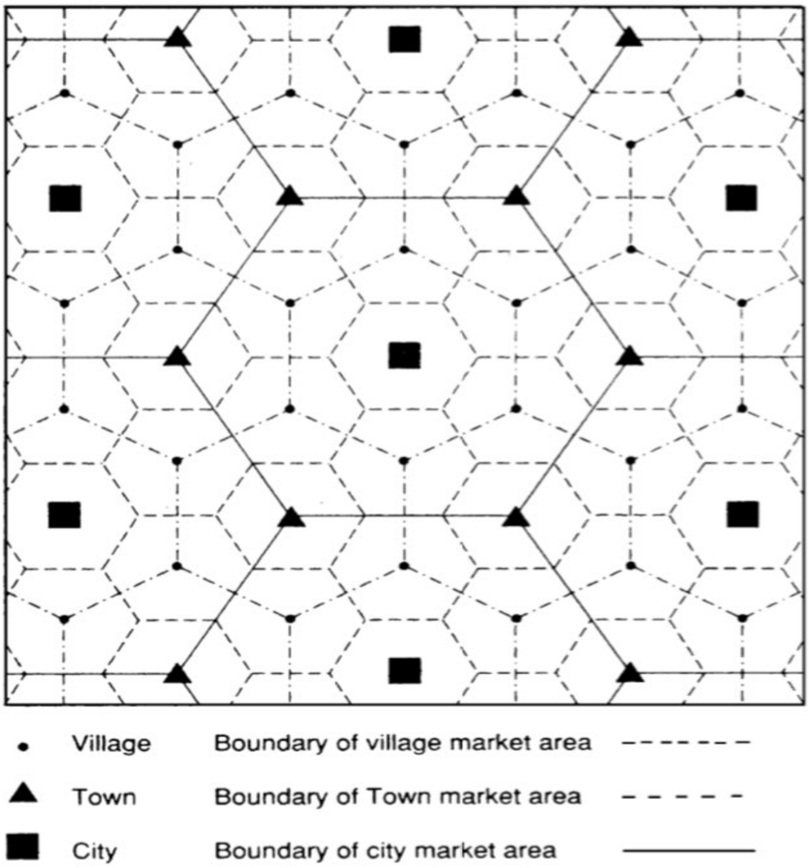


Figure 2.2. Central place theory hierarchy based upon theoretical demand areas (Source:Dennis et al., 2002:187)

Central Place Theory, although a seminal framework, suffers from limitations (Dawson, 2013). In particular, it did not account for characteristics such as technological developments, product diversity, transport, and product availability, all of which impact the choice of destination (Guy, 1998). However, Borchert (1998) demonstrated that the Central Place Theory model nevertheless adequately described the functional differentiation of urban retailing centres in the Netherlands. Despite criticisms, central place theory and the notion of a hierarchy of urban centres has had a major impact upon urban planning (Borchert, 1998; Dennis et al., 2002). For example, in the UK, Figure 2.3 shows that the idea of ranking of places by size and function is evident.

Figure 2.3 - UK Retail Hierarchy (Source: Wrigley and Lambiri, 2015:14)

While Central Place Theory seeks to explain the spatial distribution of towns and cities, urban places can also be characterised by the notion of attractiveness (or agglomeration) involving the gravitational pull of people into interlocking, high-density, nodal blocks of land use (Storper and Scott, 2016). Here, ‘people’ can be considered as heterogeneous groups of residents, tourists, visitors, consumers, and employees (Teller and Elms, 2012). This ‘pull’ factor, and how we choose between different urban locations, is an indicator of place attraction (Pal and Sanders, 1997). Place attractiveness is therefore a driver of footfall where the trade area of towns (Huff, 1964; De Beule et al., 2014), the forces of agglomeration (Hotelling, 1929; Reilly, 1931), the distance of travel (and therefore time) (Christaller, 1933; Timmermans et al., 1992) and the co-location of retailers (and consequential reduced effort of comparison) explains why similar types of retailers’ agglomerate (Hotelling, 1929; Eppli and Benjamin, 1994). Such agglomeration enables comparison shopping (i.e., the comparison of price, style, quality etc. of similar products across different stores) by the consumer (Copeland, 1923), the combination of shopping trips (Bacon, 1995), and trip optimisation for both consumer and suppliers (Ghosh, 1984).

Studying the behaviour of shoppers (Parlin and Youker, 1913; Ward, 2010; Schwarzkopf, 2016), helped develop the notion of distinguishing between the purchase of *convenience* (e.g., groceries) and *comparison* products (e.g., clothing, electrical and household goods) (Thompson, 1967). Parlin's (1914) study introduced the idea that retail activity in places can be convenience and/or comparison-based and that comparison shopping was limited to a few larger cities. The underlying assumption here is, if time is short, convenience drives location choice; whereas without any pressure on time, shopping can be more leisurely, providing greater opportunities to compare goods and prices between different outlets (Clarke et al., 1997). Hence, there is a relationship between the type of shopping and distance, where to purchase convenience products such as groceries, distance (proximity) is important whereas for other activities such as entertainment, distance is less of a consideration (Van Leeuwen, 2010) – as assumed by Christaller (1933). Footfall is therefore influenced by the composition of high street functions, the blend of convenience and comparison retail, leisure facilities, places of work, tourism (Philp et al., 2021) and the distance people are prepared to travel (Clarke et al., 1997).

Traditionally, shops were located in the centre of cities and towns; close to the market where consumers and producers met (Van Leeuwen, 2010). Hence, the spatial distribution of centres in Central Place Theory corresponds to the ideas of a trading area competitive equilibrium suggested by Huff (1964), where each place has a catchment area of potential customers (and therefore footfall) for specific products and services. This notion of trading areas and customer catchment areas began to incorporate the impact of transport infrastructure, population movements and the diversity of demand caused by differences in customer affluence and mix (Applebaum, 1965; Rosenbloom, 1976). Consequently, Central Place Theory, with a combination of range and threshold factors simulating customer catchment areas (footfall) was developed to include complex consumer patterns and retailer behaviour, incorporating changes in mobility – principally the car, mass transportation systems and the investment of capital into retail etc. (Eppli and Benjamin, 1994).

With increased mobility, rising consumerism, and a shortage of accessibility of many city centres, retailers started to develop their businesses at the urban fringe, or out-of-town (Van Leeuwen, 2010) and the focus of place attractiveness shifted from the town centre to include these new forms of retail (Carmona, 2021), thereby displacing footfall from in-town to edge-of-town or out-of-town sites (Parker et al., 2017). These stores aim at car-based customers, and the demand for convenience resulted in the abandonment of the traditional High Street as prime location for grocery shopping (de Kervenoael et al., 2006). This process of decentralisation by food-stores was followed by comparison purchases such as furniture and electrical goods (based in retail warehouses) and subsequently, the regional shopping centre, including clothing and other quality comparison goods and services that were the traditional focus of town centres (Schiller, 1988) – and therefore had a detrimental impact upon town centre footfall. Indeed, the general high levels of wealth in Southern Britain and a rising housing market, plus a car-based society, aided the powerful position of the large out-of-town superstore (Wrigley and Lambiri, 2015). Conversely however, for the poor, and an ageing and immobile population, the decline of independent food and grocery retailers within town centres resulted in reduced levels of choice and convenience (de Kervenoael et al., 2006).

Mobility and the reasons for population movements are also linked to place attractiveness. For example, mobility is related to daytime resident movements (to and from work, for example), night-time economies, tourism from abroad or from other regions in the UK (Dolega et al., 2016). This is highlighted by Newing et al. (2013) when looking at leisure-oriented seasonal demand in the Southwest of the UK and the underestimation of demand from summer visitors by retail spatial interaction models. Hence Newing et al. (2015) highlight the need for better understanding of the elasticity of demand, especially from non-residential demand (Birkin et al., 2010), as identified by Van Leeuwen (2010), concluding that non-residential demand from schools, universities, workplaces, and leisure activities were considerable drivers of sales, and therefore footfall.

Information technology and internet retailing have also helped to displace consumers' focus away from town centres (de Kervenoael et al., 2006). The rise of internet retailing and the ability to comparison shop online, has substituted the need for place-based comparison shopping (Weltevreden, 2007, 2014). Accelerated by the economic crisis of 2008, significant and complex shifts in consumer behaviour have taken place in the UK, where consumers adjusted to -

and increasingly embraced - online shopping (Wrigley and Brookes, 2014), providing customers with convenience and value for money (Jackson and Stoel, 2011). Additionally, since the 2008 economic crisis, UK shoppers have adapted their behaviours, either through choice or necessity, and sought convenience at the local/neighbourhood level, balancing household demands against supply in a more 'just-in-time' approach (Wrigley and Brookes, 2014) where lower order day to day items such as food, groceries, fuel and basic services, such as accountancy and banking are purchased locally (Wayland et al., 2003; Freathy and Calderwood, 2013). At the same time, population mobility and the locus of work versus residence has enabled working populations to have a considerable influence upon footfall and retail performance (Berry et al., 2016). Moreover, other factors affect the attractiveness of town centres, since economic crisises, rising rents, demographic changes, and competition from out-of-town shopping locations also play a major role (Weltevreden, 2014). For town centres, there is the notion that their place-based differentiation will allow traditional shopping streets to adapt and survive (Wrigley and Lambiri, 2015; Carmona, 2021). By contrast, out-of-town, which is much closer in type and function to online shopping, could suffer more severely in the ongoing evolution of retail (Carmona, 2021).

Economic theories (e.g., Central Place Theory) (Rigby, 2007) aim to model customer behaviour and competition through the development of spatial mathematics - the result is a spatial geometric approach (Cresswell, 2015). Quantitative economic measurements such as employment and population can be correlated to the scale of place (Bettencourt and Lobo, 2016). Population size is linked to the scale and degree of retail diversity (Hallsworth and Coca-Stefaniak, 2018) - the greater the population the greater the diversity in retail and in recent years, the lower the probability in retail decline (Delage et al., 2020). Retail complexity and the impact of technology can also be associated with the percentage of inhabitants working in their own municipality, population growth, the role of mobility with respect to external employment rates and employment clusters (Delage et al., 2020), thus, indicating that the macro influence of economics acts across all scales of place, therefore impacting the attractiveness and consequently footfall of individual (local) places. However, these economic factors need to recognise the additional macro dimensions of political and cultural complexity (Merriman, 2012), which are discussed in more detail below.

2.1.2 Politics

The spatial unevenness and typological differences between centre/periphery, rural/urban, metropolis/colony, North/South, or East/West cannot be captured through spatial economic models alone (Schmid et al., 2017). A more differentiated, spatial view of urbanisation is required, rather than a reduction to universal principles or mechanisms that cannot explain the diversity and richness of the urban domain (Schmid et al., 2017). Harvey (1996) argues one of the reasons for this is the impact of political-economic factors such as the increased mobility of production, capital, marketing, and the need for places to complete. For Harvey, following a Marxist framework to analyse the ways capitalism uses and produces space (Gregory, 2009), place is a form of fixed capital which exists in tension with other forms of more mobile capital. This tension between the fixed and mobile results in place investment cycles and disinvestment (resulting from political decisions), causing an unstable process of uneven development across the globe (Cresswell, 2015). Hence, politics and economics cannot be viewed separately, and Marx's economic conception of capitalism has been a dominant line of thought (Gregory, 2009) - a view that, instead of looking at economics as a spatial science based upon maintained equilibriums, views the world based upon dialectical thinking (Ollman, 2003) which emphasises oppositional processes, flows and relations, and that the temporary resolution of these contradictions brings about perpetual transformation of systems and structures.

Following Marx, Ducatel and Blomley (1990) theorised the flows and transformational effects of capital in retail which had significant impacts upon consumption and sites of consumption (and thus footfall) (Wrigley and Lowe, 1996): for example, the rise of out-of-town shopping - the decentralisation of retail activity away from town centres as characterised by Schiller (1988); and the internet, with the increasing role of home as a site of consumption (Wrigley and Lowe, 2014). This idea of the flow and uneven distribution of capital can also be identified in terms of the shifting landscape of political governance and the political-economic positionality of cities (Peck and Tickell, 1995; Peck, 2017).

For the UK high street, individual towns and cities have been differentially impacted by the varying degrees of control exercised by UK planning and political policy. Policy deregulation such as the outlawing of retail price maintenance (Parker et al., 2017) and the waves of retail decentralisation from town centre locations from the 1960s onwards, as characterised by Schiller (1988), were facilitated from 1979, by a government administration that considered planning control an impediment to economic growth, favouring development, enterprise and employment generation (Warnaby and Man Yip, 2005). Eventually, the surge in out-of-centre superstores, retail parks, regional shopping centres and retail warehouses development during the 1980s and early 1990s had several negative consequences for town centres, especially for the sales performance (and footfall) of middle order and smaller centres such as market towns and district centres (Wrigley and Lambiri, 2015). By the mid-1990s, these effects had prompted - and had begun to be reflected in - growing cross-party political support for a tightening of retail planning policy which would offer significantly greater protection for town centres (Wrigley and Lambiri, 2015).

Hence, a shift towards a ‘town centre first’ approach was first introduced with Planning Policy Guidance Note 6 (PPG6) in 1996 prioritising existing centres over out-of-town locations (DoE, 1996), and subsequent revisions including the National Planning Policy Framework of 2012, which not only focused on retail planning provision but also services (Wrigley and Lambiri, 2015). In terms of policy impact, there was a time lag of ten years before various consequences could be identified, one of which was the re-formatting among major grocery multiples to local high-street convenience stores (Bennison et al., 2010; Astbury and Thurstain-Goodwin, 2014). Evidence also suggests that this ‘town centre first’ policy appeared to save British town centres from the ‘hollowing out’ processes characterising US downtown areas (Astbury and Thurstain-Goodwin, 2014; Wrigley and Lambiri, 2015), and thereby helped maintain town centre pedestrian flows.

Whereas PPG6 was a national level policy, at the local level, town centre management (TCM) schemes were implemented in the UK from the 1990s onwards (Cotterill et al., 2019) to maintain and develop both the public and private interests in town centres (Warnaby et al., 1998). However, these early TCM schemes were limited owing to their voluntary participation and unreliable funding (Cotterill et al., 2019); hence subsequent UK Government legislation provided by the Local Government Act 2003 and the Localism Bill (DCLG, 2011) was created to facilitate the decentralisation of power (although not resources) from a centralised authority towards local people and communities (Hall, 2011). This included the creation Business Improvement Districts (BIDs) (Department for Communities and Local Government, 2015) in the Local Government Act 2003 which aimed to improve and consolidate funding and governance of town centre management initiatives.

More recently, there has been an attempt to return to a more ‘laissez faire’ approach to governance with the conversion of redundant retail and office space to residential use without the need for planning permission (MHCLG, 2021). This policy attempted to reflect – although hopefully not at the expense of damaging the quality of community life and diminishing the overall attractiveness of some towns (Kelsey and Kenny, 2021) - a growing consensus for the need to rethink the nature of town centres as places for activities other than retail (see Wrigley and Lambiri, 2015; Grimsey, 2018). This reflects the idea of places being more experiential (Coca-Stefaniak and Carroll, 2015), where town centre footfall is driven by social activities other than retail and shopping, such as meeting friends or eating out (Gehl, 2010).

For the UK high street, these policies – impacting at both national and local level - reflect the latest manifestation of ongoing change and evolution of governance since the 1960s. When combined with dwindling disposable incomes, increasing business rates for businesses (Wrigley and Lambiri, 2015; Grimsey, 2018), and more recently the impact of COVID-19 (Cresswell, 2020; Carmona, 2021), such changes impact the vitality and viability of town centres, and hence footfall. The political-economy can be viewed acting as a macro-level force field (Fujita et al., 2001; Verhoef and Nijkamp, 2008) where the spatial influence is unevenly realised by places and urban form, and therefore by people. Thus, although economics and politics can be considered macro influences, spatially, their influence upon footfall also exists at the meso (towns and communities) and micro levels (individuals).

2.1.3 Culture

Early cultural geography, according to (Creswell, 2013), was focused upon the ranking, description and classifying of cultural regions (areas) and the analysis of the ways in which cultural groups impacted and changed their habitats (Hartshorne, 1959). This focus on the macro view of cultural representations was eventually challenged (Gregory, 2009), with Relph (1976) identifying the need to distinguish between place and individual human experience as well as the concepts of region and area - although Creswell (2013) notes that the term ‘place’ as a description of locations where particular functions and populations were concentrated, was already being used in Central Place theory.

Thinking of place as somewhere to perceive and experience (Tuan, 1974; Relph, 1976; Tuan, 1977) provided different ways of understanding place. For example, the works of Jacobs (1961) and Gehl (2010, 2011) focused on human experience and culture of a place. With the dramatic increase in car traffic and the urban planning ideology of modernism and functionalism, the separation of uses of the city, emphasising free-standing buildings at the expense of urban space and city life, resulted in lifeless cities devoid of people (Jacobs, 1961; Gehl, 2010). For Gehl (2010), this concern for the human culture and experience of place has prompted a drive for better urban quality through liveliness, safety, sustainability, and health improvements.

Escobar (2001) viewed place as composed of place-based social structures and cultural practices (the result of habitual cultural and social practices, for example differences between the cultures of South America vs Asia), yet people are not only “local” but also linked to extralocal places through networks, as suggested by Castells (2010). This resonates with Massey’s (2005) relational view of ‘local vs global’, where local can be viewed as the product of the global, whilst a local place - New York, for example - can also be an agent of globalisation, whereas a country such as Chad has very little influence. This relational dispersion between global and local varies between different social groups (Massey, 2005), as people produce cultural artefacts at all scales (clothing, buildings, graffiti etc.) and patterns that identify the social, economic, and political dynamics of culture and place. The values, beliefs, languages and use of language, meanings and practices all make up people's 'ways of life' so identifying cultural meaning is complicated and contentious (Anderson et al., 2003).

With the development of different perspectives, geographers focused attention on the individual or individualised inhabitant (see Section 2.2) and focused on the role of people, events, and environments in spatial-temporal situations to help map behavioural spaces in ways useful to planning and urban research (Merriman, 2012). For this to happen, qualitative methods of enquiry (Creswell, 2013) were employed, to engage with the feelings and experiences of people. In the following examples, a broad cultural context for the individual apprehension/perception of towns and cities is provided. Focusing on the cultural aspects of consumption has provided further understanding of spaces of consumption, the process of consumption, commodity chains and exchange relations (Crewe, 2000, 2003). The role of gender (Massey, 1995; Crewe, 2001), street image and reputation (Hart et al., 2013), ethnicity and street markets (Hall, 2011; Hallsworth et al., 2015), convenience (Clulow and Reimers, 2009; Reimers and Clulow, 2009), heritage (Whitehead et al., 2006), the impact of out-shopping and in-migration into towns (Powe and Hart, 2009), tourism attraction (Richards, 2010), accessibility (Arranz-López et al., 2019), social interaction patterns (Askarizad and Safari, 2020) , festivals (Hawkins and Lee-Anne, 2013), sociable streets (Mehta, 2007, 2013) and urban design (De Nisco and Warnaby, 2014) have added much to our understanding of places and how consumers of those spaces interact and are attracted to them.

Of these, with respect to footfall of town centres, the culture of convenience is perhaps the most important (Carmona, 2021) especially as retail has always been about convenience (Wrigley and Brookes, 2014). Convenience is linked with the valuation of time spent by individuals and households and the judgement to invest time in the shopping process. Hence, alongside the rise of car ownership, the trade-off of consumer time for lower prices facilitated the shift from small counter grocery stores in the 1950's in the UK to self-service stores from the 1960's onwards, catalysing the development of out-of-town supermarket stores and shopping malls (Wrigley and Brookes, 2014). More recently, for those with digital resources, online shopping enables convenience at every stage - access, search, evaluation, transaction and post-purchase possession (Carmona, 2021).

Consequently, internet platforms, shopping malls and out-of-town retail parks represent a challenge to the traditional high street since they are curated to optimise the convenience of the shopping experience (Carmona, 2021). At the same time however, in the UK there has been a shift towards 'top-up' shopping, with an emphasis on more frequent visits to a greater number of local stores, and the shift to such a culture is strengthened by businesses supplying either a choice-edited neighbourhood version of the range and quality of the out-of-town offer, or alternatively something specialist and/or rooted in the local community (Wrigley et al., 2012; Wrigley and Brookes, 2014). Thus, in order to attract town centre visitors, many centres are well positioned for top-up shopping but need to achieve a balance between multiple and independent retailers, leisure offers such as cafes and bars which helps position a town centre itself alongside online shopping, not in direct competition with it (Wrigley and Brookes, 2014).

2.1.4 Section Summary

This review of macro-level issues suggests that economics, politics, and culture exist as a combination of macro influences. However, although economic theory provides for the spatial modelling of a geometric concept of place, the reality is that politics and culture are equally present and generate a more differentiated, non-equilibrium based, societal and contested perspective; hence why in Figure 2.1, all three circles are presented as overlapping and why, in Section 2.2 that follows, economics, politics and culture are considered as contributing influences overall. Whilst the macro view often prioritises space (Merriman, 2012), it also fails to consider quality and the needs of individual people and places (Relph, 1976). Hence, in the following section, the theoretical perspective switches from the macro view to the micro view, namely that of the individual, encapsulated by a more qualitative perspective.

2.2 The Individual and Everyday Life - a Micro View

> *"Everyday life is a life lived on the level of surging affects, impacts suffered or barely avoided. It takes everything we have. But it also spawns a series of little somethings dreamed up in the course of things." (Stewart, 2007:9)*

Just as Tuan (1977) was committed to understanding place through the experience of individual human experience and not as a spatial abstraction, so Relph (1976) was aligned to the philosophical thinking of phenomenology (developed by Franz Brentano and Edmund Husserl) and the everyday and mundane fact of our knowing where to enact out life (Cresswell, 2015). Whereas Figure 2.1 and Section 2.1 were focused on some of the top-down macro perspectives of towns and cities, this section approaches 'place' from the opposite direction taking a bottom-up or micro perspective.

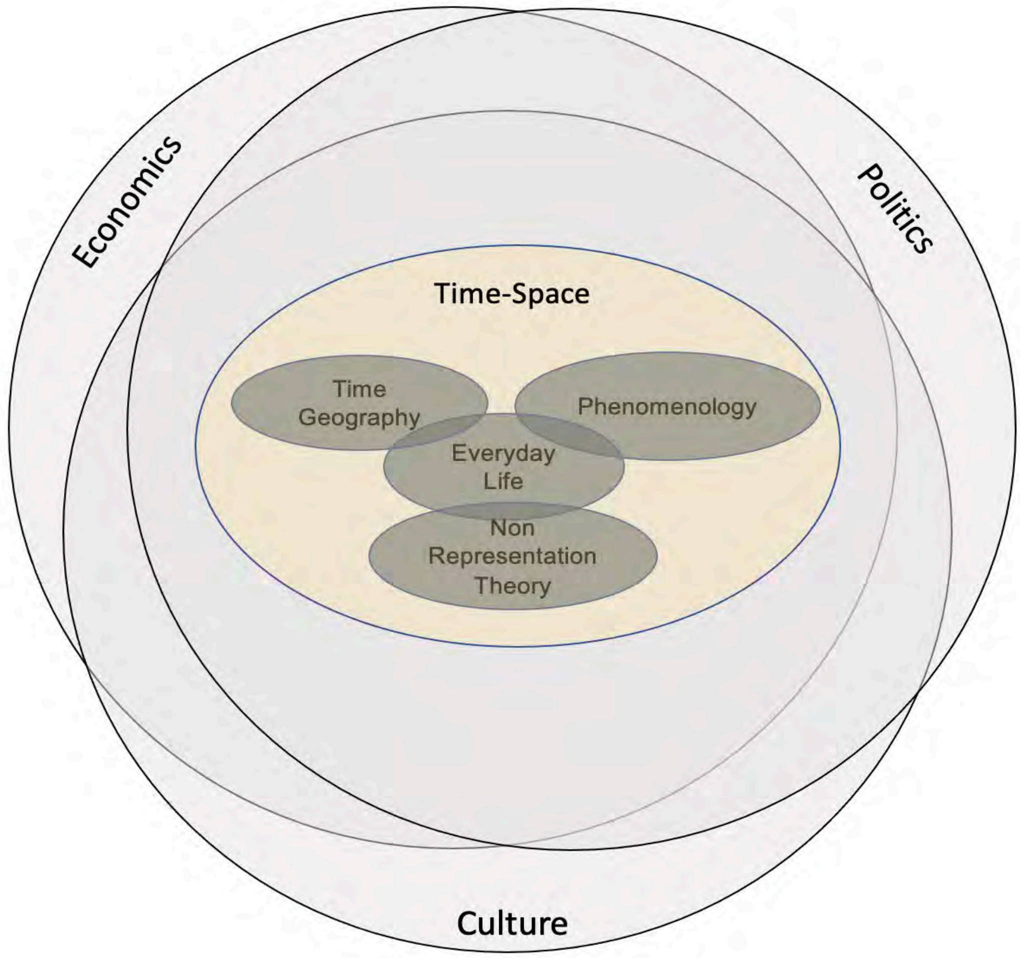


Figure 2.4 – Incorporating micro influences

The next section (see Figure 2.4 above) focuses upon time-geography, phenomenology, lifeworlds and body-ballets as highlighted by Pred (1977); Lewicka (2011); Simonsen (2012); Seamon (2015) as providing an opportunity to better understand empirically, differences and similarities between places from an individual, or micro perspective.

2.2.1 Time-geography

Time-geography was conceptualised by Hägerstrand (1970) as a philosophy that aimed to address how individuals and movements of individuals were analysed (Thrift and Pred, 1981). Time-geography involves a detailed awareness of basic time-demography of the biographies of not only people and families, but also animals, institutions, and all other man-made and natural objects (Thrift and Pred, 1981). For Persson and Ellegård (2012), time-geography is a theoretical approach built on how relationships are created between things and individual people in time and space and on the resources claimed.

Time-geography, at one level of analysis, deals with the time-space choreography of individual existence at daily, yearly or lifetime scales of observation (Pred, 1977). For Hägerstrand (1970), time and space were viewed as inseparable and specifically, an individual’s existence could be diagrammatically described as a trajectory, a daily life-path of movement weaving a dance through time-space (Pred, 1977). An element of time-geography is therefore an effort to capture in diagrammatic form the time-paths of everyday lives (McCormack, 2013). The diagram therefore becomes a technique for drawing out, abstracting these paths and is a technique for describing and notating the dynamic constitution of the trajectories of everyday life (Hägerstrand, 1970).

Apart from the mapping of everyday time-paths, Pred (1977) adds that at a second level of analysis, time-geography considers the physical existence of society within any specified bounded area. This bounded area enables everything within it to be treated as a space-time flow of organisms and artefacts where the logical unit of analysis is the individual (Parkes and Thrift, 1980). The choreographed details of the population-system are revealed by observing and analysing the ceaseless matching processes, or pairing-up ballet, that is played out between the population and activity systems of that area with activities such as employment, shopping being the most significant (Pred, 1977).

Thrift and Pred (1981) employed time-geography to study the social and cultural characteristics of a local area not only as a story of local continuity, but also the connections between micro-level interactions and wider social processes. The local being the arena within which the macro categories of social science such as class were transformed by proximity into everyday activities and contacts, or projects. The political, economic, and cultural processes of history were not simply passively received by a local area, they are transformed by it into local forms of hegemony, custom and social reproduction in general, and feedback into these processes in a constant dialectical interaction (Thrift and Pred, 1981).

In early studies (Lenntorp, 1974; Mårtensson, 1974), there was a focus on planning and development issues. Time-geography was viewed as an important tool at ensuring social processes and planning tools were consistent with goals, and, as a method, it helped to understand the people and relationships that a policy implementation aimed to both affect, and be affected by (Pred, 1977). Rekindling an interest in time-geography (Persson and Ellegård, 2012), Kwan (2002) employed the use of GIS methods to construct the space-time paths of African-American women in Portland, Oregon. In a study of the movement trajectories of 10000 mobile phone users over a six-month period, González et al. (2008) found that humans follow simple reproducible patterns despite diversity of travel history. Liu et al. (2012) investigating taxi trips in Shanghai, found the daily rhythms to contain a strong signature and a stable seven-day pattern. From a study based in Rio de Janeiro, Netto et al. (2015) aimed to map networks of movement to identify mobility patterns and the relationship to income levels. Findings suggested that those of low-income displayed higher degrees of localism, those of middle and higher incomes had a more diverse personal network. Continuing their studies in Rio de Janeiro, Netto et al. (2018) suggested that communication and connectivity between people are highly dependent on how encounters are generated as a function of distance, density, and mobility.

Yet, time-geography as an abstraction, the erasure of lived, bodily and emotional experiences (Ingold, 2007) has drawn criticism (McCormack, 2013). Merriman (2012) argues that Hägerstrand was primarily concerned with tracing, notating and visualising individual and collective trajectories or space-time paths, space-temporal constraints on individual paths and spatial-temporal patterns of socialisation. Thus, subjective experiences and lives of Hägerstrand's individuals were frequently reduced to visual representations of trajectories in an abstracted diagrammatic space-time continuum. As (Merriman, 2012) notes, Giddens in Gregory (1984) criticised Hägerstrand for the underdevelopment of agency, the weak contribution from theory of power, a focus on the constraining aspects of structures and for reinforcing the action/structure dualism. Other criticisms were made by feminists, for example Rose (1993), looking at the difference through conceiving space and agency (McCormack, 2013).

Crang (2001) highlights that time-geography often ended up dealing with the measurable and the evident, and consequently, the mappable. Yet, as Crang (2001) adds, from this mapping of the banal, comes something of the ballet of lines of motion. The sense of rhythm and repetition that connects with ideas of routinisation and the suggestion of the relationship between societal pressures and individual life (Crang, 2001). For the time-geography examples provided above, all failed to consider the more qualitative aspects of individual movements, but this is arguably due to how time-geography has been employed, rather than a weakness in the philosophy (Thrift and Pred, 1981).

Influenced by Hägerstrand's ideas of time-geography, Buttimer (1976) aimed to create a dialogue between the phenomenological approach to human geography and the concern for the relation of subjective perception and cognition to lived experience and the meaning of the everyday landscape upon which existence is set. To achieve this, it meant examining the interplay, for both human individuals and local or regional society as a whole, between deep-rooted time-geographical routines and, ideas, values and symbols such as institutions; natural rhythms; or seasonal and biological rhythms (Pred, 1977).

Reflecting upon the footfall data available for this study, a key factor in relation to time-geography is the lack of track trajectories as the unit of analysis is not at the individual level. All that is available is an aggregated scalar value, the number of people, no different to the measurement of changes in tide height by a tide gauge, with no reference to directional vectors. So, tracking individuals, as time-geography requires, is unachievable. However, as time-geography also suggests, that does not prevent thinking of movement at the aggregate, or meso level, and identifying those routines, rhythms practiced by society.

2.2.2 Lifeworlds and Phenomenology

Relph (1976) used the comparison of place with space to remove the need for place to also mean location. For example, a ship, or a gypsy camp, are both self-contained places but are mobile. Relph (1976) developed this theme to suggest that location is therefore not a sufficient condition of place and that although characteristics of places, sense of community, time can all be identified, none of these are enough to explain the deeper importance of place to human existence and experience (Cresswell, 2015); hence why Relph (1976) looked towards phenomenology to understand the significance of place to human "being" (Cresswell, 2015:36).

Phenomenology focuses upon human experience in the world (Seamon, 2018). The phenomenology lifeworld is the taken for granted patterns and context of everyday life through which the person routinely conducts their existence without making it an object of conscious attention (Buttimer, 1976; Seamon, 1979). Like Relph (1976), Buttimer (1976) explored the lack of ideas that social science had to explain the human experience of nature, space, and time. Following on from Heidigger (1971)'s notion of dwelling, Buttimer (1976) turned to phenomenology as it challenged many of the premises and procedures of positivist science, critiquing reductionism, rationality and the separation of subjects and objects in empirical research. The aim being to understand lived experience with a more humanistic orientation, requiring more concrete descriptions of time and space and their meanings in everyday life (Buttimer, 1976). Thus, for Buttimer (1976), the notion of rhythm arises, where everyday behaviour demonstrates a quest for order, predictability, and routine as well as a quest for adventure and change (Buttimer, 1976).

Seamon (1979) developed the lifeworld of Buttimer (1976) into the notion of place-ballet comparing it to the contemporary street scene described by Jacobs (1961). For Seamon (1979), there was a need to focus on people's day to day experiences and behaviours associated with places, spaces, and environments. Such a search would identify certain basic patterns which epitomise human behaviour and experiential relationships with the everyday human world. Thus, Lewicka (2011) asks the question, what was the underlying structure of everyday environmental experience, the movements, and social exchanges (Seamon, 1980)? Did it encompass certain basic characteristics which extend beyond individuals, place, and time (Seamon, 1979)? What are the processes through space-time routines that are formed, and which conditions must be fulfilled to make them successful (Lewicka, 2011)?

Just as Lefebvre (2004) observed, from a window in Paris, the rhythms of a street, Seamon and Nordin (1980) observed the place ballets that took place in an outdoor market in Varberg, a Swedish coastal town south of Gothenburg. The more general rhythms of setting up the market, the main body ballets of selling and buying followed by cleaning up and packing things away were readily observable. The study revealed that the market is an important event, not just as a means of exchange but also added interest, enjoyment, and human interaction to people's lives. It was a key element in the town's sense of community and place and gave a sense of continuity (Seamon and Nordin, 1980).

The focus on the visible and observable however has attracted criticism of the phenomenological approach. Both Rose (2006) and Wylie (2009) provide critiques emphasising the notion of experienced presences created through imagination and memories. Rose (2006) suggests that we should not start an analysis of landscape from the position of what can be seen (as is required by taking a phenomenological approach), but rather, the landscape is a presence whose object-like appearance needs to be thought. During a visit to Mullion Cove in Cornwall in the UK, Wylie (2009) identifies with not just the visible landscape, but also a landscape of absence and love marked by memorial benches. Wylie (2009) adds the presence of absence into the landscape and notes that studies of landscape and lifeworlds as described by Seamon (1979) based upon phenomenological or non-representative idioms may be felt to neglect or underplay both contested historicities and the highly differential nature of experience of different cultural and social groups (Wylie, 2009). Wylie (2009)'s aim was to highlight a tendency within forms of landscape phenomenology to place too much value upon *presence.*

In the 20th century, Habermas (1987) notes that lifeworld became the world of everyday communicative interaction (Harrington, 2006). However, how the lifeworld is considered when there is a virtualised world of near-ubiquitous digitised information is a more recent question Harrington (2006). Thrift (2011) considers the need for a new thinking that adapts to the information age which, as in previous information ages, is a transformation, most particularly in the production of space, brought about though new practices or organising, analysing, displaying, storing, and communicating information. For example, the everyday experience of a town centre is complicated by changes in communication technologies. There is the increase of substitution effects by online shopping on retail property in town centres (Verhoef et al., 2007; Weltevreden, 2007; Weltevreden and Von Rietbergen, 2007), the ability to compare products and retailers online (Herhausen et al., 2015), the impact of internet retailers such as Amazon and multichannel retailing (Doherty and Ellis-Chadwick, 2006; Blázquez, 2014; Verhoef et al., 2015) and the focus on multichannel customer experiences (Verhoef et al., 2009; Herhausen et al., 2015; Elms et al., 2016). Thus, the intermingling of the virtualised lifeworld is as relevant as that which is visible.

As well as the virtualised world, the idea of a *security-entertainment complex* is proposed by Thrift (2011) where activity tracking and information targeting through various technologies, provide views of the world that are naturally experimental. Thrift (2011) suggests that for the social sciences, there is a need for new ways to explore (probe) the *security-entertainment* data now available to discover and investigate new behaviours and assemblages. Through the use of data now captured for state security and a knowing capitalism, Thrift (2011) identifies an

Empirical Turn, where the very ubiquity of data allows for new vocabularies and experimentations with Lifeworld Inc. One of these *knowing capitalism* forms of data, as Thrift (2011:20) suggests, ‘a kind of instant phenomenology’, is footfall, providing the potential to capture general patterns of human interaction within towns and cities.

2.2.3 Everyday Life and Walking

Echoing the work of Buttimer (1976) and Seamon (1979), De Certeau (1984) writes that the examination of everyday practices does not imply a return to individuality. As a unit of analysis, the individual has been the basis from which groups are formed and to which, such groups are reducible. However, analysis shows that each individual is a locus in which an incoherent (and often contradictory) plurality of relational determinations interact (De Certeau, 1984); the implication of this being that as footfall is a count of one or more people, attempting to attribute the behaviours of the individual from the aggregated data, is theoretically difficult.

Stewart (2007) views the everyday as a shifting assemblage of practices and practical knowledges, the things that happen as impulses, sensations, expectations, daydreams, encounters, and habits. There are the public feelings that begin and end in broad circulation, but from which intimate lives are made. There is not a single static plane of analysis, nor easy means to representation of knowledge (Stewart, 2007). Likewise for Edensor (2010) everyday life is constituted out of a multitude of habits, schedules and routines that lend to it an ontological predictability and security. Once learned and followed, these habitual procedures become unreflective, are part of the way things are, though if the rhythm of the day is disrupted, and routines are thwarted, discomfort of ensures. The rhythmic structuring of the day is not merely individual but collective and relies upon the synchronisation of the practices that become part of how “we get things done”. Thus, Edensor (2010) agrees with the unit of analysis considerations of De Certeau (1984) that from the everyday assemblages of individual practice, collective rhythms can be identified.

Examples in the literature include Southerton (2009), who notes that institutionally timed events have changed over history and are no longer as fixed within the temporal rhythms of daily life. The stability of habits and routines can be tested by disruptions which test the elasticity of everyday life (Trentmann, 2009) and so a question of daily rhythms is how much alteration can be withstood and how much resilience (Amin, 2013; Martin and Sunley, 2015; Meerow et al., 2016; Singleton et al., 2016) or adaptability (Dobson, 2016) exists? O'Dell (2009) focused on commuting activity and found that the commute home from work is an emotionally 'lighter' trip than the morning commute. The morning commute was characterised by people getting ready for work, reading papers, working on laptops, consuming coffee ready for the hours ahead, whereas the evening commute featured unbuttoned collars and loosened ties (O'Dell, 2009:92). The suggestion by O'Dell (2009) being that commuting is an important corridor for ritualised processes of identity transformation. For footfall analysis, this suggested that differences might exist between morning and evening patterns in the data.

Within the theme of everyday life, De Certeau (1984) identifies walkers as the practitioners of the city. In the first half of the nineteenth century, the *flâneur*, a figure of masculine privilege and leisure, with time and money and no immediate responsibilities, was a figure who understood the city (Paris) by memorising it with his feet (Elkin, 2016). Only later would '*flâneusing*' become more acceptable for women (Elkin, 2016). The most popular mode of travel in cities is walking and therefore when seeking to make cities more agreeable, more environmentally friendly, and to improve the quality of life, the inclusion of walking habits is crucial (Gehl, 2010, 2011; Kang et al., 2018).

Contrasting different modes of travel, Ingold (2007) compares wayfaring (walking) and transport. Like the line that goes out for a walk, the path of the wayfarer wends hither and thither, and may even pause before moving on. But it has no beginning or end. While on the trail, the wayfarer is always somewhere, but every somewhere is somewhere on the way to somewhere else. Transport, by contrast, is tied to specific locations. Every move serves the purpose of relocating persons and their effects and is orientated to a specific destination. The traveller who departs from one location and arrives at another is, in-between, nowhere at all. The lines of transport form a network of point-to-point connections (Ingold, 2007).

Borrowing the idea of a meshwork from Lefebvre (1991), Ingold (2007) distinguishes between trails and routes (or networks) where a meshwork forms interwoven trails rather than trails of intersecting routes - the lines of the meshwork are the trails along which life is lived. It is the entanglement of lines, not in the connecting of points that the mesh is constituted. Since straight lines can be specified by numerical values, it becomes an index of quantitative value rather than qualitative knowledge (Ingold, 2007). Thus, the point is made that in many cases, our view of place can be likened to that made by De Certeau, whereby looking down on the city (or through statistical analysis), the daily behaviours and practices (walking, talking, reading, moving about, shopping, cooking etc) are made invisible (De Certeau, 1984). Gehl (2010) notes that the act of walking, although linear, ultimately brings the walker from place to place, but also involves stopping, changes of direction, manoeuvring, speeding up and down, or switching to a different activity such as standing, sitting, etc. Walking in the city can be goal orientated, a stroll, a walk to get fresh air, for exercise or an errand. Regardless of the purpose, walking in the city is a 'forum' for social activities, a beginning or occasion for many activities.

Walking can be fast or slow, a short distance or many kilometres - a distance of half a kilometre is supported by the size of many city centres, even those that are divided up into many centres and districts such as London. Room is a prerequisite factor for a comfortable and pleasurable walk and one hundred years ago, pedestrians in photographs are often shown moving freely and unimpeded in every direction. With the addition of the car, pedestrians have increasingly been squeezed onto pavements and crossing the road has become controlled and restricted (Gehl, 2010). In California in the 1960s, the pedestrian was viewed as the largest single obstacle to free traffic movement hence pedestrian crossing were removed (Solnit, 2001). Obstacles such as bus stops, lampposts, rubbish bins, cars parked on pavements, access to petrol stations all act as interruptions to the walker. Crowds, waiting at pedestrian crossings all cause areas of congestion for other pedestrians, steps, and stairs, are problematic and impede access for segments of society. Visual appeal at eye level or higher (Warnaby, 2009) is important, as is the walking surface material and so on. All impact the experience and pleasure of walking in cities and towns (Gehl, 2010).

Of course, walking is not the only mode by which a city or town can be traversed, bicycles, buses, and cars etc can also be used (Warnaby, 2019). However, Warnaby and Parker (2017:204) argue that such means of “assisted” movement through urban space introduce (to a greater or lesser degree) a barrier between person and environment, and that slower modes of movement such as walking “offer greater opportunity for reward through unanticipated discovery” (Warnaby, 2019:184).

Walking is about being outside, in public space, and public space is also being abandoned and eroded in older cities, eclipsed by technologies and services that no longer require leaving home (Solnit, 2001). Jacobs (1961) mentions that a street is kept safe by the number of people going by and at the same time, and Gehl (2010) points out how the car has led to a deterioration in the pedestrian experience and safety. Walking maintains the publicness and viability of public space (Solnit, 2001). As part of the everyday life of towns and cities, walking and walkability are therefore key components of place vitality (Jacobs, 1961; Solnit, 2001; Gehl, 2010). The presence of pedestrians in towns and cities, whether ambling, walking with purpose or standing still, perform everyday activities that collectively form identifiable rhythms such as the morning or evening commute (O’Dell, 2009). This collective presence of people is a measure of place vitality (Jacobs, 1961; Gehl, 2011) yet the walkable areas of places are subjected to many influences. For example, vitality is impacted by technology, which can reduce the need to be in towns and cities (Solnit, 2001), the walkability of towns and cities has had to contend with the car and the privatisation of public space, reducing walkable urban space (Gehl, 2010). This then suggests that footfall, viewed as a key performance measure of place vitality (URBED, 1994, 1997) can also provide insights into the everyday life of places and how collective everyday activities change over time (De Certeau, 1984).

2.2.4 Representation vs Non-Representation Theory

Non-representation theory (NRT) (Thrift, 2008) emerged through a need to expand the focus of cultural geography from one with a focus on interpretation and representation at the level of signification to one that emphasises events and practices (Gregory, 2009; Cresswell, 2015). By focusing on how we do things, Thrift (2008) argued we get a primal relationship with the world that is more embodied and less abstract; for example, understanding place as an embodied relationship with the world and therefore are constructed by people doing things and in this sense are never “finished” but constantly being performed (Cresswell, 2015).

Thrift (2008) considers NRT to be ongoing everyday life, a *material schematism* where the world is made up of all kinds of things brought into relation with one another by many and various spaces through a continuous and largely involuntary process of encounter (Thrift, 2008). NRT concentrates upon practices understood as material bodies of work or styles that have gained enough stability over time but are continually being rewritten as unusual circumstances arise and new bodies continually make an entrance (reflecting the ideas of Deleuze and Guattari (1988) of emergence and the refrain). Likewise, NRT also recognises the importance of things but also their mutability across different time scales. NRT is experimental, and stresses affect and sensation. For example, the memories of buildings and landscapes which intertwine with our bodies and provide a kind of poetics of space consisting of rhythms of the everyday, everydayness and everyday life (Seigworth, 2000), in which matter turns into a sensed-sensing energy with multiple centres, some of which stabilise, emerge, or mutate (Thrift, 2008).

Human life is based on and in movement (e.g., walking), the lived immediacy of actual experience (Thrift, 2008) within the sheer complexity of everyday life and place (Thrift, 1999). In NRT, Thrift (2008) therefore looks to configure geographical thought as it configures life, "*as a series of infinite 'ands' which add to the world rather than extract stable representations from it*" (Cadman, 2009:1). The infinite 'ands' omitted or hidden by representation include emotions, passions, and desires, and immaterial matters of spirit, belief, and faithful forces that move beyond our familiar world. None of these are inconsequential as they shape and drive our meaningful relation with the world (Dewsbury, 2003).

Important to NRT thinking has been the influence of actor network theory (ANT) (Latour, 2005) and the argument for non-human agency/actancy. In addition, the move from a definitive sense of subject or self, to one of "subjectivity" suggesting something more provisional, emergent, and potentially open to change (Simpson, 2017). Thus, our subjectivity, our sense of self in relation to a whole host of social and material situations, formations, and processes, is something that emerges over space and time (Simpson, 2017).

From the side of representational theory comes the belief in the representational structure as being able to give an account of everything; and from the side of nonrepresentational theory the understanding of the danger of an absolute critique of representations (Dewsbury, 2003). Dewsbury (2003) argues that the representational system, its structure, and regulation of meaning, is not complete as it needs constant maintenance, loyalty, and faith from those who practice it. In this regard, its power is in its pragmatic functions: easy communication of ideas (that restricts their potential extension), and sustainable, defensible, and consensual agreement on understanding (a certain kind of understanding, and hence a certain type of knowledge) (Dewsbury, 2003). In contrast, the nonrepresentational argument comes into its own in asking us to revisit the performative space of representation in a manner that is more attuned to its fragile constitution. The former maintains existing ideological markers whilst the latter challenges us to invent new ones (Dewsbury, 2003).

Thus, Dewsbury (2003) concludes that nonrepresentational theory is needed to 'excavate the empty space' between the lines of representational meaning to see what is also possible. The representational system is not wrong: rather, it is the belief that it offers complete understanding and that only it offers any sensible understanding at all that is critically flawed (Dewsbury, 2003). Thus, it can be said that NRT is not anti-representational nor is it seeking to supplant representationalist lines of inquiry (Hill et al., 2014). As Dewsbury (2003) notes, as gaps exist in the representation of our understandings, there are also many uncharted, or perhaps forgotten, cartographies for orientating our appreciation of the world in which we find ourselves. Modestly, we should not forget that the task of the researcher, the academic, and the philosopher is one that only arrives at a partial apprehension of the `eventhood' of the world.

So, in analysing the footfall data, which is an experiential measure (to a degree), a representational view of the world is likely to be identified. Thus, to ensure that the non-representative elements of place are accounted for, assuming that in-depth place specific understanding of causes of footfall are required, this suggests that footfall data and the representative analyses produced should also be supplemented by more specific investigations, for example like those suggested by Gehl and Svarre (2013) and case study examples such as Wunderlich (2008) and Kärrholm (2016).

2.2.5 Time-Space

In considering the everyday practices of people, through activities such as walking, there is a need to recognise that the practices being tracked and trailed are far from stable in time and space. Hence it is important to appraise the changing composition of everyday life (Shove, 2009).

In urban studies, cities can be conceived as being clusters of `spatial events', events that take place in time and space, where the event is characterised by its duration, intensity, volatility, and location. There may be interactions in time and space between events, leading to clusters and other aggregations, but the dominant way in which these descriptions are characterised is clearly temporal. The duration of an event marks how long it lasts, so `trip making' is usually measured in terms of minutes and hours, whereas `living at a residential location' is usually structured around months and years. The intensity of an event measures the impact it has at any time and place; this in turn might be indexed somehow by the numbers of persons involved in comparison with others existing at that time and place as well as the degree to which they are solely focused on a single activity (Batty, 2002).

From a philosophical perspective regarding space, Massey (2005) critiques the idea that there is a relationship between the spatial and the fixation of meaning. Representation, for example via conceptualisation, can be conceived as spatialisation although usually this is framed through a spatialisation of time, so it is space that tames the temporal (Massey, 2005). However, Massey (2005) challenges this thinking through the works of Bergson (1910, 1911) and Deleuze (1988) to move away from a focus on discrete entities and magnitudes to one where there exists a continuum of being, driven by intensities where newness and creativity is the essential characteristic of temporality. The aim being to identify the impossibility of reducing real movement/becoming to stasis multiplied by infinity and, the '*impossibility*' of deriving history from a succession of slices through time (Massey, 2005:22). Of course, this then becomes a challenge for epistemology to find a way of assessing the intensities and emergence of such continuums. For example, Soja (1986) constructs and deconstructs the landscapes and histories of Los Angeles noting the difficulties of reducing space into a localised geometry that also accounts for, for example, the history of industrial production. Mandelbrot (1967) notes the difficulties of scale in terms of measuring the length of the U.K. coastline, the greater the level of detail, the more length approaches infinity. Likewise, by using hourly counts, the footfall analysis for this study shows greater sensitivity to short time scales of 24 hours than over the period of a year. This reflects findings of Carlin and Dempster (1989) whilst investigating seasonal patterns in meteorological data.

Schatzki (2009) identifies various social theorists who have analysed space-time (Parkes and Thrift, 1980; Giddens, 1984; Harvey, 1996; Lefebvre, 2004). For Schatzki (2009), this is the thesis that interwoven activity time-spaces form a kind of infrastructure through which human activities coordinate and aggregate. Since coordinated and aggregated activities are essential to society, this infrastructure is fundamental to social life. Schatzki (2009) identifies time-space as a feature of an individual life. However, it is a social feature of an individual life, where much of it derives from and depends on social phenomena. So, time-spaces of different lives substantially depend on the same social phenomena, namely *social practices*. Thus, the time-spaces of different lives are partly the same, partly different. (Schatzki, 2009). This reflects the idea of an index to distinguish the different social practices as suggested by Batty (2002) and suggests that patterns identified in footfall also provide a measure of these convergent social practices - a consideration justified since the temporal and spatial properties of a practice include the rhythms, sequences, and periodicities of its constituent actions as well as geometric distribution of the locations where these actions are performed (Schatzki, 2009). Both Schatzki (2009) and Massey (2005) suggest the continual emergence of place and by considering the interwoven timescales and ensuring complexities, requires us to confront the challenge of multiplicity (Massey, 2005). Both suggest the idea of relational rhythms, which pulse at different beats and for Massey (2005), this is another aspect of the elusiveness of place which renders politics so difficult.

Other writers concerned with time and space include Lefebvre (1991), with more an emphasis on space than time, Harvey (1996) outlines the importance of absolute, relative, and relational space with respect to social justice. Harvey also explores the processes of time-space compression (Harvey, 1990) but in all cases, grounds human life in an *a priori* realm of spacetime (Merriman, 2012). This leads Merriman (2012) to discuss the idea of movement-space (Thrift, 2004), a world where affective forces, atmospheres and rhythms exist as found in non-Western cultures such as Australian Aboriginal cultures where the world is apprehended in non-Euclidian ways and lived through rhythms that emerge from the land, body, movement, memory, experience, and encounter (Manning, 2009; Merriman, 2012). Thus Merriman (2012) identifies a world where we are increasingly part of a movement-space, which is relative, not absolute (Thrift, 2004). Merriman (2012) also notes that processes of time and space provide important aspects for the unfolding of events and the ontologies of particular social assemblages.

For this study, the temporal and spatial nature of the data suggest that both are relevant to the chosen epistemological approach. Yet, the thought remains that patterns identified in the footfall could represent different movement spaces which can be switched on and off by circumstance, for example, the impact of COVID-19 upon the daily commute. Additionally, the consideration that the footfall data can provide a measure of the meso-level aggregations of social practice Schatzki (2009), suggests a unit of analysis of collective social activities.

2.2.6 Section Summary

Section 2.1 focused on the differentiated influences of economics, politics, and culture, at the macro and micro levels and in particular, their contribution to understanding of spatial distributions of place. This section focused on the micro-level, the individual, the literatures of phenomenology, lifeworlds and everyday life and a more focused consideration of temporality. Issues identified included how day to day rhythms of social activity emerge from the collective actions of individuals (Schatzki, 2009). In addition, not everything can be represented through conceptual models yet non-representative entities have the capacity to render such models as misrepresentations of reality (Dewsbury, 2003). Finally, when considering how social activity takes place in time and space, more focus could be placed upon relative processes, the movement-space (Merriman, 2012) than simply describing visible patterns (Brighenti, 2016) of footfall in space and time.

Following initial analysis of the footfall data at the start of this study, different periodic rhythms (daily, weekly, and annual) in the data were apparent. Like the annual patterns identified by Mumford et al. (2021), these rhythms are not static, they adjust over time as different periods are analysed. That suggests that the footfall changes identified over time, although viewed as a count based (Gehl and Svarre, 2013) performance measure of overall place vitality (URBED, 1994), also provide an opportunity to identify the aggregated activities (rhythms) (Schatzki, 2009) of social practices. From Thrift (2008) and non-representative theory comes the idea of movement and everyday life being a collection of encounters from which, where there is convergence, practices materialise and stabilise. This reflects the thinking of Deleuze and Guattari (1988) and their ideas of the refrain, milieus, and rhythms and with these the idea of territorology, where territorialisation is viewed as an act of rhythm and, “the territory, and the functions performed within it, are products of territorialisation” (Deleuze and Guattari, 1988:367).

Rhythms of everyday walking/pedestrian activity (De Certeau, 1984; Solnit, 2001) are therefore important to understand how space is territorialised. Thus, in the next section, the ideas of rhythmanalysis (Lefebvre, 2004) are explored, followed by how rhythms then can explain how territory is created through assemblage theory (DeLanda, 2006, 2016) and the theory of territorology (Brighenti, 2010a, 2013). Finally, the footfall data provides an opportunity to analyse place rhythms that represent aggregated social practices (Schatzki, 2009) at each footfall counter location. These aggregated rhythms of social activity represent not the actions of the individual, rather they are the convergences of the everyday practices of many individuals, the irreducible meso-level of everyday (De Certeau, 1984).

2.3 Rhythm, Territorology and Assemblages – a Meso View

> *"The ordinary is a shifting assemblage of practices and practical knowledges, a scene of both liveness and exhaustion, a dream of escape or the simple life. Ordinary affects are the varied, surging capacities to affect and to be affected that give everyday life the quality of a continual motion of relations, scenes, contingencies, and emergences."* (Stewart, 2007:1-2)

The previous section established the need for a theoretical conceptualisation that supported the rhythmic patterns in the footfall data. Further, the patterns identifiable from the footfall analysis could also provide insights into the ebb and flow of social practice at any place.

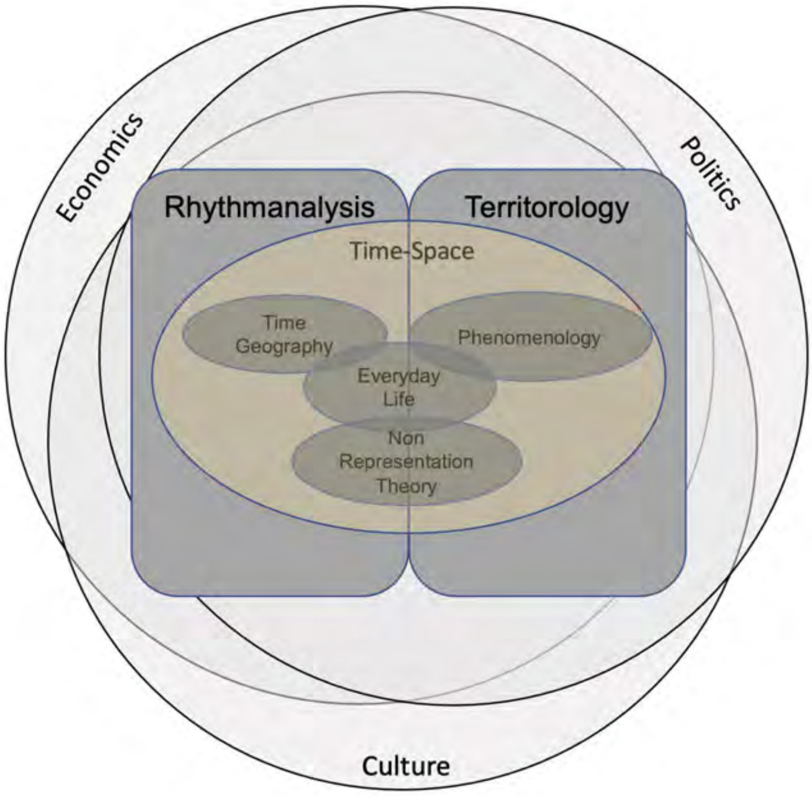


Figure 2.5 – Macro, micro and meso influences discussed in the literature review

As identified in section 2.2, this section is focused on the meso-level where social activities are based upon groups of people and their common everyday rhythms. In Figure 2.5 above, this is represented by the addition of rhythmanalysis and territorology as combining the more micro-level influences based upon the individual but still contextualised by macro influences identified in section 2.1.

Thus, the following sections (see Figure 2.5) explore how movement, rhythms and territory have been discussed in the literature. The section begins with rhythmanalysis, then moves onto territorology, incorporating the ideas of rhythms into territory. Finally, territorology is framed within assemblage theory. The section concludes by arguing that this study can use territorology as an analytical tool to identify assemblages in the footfall data and that at the meso-level, assemblages of social practice can theoretically be identified from the footfall data.

2.3.1 Rhythmanalysis

The idea of using rhythms as an analytical tool to understand the urban landscape has been of particular interest to geographers researching social life (Crang, 2001; Latham and McCormack, 2004; Kärrholm, 2009; Southerton, 2009; Simpson, 2012; Paiva et al., 2017). Edensor (2010:8) writes that everyday life is constituted out of a multitude of habits, schedules and routines that lend to it an ontological predictability and security. Once learned and followed, these habitual procedures become unreflexive, are part of the way things are, though if the rhythm of the day is disrupted, and routines are thwarted, discomfort can ensue. The rhythmic structuring of the day is not merely individual but collective and relies upon the synchronisation of the practices that become part of how “we get things done”. From these rhythmic rituals and habits, places are produced, landscapes and nations recognised although the very familiarity of these rhythms also make them difficult to analyse Edensor (2010).

Kärrholm (2009) researched the synchronisation of retailers and commercial rhythms with everyday urban rhythms and mobilities, arguing that commercial activities and retail areas have become more predominant in urban space, public life increasingly taking place in shops, pedestrian precincts, and shopping malls, not to mention previously uncommercial spaces such as museums, libraries, and airports. This results in new strategies for urban synchronicities through the flows and rhythms that are framed in timespace to bring people and activities together. Shops both create urban rhythms through their opening times which are becoming extended, and through their alignment with other rhythmic activities, such as attending cultural festivals and events, and taking holidays. The suggestion being that in seeking to maximise commercial interests, businesses then reduce the complexity of multiple unrelated (polyrhythmic) place rhythms into isorhythmic, singularly related ones through which other rhythms are orchestrated to coincide with the rhythms of shopping (Kärrholm, 2009).

The urban landscape is a place of heterogeneous temporalities and rhythms and for Kärrholm (2012), these are set by clock time, working hours, seasons, timetables, bodily functions, and so on, leaving places hectic and dense at some times and deserted at others. Synchronisation is proposed by Kärrholm as a strategy of assembling, framing, and coordinating these flows and rhythms in time. The use of rhythms provides the opportunity to analyse the dynamics of how places are always becoming, full of emergent properties, but usually stabilised by regular patterns of flow that possess rhythmic qualities whether steady state, emergent, intermittent, or volatile (Edensor, 2010; Simpson, 2012).

Rhythmanalysis, originally *Éléments de rythmanalyse* (Lefebvre, 1992), and later translated into English (Lefebvre, 2004) provides a starting point to investigate this idea. Note however that although Rhythmanalysis is attributed to Lefebvre (2004), Brighenti and Kärrholm (2018) point out that the use of rhythms to understand subjective situations was originally proposed by Pinheiro Dos Santos in his lost treaty, *A ritmanalise* (1931). Brighenti and Kärrholm (2018) adds that in the 1970s, other contemporary French thinkers such as Georges Perec and Roland Barthes, were also interested in the rhythms of everyday life.

For Lefebvre (2004) everyday life is modelled on abstract, quantitative time, the time of watches and clocks (and today, mobile devices). This everydayness of time, the hours of sleep and waking, mealtime, private life, entertainment, hobbies, work etc results in the perpetual interaction of rhythms with repetitive processes linked to homogeneous time (Lefebvre, 2004). Crang (2001), taking inspiration from the original French version of Lefebvre (1992) to listen to the rhythms of the city, discusses how Lefebvre identifies (although how, is not at all clear) how to discriminate between different cities of Northern and Southern Europe. Not just in terms of tempo, but as an assemblage of different beats that included a multiplicity of rhythms, dominant and quieter, cycles of daily, weekly, annual rhythms that continue to structure the everyday as ‘linear time’.

Lefebvre (2004) suggested that wherever there was interaction between a place, a time and an expenditure of energy, there is rhythm. Therefore, the kinds of rhythms that can be analysed include:

- Repetition (of movements, gestures, actions, situations, differences)
- Interferences of linear processes and cyclical processes
- Birth, growth, peak, then decline and end

Lefebvre (2004) also considered the inter-relationship of multiple rhythms so added the notions of ‘*polyrhythmia’*, ‘*eurhythmia’* and ‘arrhythmia’. In eurhythmia, the rhythms unite with one another in normal everydayness – (Lefebvre used the example of body rhythms such as breathing and heartbeat). Arrhythmia (irregularity or abnormality) was generally a symptom, a cause and effect. An example of which, Simpson (2011) found that by requiring street performers by stick to a timetable (in Bath, UK), performances would suddenly stop after gaining an audience even if another performer was not waiting to perform.

In addition, Lefebvre (2004) considered rhythm perspectives: by crossing the notion of rhythm with those of secret and public, the external and internal. So that rhythms could be:

- Secret Rhythms - first physiological rhythms but also psychological ones (recollection and memory, the said and the unsaid).
- Public (therefore social) rhythms - calendars, fêtes, ceremonies, and celebrations etc.
- Fictional rhythms.
- Dominating-dominated rhythms: everyday or long lasting.

Critiquing his own approach, Lefebvre (2004) defended rhythmanalysis as not being limited to phenomenology. For him, his approach connected space, time and energies of the world that unfolded here and there in space and time, namely as rhythms. Lefebvre (2004) provides, as an example walking down a street, being immersed in the crowd, and experiencing the variety of noises, murmurs, rhythms (including those of the body). Whereas observing the same scene from a window in a building above, Lefebvre notes how the noises distinguish themselves, how one does not chatter when crossing a dangerous junction. For McCormack (2017) (stemming from work by Gaston (2013)), this raises a tension between immersion and distance and is central to how place figures as a concept for geographical thinking. It is also important when considering the capabilities of identifying rhythms from the footfall data, as the granularity and lack of closeness to the individuals being counted, will mean many micro based rhythms remain invisible.

From his window in Paris, Lefebvre (2004) identified the rhythms of schoolchildren, shoppers, tourists as being cyclical of large simple intervals whereas alternating rhythms such as cars, regular customers, employees, bistro clients were more complicated, and the interaction of diverse, repetitive, and different rhythms animated the street. As Simpson (2012) suggests, Lefebvre differentiates linear and cyclical rhythms where:

- Linear rhythms come from social practice and human activity, the monotony of actions and movements, or *imposed* structures.
- The cyclical rhythms originate in *nature*, such as day, night, seasons, and monthly cycles.

For Lefebvre (2004), no camera, no image or series of images could sense and capture the presence of rhythms. The analysis required attentive eyes, ears, a head and a memory and a heart. Thus, Lefebvre notes that for his analysis there is the need to live the recollection of moments, to live through all the diversity which is made up of subjects and objects, subjective states, and objective figures. Additionally, Lefebvre (2004) emphasises the body as being the central reference point of study for the analysis of rhythms.

However, applying Lefebvre's Rhythmanalysis is problematic. How do you actually *do* rhythmanalysis or research rhythm in an empirical and practice-based context (Simpson, 2012)? The emphasis that the rhythm-analyst should be actively using their body as a tool for the research explains Lefebvre’s hostility to the idea of using images. For Lefebvre, images could not capture the quality of rhythms needed to be sensed in relation to the analysts own corporeal rhythms. Yet, Simpson (2012) does observe the rhythms of a street performance using time lapsed photography and is able to pick out the rhythms of the performers, the audience and those not interested. Similarly, by focusing on pedestrians, Paiva et al. (2017) identify changes in pedestrian habitual trajectories during artist performances in Lisbon.

Edensor and Holloway (2008) develop rhythmanalysis to explore the rhythmic qualities of taking a coach tour in the Ring of Kerry in the Republic of Ireland. Central to this work is the ordering of different rhythmic assemblages, which connect and disconnect in multiple ways. What is shown is that rhythmanalysis can capture the emergent regularities of tourist production, consumption, and performance, yet simultaneously allow for other rhythms and arrhythmic experiences that displace strategies aimed at providing a timed, controlled experience.

Sulis and Manley (2018) and Sulis et al. (2018) explore the idea of place and people rhythms to assess place vitality, with reference to Jacobs (1961). Sulis et al. (2018) highlights that Jacobs (1961) considered the trait of vitality to mean the spatiotemporal continuity of human presence and activities in a place. Hence Sulis et al. (2018) explore rhythms and their temporal variations through data exploratory techniques, in terms of intensity and duration of flows that arise from different place activities, to evaluate urban vitality.

So, at the very least, as Edensor (2010) suggests that from the ideas of Lefebvre, we can identify repetition of movements and actions, the blending of linear and cyclical rhythms and phases of growth and decline. Pink (2007) adds that such rhythms shape the diurnal, weekly and annual experience of place and inform the ongoing formation of its materiality. This perspective avoids conception of place as static, for rhythms are essentially dynamic, part of the multiplicity of flows that emanate from, pass through - and centre upon - place, and contribute to its situated dynamics. Those rhythms that emerge from human practices are part of the continuous process of ‘emplaced engagement with the material, sensory, social and cultural contexts in which we dwell’ (Pink, 2007:62). Not only are rhythms continually evolving but also exist at different scales of analysis, from the individual and the micro-level to social entities and the meso-level (Lyon, 2016).

Brighenti and Kärrholm (2018) summarise that society has a rhythmical constitution; rhythms have a non-linear interaction that are not bound by time; a given rhythmic configuration provides a portrait of a specific society; and rhythms become the support of meaning and that of basic regulatory devices. Additionally, rhythms not only intersect with time and space, but they also interweave energy. Rhythms then can be seen as a component, one of many, in the life of territories (Brighenti and Kärrholm, 2018). Thus, Brighenti and Kärrholm (2018) expand rhythmanalytics, into a more complex concept that combines territories and the processes of territorialisation (including rhythms) - which is discussed in the next section.

2.3.2 Territorology

Territorology theory (Brighenti, 2006, 2010a, 2013, 2014; Kärrholm, 2008, 2016; Brighenti and Kärrholm, 2018) aims to incorporate the notion of rhythm into a theoretical framework that enables the integral study of processes of social formation and territorialisation (Brighenti and Kärrholm, 2018).

Kärrholm (2012) focused on the role of architecture in ongoing territorial productions of urban public spaces, particularly in understanding the territorial roles of architecture and in what ways the built environment stabilises or participates in the territorialisation of public space as brought about by retail business and retail spaces. Kärrholm (2012) identifies how Henri Lefebvre (Lefebvre, 1991, 2004) describes the ways in which our bodies and everyday life are saturated and produced by rhythms. For example, Kärrholm (2012) found that retailers attempted to organise and synchronise commercial rhythms with important urban rhythms and the mobilities of everyday life. Conceptualising this through territorialisation, this indicated an increase of specific spatial control, where synchronisation also implied a de- and reterritorialization of space, where new commercial activities were added and coordinated with the existing rhythms of a place (Kärrholm, 2012).

For Kärrholm (2012), synchronisation and territorial stabilisation are related. On the one hand, the synchronisation of retail might also involve a destabilisation of a certain territory, suggesting or temporarily establishing usage that is considered improper from the perspective of a certain territorial regulation or regularity. On the other, synchronisation of steady rhythmic flows of people with the opening hours of shops and malls could also be the beginning of the territorial stabilisation of a certain shopping area such as a pedestrian precinct. Urban territories can be stabilised by material design, laws and regulations, and social behaviour but also by means of synchronisation. By scheduling events such as markets, car-boot sales or festivals to certain places, this synchronisation also plays an important part in territorial production, and therefore also influences territorial complexity (Kärrholm, 2012). Kärrholm (2012) used Brighenti's (2010a) definition of the expression *territorology* where the basic components of a territorology can be described as a non-essential, imagined (not imaginary) expressive and functional phenomenon. Brighenti (2010a) has an approach to view territory as dynamic and as territorial issues that are interesting but rich and diverse, so territory must be seen as an act or a process, rather than an object (Kärrholm, 2012).

Brighenti (2006) identifies that territory is fundamentally to do with functions for both animals and humans, such as defence, control, reproduction, and access to resources. Territory is also imagined, a space that is carved out, excerpted, and circumscribed in view of a set of tasks to carry out. Brighenti (2010a) notes that territory constitutes a convergence of actors who attempt to manage visibilities and invisibilities and reciprocal affections (including, the spread of moods, attitudes, desires, beliefs etc.).

Brighenti (2010a) utilises the appraisal by Sassen (2006) of the state of territory as a complex, heterogeneous composition (an assemblage) including legal, political, and economic dimensions which is analysed using a process-based framework for understanding territoriality. Brighenti (2010a) therefore argues that an inquiry into understanding assemblages is what is required to understand the role of territory and its relation to disciplines like law, political science, and social theory. Brighenti (2010a) suggests that territories should be studied through the processes that constitute them and that this requires a combination of insights and cannot be built positivistically, through the mere accumulation of 'facts', but must emerge, if at all, from the unrestrained trans-disciplinary study of situated problems, as demonstrated by Foucault (2009) and Deleuze and Guattari (1988). So, the discussion of territory needs to account for geographical, behavioural, political, and legal concepts. For Brighenti (2010a), territory exists as a bounded entity. Boundaries are an accepted prerequisite of territory, to the point that the analysis of territories cannot avoid the phenomenon of boundary making. Yet boundaries are not the opposite of flows but the moment when flows become visible (Brighenti, 2010a). So, in this study, footfall sensors are counting pedestrians in a specific bounded area and therefore measure the 'flow' of people that exit the area of measurement. So, the 'flow' is a measure of inter-territory movement, a measure of people walking from an unknown territory to another.

As Brighenti (2010a) discusses, the question whether a street is a territory, or a network depends on the scale at which the street is observed. If it is viewed from a map, then it is a network, as suggested by Ingold (2007), but if it is viewed by walking down the street, it becomes appreciated as a territory. As territories articulate speeds and velocities of entry and exit, they are rhythmic, they determine specific patterns of concentration and dispersal of objects and events. Rhythms are superposed onto each other, so that they modulate with each other, creating complex rhythmic patterns (Lefebvre, 2004), where the rhythms represent ways to cope and articulate intensity in social encounters (Brighenti and Kärrholm, 2018). The stratification of rhythms is also a stratification of modalities. For instance, the rhythms of public transport can become a modulator for private displacements (e.g., employees), which in turn becomes a modulator for other displacements (e.g., customers). Territories are not fixed entities but are instead thoroughly constituted through these rhythms. That is, they are a series of events occurring at different places and times (Brighenti, 2010a).

The foundation Brighenti (2010a) uses for a process-based and eventual perspective of territory is that of Deleuze and Guattari (1988). Deleuze and

Guattari (1988) identify three movements, or vectors, in the territorial process: deterritorialisation, reterritorialization and territorialisation. These processes do not occur temporally one after the other (vectors coexist and affect each other) and Deleuze and Guattari (1988) note that territories are actualised when one leaves them (hence, their description begins with deterritorialisation). It is the moment of exit, which can be due to the most diverse causes which makes a territory visible. However, it is not possible to leave a territory, Deleuze and Guattari (1988) argue, without at the same time creating another territory somewhere else. In other words, one cannot deterritorialise from some relations without concurrently re-territorialising on some others. It is this double movement of deterritorialisation and reterritorialization that evokes the primitive movement of territorialisation, which otherwise tends to be taken for granted, perceived as a degree zero of territory, as non-movement. These three territorial movements proceed together precisely as movements, or directional vectors. In fact, each territory is constantly crossed by de-territorialising tendencies, tendencies that push out of a territorial series towards other series (from intra- to inter-series) (Brighenti, 2010a).

These three movements define the type of relationship that exists between the *territoire*, and the *milieu* it territorialises and the relationship between territory and its world is expressed through a specific rhythm and melody posed by territory (Deleuze and Guattari, 1988; Brighenti, 2010a). The notion of ‘refrain’, which Deleuze and Guattari (1988) define as ‘blocks of becoming’ (Brighenti and Kärrholm, 2018) is the sum of the three territorial movements of de-territorialisation, re-territorisation, and territorialisation. The refrain is the coming together of rhythms and melodies (McCormack, 2013) into a territory. Whenever a territory appears, new functions are created (Deleuze and Guattari, 1988; Brighenti, 2010a).

From this philosophical conception by Brighenti (2010a), some important implications follow. First, territories have constitutions. There are specific constitutions that depend upon the combination of functional and energetic matters assembled into a territorial regime. Second, because they are created by and through refrains, territories enable the fixing of patterns. These are rhythmic patterns; i.e., patterns of difference embedded in series of reputations. Territories are affective as reciprocal and differential capacities of affecting and being affected within a series of territorial operations or between series or lines. These series are linkages, or assemblages and a study of territories should conceptualise assemblages (Brighenti, 2010a).

Thus, footfall provides a quantitative means of measuring these linkages and their associated assemblages from the patterns. Although territory is made up of a plurality of events, movements, and relations, some combine to have enough in common to form rhythmic patterns in pedestrian movements (Sulis et al., 2018; Nemeškal et al., 2020; Mumford et al., 2021). These though are representative accounts and can only provide insight to a point, there are still the non-representative elements unaccounted for, and the invisible (unmeasurable) political, legal, and social contributions. It should be noted that Brighenti (2010a) stresses that insight into territory cannot be built positivistically.

Brighenti (2010a) suggests that a serious consideration of territorial movements requires the recognition that territorology can take as its basis neither individuals nor societies as such. However, that does not mean that territorology is not interested in describing small and large-scale phenomena, but rather that individuals and societies must themselves be described and analysed in terms of territorial relationships, traits, operations, and vectors. Brighenti and Kärrholm (2018) also argue the need to consider the ecological viewpoint. Whereas phenomenology supports the analysis of the absolute local here-and-now, ecology provides the complementary view of global elsewhere-at-other-times view. This is argued by Brighenti and Kärrholm (2018) why when rhythms encounter territories, there are as much phenomenal (imbued with meaning) as ecological (generated by operative relations) processes to understand. In conclusion, Brighenti (2010a) notes territory is a social event and amounts to a sociology of territorial acts, movements, and relations. Hence this suggests a meso-level of analysis using the footfall data, where the everyday rhythms of people can be identified as part of a territorological analysis

Kärrholm (2012) argues that routinisation and socialisation are important ways in which we use different territories that have incorporated behaviours and practices that are not so quickly undone. He follows the actor-network approach (Latour, 2005; Law, 2009) finding that territories are never static, since as soon as new actors and actants are mobilised or old ones disappear, a process of de- or reterritorialization begins. In other words, territories are constantly adapting and evolving. This notion is very evident in the way Deleuze and Guattari (1988) handle the concept when they use musical metaphors and bird song to treat territory as a part of an ongoing process of territorialisation. Every territory has a certain rhythm or territorialising refrain, setting the theme for the coding of a certain space, moment, or artefact (Kärrholm, 2012). What Kärrholm (2012) suggests by incorporating actor-network theory, is a territorology that focuses on traceable behaviours, activities, rhythms, materialities that bring about the territorial effect at a certain place. The territorial strategy therefore needs to be considered and described from the territorial effect, where the intentions behind the territory are of less interest than the actors that stabilise the territory and make it work (Kärrholm, 2012). This suggests then that footfall data can provide one such measure that allows territorial strategies to be judged by analysing the representative rhythms of a territory.

Through Actor Network theory and qualitative research methods, Kärrholm (2016) studied the time-spaces of public life (Simpson, 2008; Wunderlich, 2008; Simpson, 2012) of a central square, Stortorget in Malmö, Sweden. Taking a *territorial perspective*, Kärrholm (2016) aimed to develop the temporal aspects of territorology and therefore the time-space of the ongoing activities and situations of everyday life (Schatzki, 2009). Kärrholm (2016) found that overall, the territorial complexity of the square had decreased due to the increasing dominance and stabilisation of certain kinds of territorial productions (e.g., people walking by, scheduled events) at the cost of others. For Kärrholm (2016) therefore, territorial complexity is an important issue to address, since to some extent it can be seen as a constituent of public space. Public space needs the complexity of territorial productions, as this complexity comes with a proliferation of borders and interstices and opens up the possibility of constant renegotiations. A thought regarding footfall is that with reduced complexity, would the variability of footfall also reduce or, would patterns become more apparent as the number of territorialisation processes are reduced?

Kärrholm (2016) suggests a thorough development of a time–space territorology that might be one way of studying public space use as a complex system, acknowledging that the territorial production of time spaces is never static or independent, but always relational, interdependent, and entangled in transformative processes. Kärrholm and Wirdelöv (2019) adopt a qualitative approach to understand how time spaces are both claimed and produced and how certain activities, groups, rules, and people become associated with and expressed through a specific territory. Kärrholm and Wirdelöv (2019) find that local spaces are becoming more reduced or dispersed where formerly vibrant places such as the local square are losing both services and certain groups or kinds of visitors. They suggest that in today's world, local connections and belonging seem to grow ever more complex as people connect through and shop on the internet, for example, and live their lives in urban regions rather than within the boundaries of a single town or neighbourhood. So Kärrholm and Wirdelöv (2019) suggest that mappings of the territorialisation of local public spaces in relation to a discussion of differences in public space dependency could be one way to illuminate how slow changes, for example through seemingly neutral densification projects, might accumulate problems on a larger scale (Kärrholm and Wirdelöv, 2019). Footfall and in particular, changes to footfall rhythms could provide useful insights for identifying and tracking these changes.

In summary, this current study focuses upon the meso-level as this is the level at which the footfall data is considered to best identify the assemblages of territorialisation. Having introduced the ideas of territorialisation as the framework for analysing the assemblages of social patterns that emerge from the footfall data, the next section discusses Assemblage Theory.

2.3.3 Assemblage Theory

Just as Kärrholm (2016) employed actor-network theory (ANT) (Latour, 2005; Law, 2009) in an investigation of territorialisation within a local square in Sweden, other researchers have referred to *assemblages* (Dewsbury, 2011; Featherstone, 2011; McFarlane, 2011; Dovey, 2012; Dittmer, 2014a; Briassoulis, 2017a; MacFarlane, 2017; Hoffman and Novak, 2018; Bridge, 2020). Both ANT and assemblages have a relational view of the world, in which action results from linking together initially disparate elements. Both emphasise emergence, where the whole is more than the sum of its parts and each underscores the importance of the socio-material, the world made up of associations of human and non-human elements (Müller and Schurr, 2016).

Starting from the mid-1990s, ANT has had a sustained impact in geography (Callon, 1984; Whatmore, 2002; Law, 2009; Bajde, 2013; De Munck, 2016; Hinchliffe et al., 2016; Shilon and Shamir, 2016). ANT sees agency as a distributed achievement, emerging from associations between human and non-human entities (the actor-network). Tracing the processes by which these associations are built, maintained, and severed is at the heart of ANT (Müller and Schurr, 2016). At the same time, engagement with Deleuze and Guattari's work (Deleuze and Guattari, 1988) also started drawing upon the conceptualisations of flux, becoming and process (Massumi, 1996; Müller and Schurr, 2016). Yet, as noted by Müller and Schurr (2016), it would take another 10-15 years before a deeper concern with 'assemblage' (*agencement* in the French original) appeared (see Assemblage Theory (DeLanda, 2006, 2016; DeLanda and Harman, 2017)) with contributions identifying 'assemblage geographies' (Anderson and McFarlane, 2011; Anderson et al., 2012). In some cases, some scholars (Greenhough, 2011) drew no lines of distinction between the two concepts and drew on them interchangeably for the purposes of theorising a dynamic, lively socio-material world (Müller and Schurr, 2016).

As Briassoulis (2017b) highlights, this is not too surprising as both share commonalities with respect to terms such as assemblage, network, emergence, among others, in relational thinking and the Deleuzian philosophy. Both recognise the heterogeneous composition of places, assign actor status to human and nonhuman entities, and stress the processual and nonlinear nature of socio-spatial relations where processes of assembling, disassembling, and reassembling endlessly produce new formations (networks and assemblages, respectively), orders, and scales to serve a purpose (Gale and Botterill, 2005; Müller, 2015; Müller and Schurr, 2016) . Criticisms of ANT include the failure of the concept to sufficiently address the capacities of the environment and space outside of the network (Duffy and Stojanovic, 2017). Müller and Schurr (2016) notes that Thrift (2000) identifies the failure to accommodate the unexpected, its lack of a notion of the event and the neglect of the corporeal capacities of humans - making Thrift turn back to Deleuze. In addition, some authors consider assemblages to have a greater openness to the unexpected (McFarlane, 2011) in contrast to ANT's preference for the fixed and stable (Müller and Schurr, 2016). A major distinction between ANT and assemblages is ANT's preoccupation with the actual in contrast to the virtual in assemblage thinking (Müller and Schurr, 2016).

Briassoulis (2017b) considers the qualitative orientation of ANT to be insufficient to handle the tangible and measurable aspects, the complex nature–society interactions, and the dynamics of social environments. While assemblage theory sanctions methodological pluralism to satisfactorily capture all aspects of reality through the combined use of quantitative and qualitative analytical resources, Müller and Schurr (2016) point out that assemblage thinking provides few concepts for empirical work since it is a philosophical perspective, not an empirical toolbox. Thus, assemblage theory lacks analytical power to identify and define assemblages (Allen, 2011; Buchanan, 2015), whereas ANT does – given that empirical work is at the heart of ANT (Müller and Schurr, 2016).

Kärrholm (2016) approaches territorology using the concepts of ANT and associated qualitative techniques to identify the *in-vivo* interactions of people and architecture. However, since the footfall data is obviously quantitative, this study cannot approach territorialisation using the same conceptual perspective. With no actors or actants as such, actor-network theory cannot be employed so a different conceptual framework is required. Thus, this study has chosen assemblage theory (DeLanda, 2006, 2016). As DeLanda (2016) recognises, any whole at a given scale is composed of smaller molecular parts. So, at any level, assemblages exist as parts of populations, populations of persons, pluralities of communities, collectives of urban centres and it is from the interactions within these populations that larger assemblages emerge as a *statistical result*, arising as collectives of social action (DeLanda, 2016).

Thinking in terms of hierarchical structures is a convenient tool (Fujita et al., 2001) and once hierarchies are assumed, considerations such as globalisation and localism are assigned a spatial register in our imaginations (Marston et al., 2005). Marston et al. (2005:427) adds that “invariably, social practice takes a lower rung on the hierarchy, while 'broader forces', such as the juggernaut of globalisation, are assigned a greater degree of social and territorial significance”. This idea of scale, the idea of macro vs micro is viewed as a problem for social theory as most social entities exist in a wide range of scales (Escobar, 2007). Whether following conventional approaches of micro vs macro or a nested set of levels (like the proverbial Russian doll), identifying the causal mechanisms that account for the whole are problematic (Escobar, 2007). Escobar (2007) adds, agreeing with Marston et al. (2005), that as the processes of assembly through which physical, biological or social entities come into being are recurrent, assemblages can be identified by the repeated occurrence of the same processes which results in more or less stable assemblages (Escobar, 2007). Thus, the patterns that are identifiable from the footfall data, represent meso-level assemblages of social practices at any given location.

Dovey et al. (2018) write that assemblage thinking is primarily developed from the philosophy of Deleuze, particularly his collaboration with Guattari with the book *A Thousand Plateau*s (Deleuze and Guattari, 1988). Assemblage thinking is a practice of looking for relationships more than looking at things; seeking to understand how synergies and flows work. While Deleuze and Guattari made no claim to the status of theory, it has been developed as assemblage theory (DeLanda, 2006, 2016). Dovey et al. (2018) adds that assemblage theory and the concept of assemblages originally developed by Deleuze and Guattari (1988) has been modified and made more comprehensible by DeLanda (2016), influenced by works such as Braudel (1986) (who viewed society as an intertwined assemblage of all different sizes).

DeLanda (2016:9) asks the question of how social entities can be considered as legitimate agents. On the one-hand, human beings as agents can be considered as rational decision makers as assumed by micro-economics whereas on the other, they are phenomenological subjects as assumed by micro-sociology. If however, a social whole is considered, then DeLanda (2016) suggests the following two steps are required for such a concept to be considered. Firstly, a step is required that allows for properties to emerge from the interactions between people and DeLanda (2016) identifies these as *emergent properties*. As these are interactions associated with a group and not individuals, the reduction to aggregates of many rational decision-makers or many phenomenological experiences is not possible. Thus, micro-reductionism is blocked. Secondly, macro-reductionism where the idea that a society fully determines the nature of its members is also blocked by the concept of *relations of exteriority* between parts (DeLanda, 2016:10). Unlike wholes in which parts cannot exist independently of the relations they have with each other (*relations of interiority*), DeLanda (2016) conceives of emergent wholes in which the parts retain their autonomy, so that they can be detached from one whole and plugged into another, entering into new interactions. Thus, despite the convenience of thinking (Fujita et al., 2001) in terms of place hierarchies (DCLG, 2012), the hierarchical structure itself is a macro-reductionism and cannot conceptualise the complexity that exists between places.

DeLanda (2016) then suggests that using both the above concepts of emergence and exteriority, social wholes can be defined as assemblages, like interpersonal networks or institutional organisations that cannot be reduced to the persons that compose them, nor can they be subsumed into a seamless whole in which their individuality is lost. As an example, DeLanda (2016) identifies how the degree of connectivity within a neighbourhood community forms an emergent property that is non-reducible for the entire community. Yet, any individual of that community can move to another area keeping their identity intact (exteriority).

The concept of assemblages as defined by DeLanda (2016) therefore includes the following:

- Assemblages have a fully contingent historical identify, and each of them is therefore an individual entity such as an individual person, community, or city. The ontological status of all assemblages is the same, entities can operate at different scales and interact directly with each other as there is no hierarchical ontology such as genera, species and individuals as defined by Aristotle. In assemblage theory, there are only individuals.

- Assemblages are always composed of heterogenous components. This includes not just people and material objects, but the day-to-day practices of people that take place in well-defined locations.
- Assemblages can become component parts of other assemblages. At any nested level, assemblages exist as part of populations and from the interactions within these populations, larger assemblages emerge.
- Assemblages emerge from the interactions between their parts, but once an assemblage is in place, it immediately starts acting as a source of limitations and opportunities for its components (downward causality).

Not surprisingly, given that the philosophical starting point is Deleuze and Guattari (1988), McCormack (2016) also points out refrains are never complete but instead are the differential pattern emerging through the relations between components. The refrain is the sensed consistency of these components, the distinctive way in which heterogeneous elements are held together as a matter of expression. Some refrains assemble territories, for example a home, where these refrains mark space, drawing lines. McCormack (2016) suggests the refrain does not provide a concept to be applied, but rather it provides a conceptual machine. Although Dovey et al. (2018) suggests assemblage thinking is a practice of looking for relationships more than looking at things, the 'thing' provides the starting point of investigation and is the consistency as identified by McCormack (2016)? So, what is an assemblage?

DeLanda (2016) identifies the following as the parameters needed to build an assemblage. The first quantifies the *degree of territorialisation and deterritorialisation.* Territorialisation refers not only to the determination of spatial boundaries of a whole, such as a community or city, but also the degree to which the parts of assemblages are drawn from a homogenous whole or the degree to which an assemblage homogenises its own components. Thus, the concept of territorialisation provided by DeLanda (2016) includes the territorology of Brighenti (2010a), the concept of territory, the historical and political constructs, and overall social process. DeLanda (2016) examines the notion of territorialisation within human history, language, war, scientific practice, and the virtual world. For example, the territorialisation of routine everyday activities, in the form of repetition of traditional rituals or the systematic performance of regulated activities, stabilises the identify of organisations and gives them a way to reproduce themselves. Technology on the other hand, can destabilise this identity. Transportation and communication technologies can have deterritorialisation affects upon organisations allowing the breakaway from the limitations of spatial location (DeLanda, 2016).

The second parameter (DeLanda, 2016) quantifies an assemblage's *degree of coding and decoding*. Coding refers to the role played by special expressive components in fixing the identity as a whole, for example chromosomes and language. A process which is "coding" will consolidate and increase the rigidity of an assemblage, whereas a process with a "decoding" role will allow for a certain degree of flexibility within the assemblage operations (DeLanda, 2006; Duffy and Stojanovic, 2017). DeLanda (2016) argues that assemblages are characterised by their everyday state defined by properties that are always actual, exist in the here and now. However, he also notes that assemblages also possess dispositions, tendencies and capacities that are virtual (real but not actual) when not being currently manifested or exercised.

In terms of the assemblage parameters, DeLanda (2016) expresses the idea of intensity of processes vs their extensive existence. For example, we can see hurricanes but not the gradients of temperature or pressure responsible for their formation (DeLanda, 2016). The point DeLanda (2016) is making is that all the diversity provided by experience depends on its existence as something that is not phenomenologically given (DeLanda, 2016). This suggests then that intensity of processes within an assemblage is something that can be measured, and that maybe the intensity of territorialisation processes as suggested by DeLanda (2016) can be inferred from the footfall data. Indeed, intensity is also noted by Brighenti (2014) as being required for territorialisation as a '*intensification of a shared (communal) environment'* (Brighenti, 2014:20). Hence, combining intensities with the processes of territorialisation, presents a means of conceptualising changes in footfall counts, across all timescales as displayed below in Figure 2.6. If the processes of territorialisation and deterritorialisation are balanced, then footfall counts remain constant but if either of these processes dominates, then footfall increases or falls as a result.

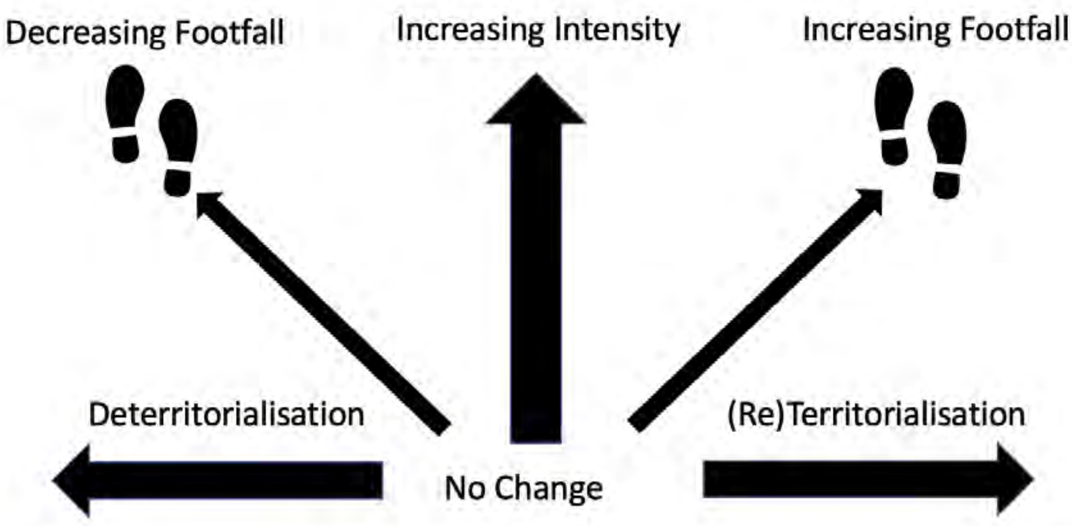


Figure 2.6 - Footfall, Territorialisation, and Intensity

Regarding urban space as assemblages of practice is not without critics. Scott and Storper (2015) and Storper and Scott (2016) have sought to counter the rise of assemblage thinking in urban studies, suggesting it is indeterminate, jargon-ridden and lacks the power of critique (Dovey et al., 2018). Critiquing assemblage theory, Storper and Scott (2016:15) write:

> *"One searches in vain in assemblage theory and urban research based on it to know what larger difference assemblages make, which assemblages are important, and which are insignificant and fleeting, which are empowering, and which are disempowering and what kinds of policy interventions are most likely to bring about desired forms of social change."*

Storper and Scott (2016) view the city as derived from its properties as a locus of agglomeration, gravitation, and density as well as from its specific daily and weekly rhythms of life. These rhythms are embodied most notably in its local labour markets and its regular patterns of commuting (Kerr and Kominers, 2015; Storper and Scott, 2016). In defence of assemblages, Dovey et al. (2018) do not dispute that the main purpose for cities is economic production and exchange (Scott and Storper, 2015) but do dispute that cities can be reduced to economics, and that agglomeration might be able to explain the why and where of cities as this does not show how they exist day to day. For Dovey et al. (2018), assemblage theory provides a mode of thinking through which a more open theory of urbanity becomes possible.

Thinking the city as an assemblage McFarlane (2011) considers assemblage thinking to be is particularly useful for grasping the spatially processual, relational, and generative nature of the city, where ‘generative’ refers to both the momentum of historical processes and political economies and to the eventful, disruptive, atmospheric and random juxtapositions that characterise urban space. Here, the emphasis is upon relational thinking and considering the agency of wholes and parts, not one, or the other - plus the play between stability and change, order, and disruption (Anderson and McFarlane, 2011; McFarlane and Anderson, 2011; Anderson et al., 2012). In terms of how assemblage is applied, Anderson and McFarlane (2011) identify description, concept, and ethos (Briassoulis, 2017a). For example, Dittmer (2014a) looks for ways of narrating the city, as a way of giving sense to its life and vitality that unfold at different scales and temporalities.

With an emphasis upon population studies, Duffy and Stojanovic (2017) view a key starting point for identifying and analysing assemblages is to take persistent configurations as relatively stable assemblages and then examine the contingent conjunction of different components. This is done by analysing the processes and practices of these population spaces, deploying concepts (such as territorialisation–deterritorialisation) to understand the relative roles that social and demographic processes play and encouraging critical reflection on these processes, drawing on the resources of relational and critical theory. Duffy and Stojanovic (2017) also highlight that assemblage thinking discards the assumption that a particular cause will always have the same effect or will always produce the same outcome.

2.3.4 Section Summary

To summarise this section, in order to identify the assemblages in the footfall data, it is the persistent patterns of shared societal activities at different temporal periods, as suggested by Duffy and Stojanovic (2017), Escobar (2007) and Bridge (2020) that this study focuses upon. With foundations drawn from Deleuze and Guattari (1988), both assemblage theory and territorology appear very similar. This study considers that assemblage theory is a philosophical concept about everything, which DeLanda (DeLanda, 2006, 2016; DeLanda and Harman, 2017) grounds in Realism and provides an ontological foundation. By contrast, territorology (Brighenti, 2006, 2010a, 2013) is focused upon social processes, and is more a analytical tool to describe the social sphere (Brighenti, 2010a) - in other words, can be viewed as more epistemological. So, for this study, the analysis of the footfall employs the analytical thinking of territorology and grounds this within the ontology of assemblage theory. As Merriman (2012) argues, we live in a world where we are increasingly part of a movement-space, which is relative, not absolute (Thrift, 2004). This is a world where a range of epistemological devices and technologies for thinking, measuring and framing movement-space have worked into ontological assemblages and our apprehensions of the world (Merriman, 2012).

2.4 Summary of Chapter

In order to identify a theoretical conceptualisation for the footfall data, this chapter reviews different theoretical perspectives from the macro to micro levels and their influences upon town centres and the high street. At the macro-level, the spatial influences of economics, politics, and culture are considered, viewing them as a combination of macro quantitative influences, which generate spatially differentiated, non-equilibrium based, societal and contested perspectives and influences upon town centres (Peck and Tickell, 1995). At the micro-level, with a focus upon the qualitative and the individual, the notion of rhythms is considered (Lefebvre, 2004) and subsequently, that these are discoverable in social activity at the meso-level, from the collective actions of individuals (Schatzki, 2009). It is these aggregated rhythms of social activity, that include the actions of the individual, but also are the convergences of the everyday practices of many individuals, that are considered the irreducible meso-level of everyday (De Certeau, 1984). Hence, the theoretical perspective for footfall is positioned within this everyday meso-level.

In the next chapter, the literature regarding place performance management is reviewed, initially at a more general level, and then in a more place specific context. Then, by combining the theoretical considerations from this chapter, a conceptual model for the footfall analysis is then proposed.

3 Performance Measurement, Footfall and Territorality

3.1 Introduction

In the previous chapter, the convergence of social activity at the meso-scale is highlighted as a perspective for conceptualising footfall. It is at the meso-scale, that of individual towns and streets, where the economic performance (and therefore attractiveness) of British retail centres varies spatially and largely depends on size, form, and function, including composition and catchment demographics (Dolega and Lord, 2020). As Reilly (1931) modelled with the Law of Retail Gravitation, the bigger the centre, the greater the pull to attract customers from a specific catchment area (Carruthers, 1957; Dennis et al., 2002; Teller and Reutterer, 2008). Since the economic crisis of 2008, those centres that offer a 'multi-purpose' shopping experience and act as regional hubs for employment have proved to be more resilient than secondary and tertiary centres to the economic consequences of austerity and increased use of e-commerce (Wrigley and Dolega, 2011; Singleton et al., 2016). Although catchment size is a significant factor, other meso factors also influence overall place attractiveness, including retail and tenant mix (De Nisco and Warnaby, 2014) and the presence of entertainment and leisure facilities (Coca-Stefaniak, 2013; Dolega and Lord, 2020) - and consequently, these factors are key footfall drivers.

Dolega and Lord (2020) comment that typically, larger urban shopping destinations have geographically large catchment areas (Teller, 2008) facilitated by transport networks and can serve as the locus for working, student and tourism-based populations (Berry et al., 2016); in which case, demand is not simply based upon residential locations (Waddington et al., 2017). Such centres comprise a higher number of anchor stores, premium brands, chain restaurants and other leisure units. These attributes have been shown to increase not only footfall but also dwelling time, which is directly linked to customer spending (Hart et al., 2014; Dolega and Lord, 2020). For smaller centres, these tend to be more regularly visited by local residents (Bennett, 1944; Powe and Shaw, 2004).

The importance of daytime population on retail centre performance is linked to the so-called 'convenience culture' (Wrigley and Lambiri, 2015) which is often reliant on patronage from large employment sites with numerous convenience stores and leisure units located in close vicinity (Dolega and Lord, 2020). This notion of mixed-use development that incorporates places of work, eating, shopping etc. is not new (Carmona, 2021): for example, Jacobs (1961) argued that the vitality of city neighbourhoods depended on the overlapping and intersection of multiple activities, a view also expressed as interrelated multiple-uses with different levels of territorial complexity by Kärrholm (2016).

The size of catchment area is very different for different locations, as is the mix of retail and non-retail functions. For example, adapting town types hypothesised by Millington et al. (2015), Mumford et al. (2021) find that places throughout the UK can be differentiated by four town types based upon their annual footfall signatures:

- Comparison towns tend to be locations with large catchment areas, with accessible and diverse forms of transport, strong retail anchors, a strong presence of multiples and international brands with a wide range of retail choice, leisure, food, and beverage outlets. Such locations organise themselves to compete with other comparison towns, out-of-town shopping centres and ecommerce.

- Holiday towns have a seasonal catchment area and are dominated by people visiting during the holiday periods and weekends. They have a focus upon entertainment and leisure facilities rather than retail with people potentially travelling significant distances – as also identified by Newing et al. (2013).

- Speciality towns tend to have an anchor, but this is not necessarily retail focused but rather something unique such as heritage, a coastal location, a book fair (Seaton, 1996) and so on. Such places attract seasonal visitors but also serve a local population. In this way, the notion of retail anchors and their impact upon tenant mix (Nevin and Houston, 1980) is extended to include features of a place (Mumford et al., 2021), which can include day-to-day services as mundane as a pharmacy store acting as a focal point for footfall (Meserole, 1935).

- Finally, multi-functional towns are identified as encompassing both large and smaller towns. For the larger locations, such places can drive local economies and have anchors such as professional services, financial centres, universities etc. and are often connected both nationally and internationally. The smaller centres have a retail offer, opening times, events and services that serve their local community, often including convenience anchors, markets, and local transport networks (Mumford et al., 2021).

Other meso-level factors, that have been considered as being related to footfall include length of residency and the impact this has upon using local shops (Van Leeuwen, 2010) which for rural areas, is related to out-shopping (Lumpkin et al., 1986), town focused convenience (Clulow and Reimers, 2009; Reimers, 2014), cleanliness and litter (Roper and Parker, 2013) and place-based demographic factors such as an ageing population (de Kervenoael et al., 2006). Finally, as these meso-level factors are important drivers of footfall, how they are measured and evaluated contributes an important part of performance management for place management (Millington and Ntounis, 2017).

3.2 Place and Performance Measurement

It is the dynamism and nuance of the macro, meso and micro influences acting upon place that makes understanding their impact a challenge. One approach has been through hierarchical and classification models (Guy, 1998; Dolega et al., 2021). For example, despite criticisms, central place theory has been widely accepted by the planning profession as a model of retail organisation (Dennis et al., 2002; Jones, 2020) as exemplified in Figure 2.3 and the UK retail hierarchy is used as part of the Governments National Planning Policy Framework (see DCLG, 2012) illustrates. Additionally, Borsekova et al. (2018) employ a hierarchal view of city size to determine which metrics should be used to assess smart city performance. In the UK, Figure 2.3 shows that the idea of ranking of places by size and function is clear.

An early view of place classification comes from a data-driven approach and analysis of department store sales data by Parlin and Youker (1913) in the USA. Parlin gathered data for the country's 100 largest cities (Parlin and Youker, 1913; Ward, 2010; Schwarzkopf, 2016) and created a classification scheme that distinguished between convenience and comparison products and the behaviours of shoppers (Thompson, 1967). Parlin's (1914) study introduced the idea that retail activity in places can be convenience and/or comparison based, and that comparison shopping was limited to a few of the larger cities. Thus, implicit in this scheme were the differential spatial influences of the political-economy and cultural practices at that time.

Functional urban classification research has focused upon differences and specialisations (Smith, 1965). Apparent in the classifications of Aurousseau (1921), Dickinson (1932) and Smailes (1944) is the idea of hierarchy based upon the functional representation of a place (Smith, 1965). The functions chosen were not solely retail functions but included other services, providing a broad base of functional categorisation. The weakness of these classification schemes was the changing nature of functions over time - for example the role of the high street bank. From the UK, public transport passenger movements (Carruthers, 1957), the 1961 Census Distribution data (Thorpe, 1968) and retail store type (Reynolds and Schiller, 1992) have all yielded useful information about the functional structure of places despite the stopping of Census data after 1971 (Sparks, 1996). However, Thorpe (1968) advised caution when using hierarchies of centres as these could overstate the case that specific functions were found in centres of a given rank, based on the findings of Cole (1966). Hall et al. (2001) also cautioned against comparing classifications across time due to the changing nature of places, for example, the decentralisation from town centres of services such as hospitals.

More recently, the use of technology has enabled data-driven investigations to process much larger datasets and apply techniques of pattern matching previously not possible. For example, Comber et al. (2020) extracted visual features of retail and leisure environments to classify and judge functional utility and customer behaviour. Likewise, Singleton and Spielman (2013) have derived geo-demographic classifications and Schirmer and Axhausen (2015) developed urban typologies that model the urban morphology. As with this study, the development of these techniques has the potential to enable continual monitoring of place characteristics and the ability to monitor changes over time, rather than via the snapshot slices through time, criticised by Massey (2005). The classifications suggested by Mumford et al. (2021), using footfall instead of sales data, support and enhance Parlin (1914)'s findings. In the signatures identified by Mumford et al. (2021), the original ideas of convenience and comparison places considered by Parlin (1914) are developed further into classifications of Comparison, Holiday, Speciality and Multifunctional places. Thus, convenience becomes a part of all the signatures and the signatures themselves can be viewed as a product of the macro, meso and micro influences interacting upon each place. Additionally, using a data-driven clustering approach Dolega et al. (2021) have created a two-tier classification of consumption spaces based upon the composition, diversity, size and function, and economic health of a place.

Despite criticisms and the need for post-hierarchical approaches (Brown, 1991a; Coca-Stefaniak, 2013; Dolega et al., 2021), the traditional models of classifications and commercial structures prevail in retail and planning practice (Brown, 1992) and there is still no agreed typology of classification for towns and cities (Guy, 1994; Jones, 2020). This helps (in part) explain the lack of performance evidence for assessing the success of high street strategies identified by Hart et al. (2014); Wrigley and Lambiri (2015); Millington and Ntounis (2017) and emphasises the need to reassess the performance measures that are driving the high street and also ensure these recognise the constant evolutionary nature of towns and cities (Parker et al., 2016). The data-driven approaches (Kitchin, 2014a; 2015) used by Mumford et al. (2021), Comber et al. (2019) and Dolega et al. (2021) have the potential to provide insights of this evolutionary nature particularly when combined with performance measures such as footfall as evidenced by Mumford et al. (2021).

Hence, footfall is viewed as a key performance measure for place vitality (URBED, 1994, 1997; BIS, 2011; DCLG, 2012; Digital High Street Advisory Board, 2015; HCLGC, 2019), where vitality refers to activities of people, the businesses of a town at different times (URBED, 1994), or more descriptively, the liveliness, diversity and intensity of a town or city (Jacobs, 1961). This reflects the fact that places are not just locations of necessary activities such as commuting to work and food shopping, but can also include optional and social activities of strolling, entertainment, meeting friends and people watching (Gehl and Svarre, 2013). However, despite the assumed objectivity of the measure, issues such as the standardisation of data collection methods, the multiplicity of figures, the mass of data and presentational formats have been considered problematic (URBED, 1997:56). In terms of a definition of footfall, the following is suggested by (Coca-Stefaniak, 2013:24):

> *"This indicator refers to the number of people walking up and down a given town centre (or single street) regardless of their reasons for doing so. Typical reasons may include shopping, a pleasant stroll, going to work or college, to the cinema or for a meal, accessing public services, visiting friends, or simply passing through. "*

Footfall, or pedestrian counting, is recognised in town centre policy and planning as a key performance indicator of vitality (DoE, 1996). As places are inherently dynamic in nature (Dolega et al., 2021), the sensitivity of footfall to change in everyday practice provides a means to analyse dynamic patterns of behaviour and levels of activity within the urban domain (Mumford et al., 2021). Hence this study aims to explore these rhythms of social activity which provide an opportunity to identify the influences acting upon individual streets and town centres.

Footfall is vital to retailers, although knowing how street level footfall converts into in-store footfall is not straightforward (Graham et al., 2019). Footfall can also provide insight into the impact of strategic and tactical town management decisions. For example, between 1993-2004, a range of quality improvements were made in Melbourne, Australia that resulted in a 39% increase in pedestrian traffic (Gehl, 2010). Similarly, Gehl (2010) adds the example of New Road in Brighton, UK which upon conversion to being pedestrianised, saw an increase in

footfall of 62% but also a 600% increase in ‘staying’ (optional and social) activities, such as sitting, having a coffee etc. In the case of natural disasters, after the 1989 earthquake in San Francisco, changes in how people arrived into the city meant that a collapsed freeway was never rebuilt, as the need no longer existed (Gehl, 2010). Presumably, with COVID-19, similar changes in place activity could lead to rethinking of how we interact with our towns and cities. Footfall, assuming that the data is captured, provides an objective view of these behavioural changes.
In the previous chapter, it was established that territorology and assemblage provide a theoretical lens for analysing the collective movements (rhythms, melodies, and refrains) in space and time of people as measured by footfall sensors.

As one of the aims of this study is to support place management decision making, the following section aims to determine where the theoretical approach and footfall fit within the literature of performance measurement and management and subsequently town performance management.

3.3 Performance Measurement

Performance measurement is part of a broader area of research investigating performance measurement and performance management (PMM) (Franco-Santos et al., 2007; 2012). PMM research draws from strategic management, operations management, human resources, organisational behaviour, information systems, marketing, and management accounting and control (Franco-Santos et al., 2007). In the public sector, what began as a peripheral activity, with the ever-increasing integration of measurement into public organisation governance the quantitative approach to policy and management is today an important part of government (Van Dooren et al., 2015).

In seeking a definition for performance measurement and management (PMM), due to the diversity of disciplines involved and changes over time, Franco-Santos et al. (2007) note that there is a lack of agreement in the research literature. Melnyk et al. (2014) identify PMM as facilitating efficient and effective control (Neely et al., 1995; 2002) and correction by assessing the desired level of performance of an organisation through a reporting process that gives feedback to employees on the outcome of actions (Bititci et al., 1997). From a strategic perspective, both Melnyk et al. (2014) and Franco-Santos et al. (2007) add that PMM also communicates strategic intent and importance to the rest of organisation in terms of what has been measured and, as importantly, by what has not been measured as well as the capacity to provide the information necessary to challenge strategy (Ittner and Larcker, 2003).

From a public organisation perspective, Van Dooren et al. (2015) write that PMM connects the performance measurement mechanism with management use of information (Atkinson, 2017). Fryer et al. (2009) summarises the above with the following definitions from Radnor et al. (2007:393):

- Performance measurement is quantifying, either quantitatively or qualitatively, the input, output, or level of activity of an event or process.
- Performance management is action, based on performance measures and reporting, which results in improvements in behaviour, motivation and processes and promotes innovation

Therefore, PMM comprises two entities, performance measurement and performance management where processes convert data into information that is used to assess the effectiveness and efficiencies of organisational actions (Melnyk et al., 2014). PMM is therefore both a technological process and a social one (Pavlov and Bourne, 2011).

In describing the nature of performance measures, Carter (1991) identifies that metrics can be used as ‘dials’ or ‘tin-openers’. Dials allow performance to be measured against a set of norms (benchmarks) and standards when they exist, whereas tin openers are simply descriptive and provide a signal that an unusual state (or outlier) exists but are unable to aid the formation of conclusions, and so are an invite to investigate, to probe and ask questions. The ideal characteristics of a performance measure are defined by Carter (1991) and Maskell (1992) as:

- Relevant to the needs and objectives of the organisation and can change over time and vary between locations

- Intended to encourage improvement, not just monitoring
- Should measure aspects of performance that are central to the efficient and effective delivery of quality services - primarily using non-financial techniques.
- Not susceptible to manipulation by a person or unit to be assessed.
- Should be reliable, being based on data produced by accurate information systems.
- Also need to be unambiguous - not open to challenge by staff.
- Also, comprehensible, and usable and timely.

Summarising the above, Fryer et al. (2009) identify the four aspects of performance measurement as being: deciding what to measure; how to measure it; interpreting the data and communicating the results. Using the analogy provided by Carter (1991), footfall as a performance measure would appear to fit best into the tin-opener category. For this study, the third and fourth categories identified by Fryer et al. (2009), interpreting the data and communicating the results are part of this study's objectives. In addition, the performance measure characteristics identified by Carter (1991) and Maskell (1992) provide a checklist against which footfall can be assessed.

Enhancing the distinction between measures and metrics, Melnyk et al. (2014) views a measure as informative (a tin opener), whilst a metric (dial), or performance indicator (Godin, 2003), is critical from an organisational perspective. Therefore, for Melnyk et al. (2014), performance metrics (in contrast to performance measures) are defined as composing of:

- A performance measure that quantifies what is happening
- A performance standard or target, that indicates what is considered good and bad performance so guides the direction of an organisation
- Consequences for being on, below or above target

This supports the view that footfall is more of a performance measure. How can targets be set for footfall that can diagnose good performance and guide direction?

How, can a town manager be capable of influencing all the territorialisation forces acting upon any specific point in a town, when these are an aggregate of micro to macro internal and external influences?

Metrics can also be grouped into metric sets (Melnyk et al., 2014), alternatively known as measurement frameworks (Folan and Browne, 2005; Abdolvand et al., 2015), which are used to guide and influence the actions of people, groups, teams, functions, or event organisations. Examples would include the Balanced Scorecard (Kaplan and Norton, 1992, 1993) and reflect the strategy of an organisation (Melnyk et al., 2014). Over time, performance measurement has changed from being a study of measurement, analysis and response (Ridgway, 1956; Charnes et al., 1978) to become encompassed within performance management of an organisation as a whole (Anthony, 1965; Johnson and Kaplan, 1987; Otley, 1999; Drucker, 2007; Tessier and Otley, 2012), the assessment of strategy and the external environment to an organisation (Folan and Browne, 2005), although Melnyk et al. (2014) would question the effectiveness of external environment monitoring.

Combining both performance measurement and management, perhaps the best way to sum up the nature of PMM is by thinking of the different roles served by both performance measurement and management as provided below by Franco-Santos et al. (2007):

- **Measure Performance -** encompassing the role of monitoring progress and measuring performance/evaluating performance.
- **Strategy/Policy Management** - encompassing the roles of planning, strategy/policy formulation, strategy/policy implementation/execution, and focus attention/provide alignment.
- **Communication** - comprising the roles of internal and external communication, benchmarking, and compliance with regulations.
- **Influencing behaviour -** this category encompasses the roles of rewarding or compensating behaviour, managing relationships and control.
- **Learning and Improvement** - that includes the roles of feedback, double-loop learning and performance improvement.

A common research theme is the need for PMM not to be static but to have the capacity to evolve as management style, organisational culture and external factors change and evolve (Carter, 1991; Bititci et al., 2006; Armstrong, 2014). Ferreira and Otley (2009) agree and view PMM as the evolving formal and informal mechanisms, processes, systems, and networks used by organisations to convey the key objectives and goals including facilitating organisational learning and change. For this study, learning and change are of particular interest, as footfall is viewed as a performance measure considered by this study to support such capability.

Today, performance and the management of performance has become common throughout contemporary societies, as it is used to assess the quality of individual and collective efforts (Micheli and Mari, 2014). Value for money, fairness, integrity, robustness, and resilience (Hood, 1991) helps question whether public services are produced in an efficient and effective way and also helps assess the impact of a programme/policy (Van Dooren et al., 2015). However, Carter (1991) observed that many of the performance indicators used for public services were measures based upon process, measuring time taken and cost, rather than being customer orientated and quality focused. Hence, there has been a concentration on efficiency rather than effectiveness, not least due to the complexity and practicality of being able to measure effectiveness outcomes, not least in relation to town centres (Houghton, 1997).

Another difficulty is the problem of ownership (Carter, 1991). The responsibility for performance within an organisation (or across different collaborating organisations) may depend on central decisions over which an individual organisation, branch or unit manager has no control. Alternatively, the complexity of an organisational network can provide the opportunity for individuals to act autonomously (Van Dooren et al., 2015). Moreover, multiple goals can lead to conflict in goals (Cheng et al., 2007). External factors also have an impact (Van Dooren et al., 2015) and hence there is uncertainty of the cause-and-effect relationship and how to measure effectiveness, thereby making the construct of performance measures very difficult. (Carter, 1991). The main limitation of performance measurement therefore is in its inability to provide a conclusive answer to the performance question (Van Dooren et al., 2015). Disfunction behavioural effects can also occur as manipulation of measurement processes or manipulation of the output (Van Dooren et al., 2015). The first leads to measurement that is not a good representation of reality (some effects are unplanned side effects rather than being manipulative by design). The second alters the daily operations of an organisation and can influence what customers/citizens directly or indirectly experience from public services (Van Dooren et al., 2015).

Hamel (2009) criticises the suitability of performance measurement theories and practices for modern organisations, suggesting that PMM in organisations increases fear, reduces trust, promotes "command and control" systems, diminishing employee engagement (Smith and Bititci, 2017). The motivation for using performance measures affects the performance outcome and a balance is required when designing and implementing a PMM that accounts for technical and social dimensions (Smith and Bititci, 2017). Numerous researchers (e.g. Ittner and Larcker, 2003; Burney et al., 2009; Kolehmainen, 2010) agree that PMM systems bring in subjectivity, but the extent to which this subjectivity is helpful or not is still debatable (Franco-Santos et al., 2012). When subjectivity is perceived in terms of flexibility, the data show that PMM systems can help organisations deal with change (Franco-Santos et al., 2012).

More positively, in their literature review Franco-Santos et al. (2012) conclude that PMM systems play a key role in strategy, communication and management processes (see also Ahn, 2001; Malina and Selto, 2001; De Geuser et al., 2009; Dossi and Pateli, 2010; Gimbert et al., 2010; Kolehmainen, 2010), generating organisational capabilities to the benefit of the organisation. Franco-Santos et al. (2012) also find that for a PMM system to have a positive impact, then collaboration (Malina and Selto, 2001; Godener and Söderquist, 2004; Decoene and Bruggeman, 2006; Hall, 2008), design (Lipe and Salterio, 2000; Grafton et al., 2010), development (Mundy, 2010), use and how well it fits the context of an organisation are important. The findings relating to the importance of collaboration mirror those of Ntounis and Parker (2017) in a specific place, whereby to facilitate strategic objectives, then town centre stakeholder engagement at all levels is important.

In recent times, rapid changes provide very different problems for managers (Bititci et al., 2012). Today, reflective thinking and 'double-loop thinking' (Argyris, 1991), creative problem solving, and 'value-driven thinking' are required (Hamel, 2009). The evidence suggests that the purpose of PMM is changing with a diminishing emphasis on control (diagnostic use), to an increased emphasis on learning (interactive use) (Davenport et al., 2010; Bititci et al., 2012). Bititci et al. (2006) suggests that traditional PMM systems have tended towards the specific, with firms using metrics (KPIs and targets) to drive specific outcomes and focus on specific solutions. In stable environments, such systems are appropriate, but such PMM systems are not resilient to environmental change (Melnyk et al., 2014). The suggestion by Melnyk et al. (2014) is that organisations have a choice of a more focused but brittle PMM, or alternatively less focused and more resilient.

Thus, Melnyk et al. (2014) question the "fit" or "lack of fit" between the business/public service environment, strategy and what is being measured. Melnyk et al. (2014) find that "fit" has received little attention and in fact, most of the literature assumes that a change in environment will necessitate a change in PMM system (Bourne et al., 2000). Further, often a process is assumed, where the PMM system detects a change in environment, which leads to a change in strategy and finally a change to the PMM system. However, what happens if the environment is so turbulent, steps 2 and 3 never take place? Can the PMM remain resilient to change in the environment and so continue to provide appropriate guidance to managers in real-time (Melnyk et al., 2014)? Since organisations rarely achieve steady state but are continually realigning their strategies and moving from one temporary state to another (Mintzberg and Waters, 1985), identifying organisational trends that impact PMM is no trivial task (Bititci et al., 2012).

Thus, an important element of PMM is to provide a measure of the environment within which an organisation operates, for example the impact of COVID-19 (N. Ntounis et al., 2020). Organisations utilise performance measures to improve an organisations' performance (Bititci et al., 2012) although Davenport (2006) suggests that the ultimate goal of PMM should be learning rather than control. In particular, Koufteros et al. (2014) investigated the balance between diagnostic use (one-way and controlling) and interactive use (two-way and learning) (Simons, 1995a, 1995b) PMMs. They identified that limiting measurement to diagnostic controls would produce negative outcomes, suggesting that interactive use is a critical component of a PMM (Koufteros et al., 2014). Canonico et al. (2015) also looked at a variety of organisations that needed to swiftly adapt to ever more rapid and unpredictable environmental changes and like Koufteros et al. (2014), they identify the need for existing control systems to enable organisational learning. Similarly, Moxham (2013) in a study of the public sector, provides a similar conclusion that compliance to targets and expenditure requirements may be the only intended outcome of many public sector performance measurement systems. If, however, the purpose of performance measurement is service improvement, it is unlikely that a control focused system can deliver the anticipated quality improvement objectives.

The ability for a PMM and associated performance measures to provide learning and environmental change measurement are therefore considered important (Davenport, 2006; Bititci et al., 2012; Moxham, 2013; Koufteros et al., 2014; Melnyk et al., 2014; Canonico et al., 2015). The findings of Mumford et al. (2021), with the identification of distinct annual signatures, indicate that footfall is more than a measure of weekly, monthly, daily totals and means and that there are patterns to be discovered in the data, and that these patterns vary from place to place. This suggests that for town centre management, footfall is well placed to support the ideas of learning and environmental change.

3.4 Town Centre Management

Whereas the previous section comprised a broad overview of the performance measurement and management (PMM) literature, this section narrows the focus to the management of town and city centres. Having established that some of the challenges facing PMM include the balance between command and control and learning, stakeholder involvement, strategic agility, and the ability to measure external to an organisation, this section looks at the issues facing town and city performance measurement and management.

A general theme in the town centre management literature is the lack of performance evidence for assessing the success of high street strategies (Hart et al., 2014; Wrigley and Lambiri, 2015) and the need to recognise the constant evolutionary nature of towns and cities (Parker et al., 2016). Various reports exist outlining the issues and possible solutions (BIS, 2011; Portas, 2011; Grimsey, 2013, 2018), but arguably, a key issue is better understanding and addressing the current situation rather than some future state (Millington and Ntounis, 2017). The next sections explore the urban centre management schemes prevalent in the UK and include the issues of measurement faced by these schemes, the established performance measures, and various performance management schemes.

3.4.1 UK Urban Management Schemes

In the UK during the late 1980s, there was a shift of retail development away from the traditional shopping areas in town and city centres towards out-of-town retail locations (Warnaby et al., 1998). A response to this decentralisation was the URBED (1994) report, the result of a year's work by the Urban and Economic Development Group (URBED) and a multi-disciplinary team of consultants and researchers. The report consisted of three parts: first, identifying the challenges faced by 32 towns; second, a consideration of the responses local authorities could make, both in assessing vitality and viability and devising town centre strategies which included a series of performance indicators; and thirdly, identifying good practice. As reported by URBED (1994) the impact of decentralisation upon established town centres where peripheral places were attracting the more mobile and affluent consumers, left the old centre dependent on a more local and poorer market. As a result of a reducing turnover as footfall reduced and subsequent loss off trade, stores closed and moved. This in turn reduced footfall and attraction, deterring customers from using the centre, thus discouraging private investment and buildings became neglected and decayed then fall empty and derelict - the result being an overall impact upon vitality and viability of the centre as a whole (Schiller, 1994; URBED, 1994).

To counter the impact of this decentralisation, the most prevalent reaction from 1987 onwards (URBED, 1997), was the development of the concept of town centre management (TCM) schemes, defined by Warnaby et al. (1998:17-18) as:

> *"Town centre management is the search for competitive advantage through the maintenance and/or strategic development of both public and private areas and interests within town centres, initiated and undertaken by stakeholders drawn from a combination of the public, private and voluntary sectors."*

Warnaby et al. (1998) suggested that the implications of the above definition for individual TCM schemes in urban places included articulating the basic aim or mission of the TCM scheme, the acknowledgement of relationships between all urban stakeholders and the activities undertaken. The ultimate objective of the schemes and their initiatives being to increase footfall (URBED, 1994).

From the start, Town centre management (TCM) gained widespread acceptance from both private and public sectors as a means of maintaining and improving town centres (Pal and Sanders, 1997). Other, similar initiatives included Town Improvement Zones where the aim was to build trust between private and public sectors, and which emphasised the need for ongoing funding and an overseeing organisation (URBED, 1997). In 1991, the Association of Town Centre Management (ACTM, 2020) was formed to support the various schemes, most of which comprised of some form of partnership between public and private sector stakeholders (Cotterill et al., 2019). Although the earlier schemes were viewed as 'janitorial' (Warnaby et al., 1998), with the objective to remedy deficiencies caused by off-centre retail, TCM developed more long term, strategic perspectives for managing the retail mix, marketing, and promotional activities (Cotterill et al., 2019). In terms of performance monitoring, URBED (1994) notes examples from Manchester and Worcester, where manually conducted footfall surveys were used to monitor Christmas promotional activity and the opening of a new shopping centre. The usefulness of this data leading to the conclusion by URBED (1994) that regular counts in all town centres should be implemented.

Coca-Stefaniak et al. (2009) found the archetype of TCMs (throughout Europe) was a blend of private and public sectors with an important contribution from the voluntary sector. Although, whereas in the UK the emphasis was upon creating competitive advantage of the town and city centres (for example, through better quality of life for residents, diversity in the retail and leisure offer, attractions for visitors, etc.), the continental European approach was dependent upon the involvement of retailers and other town centre small business, with the aggregation of these businesses to develop collective initiatives being the major objective (Coca-Stefaniak et al., 2009). Therefore, each individual TCM scheme reflected the balance of power between the stakeholders and was determined by the resources they offered, the level of influence and the financial contribution available (Warnaby et al., 1998). Objectively though, the different schemes were often aiming to counteract falling footfall in the town centres because of out-of-town shopping centres and the development of other nearby centres (Coca-Stefaniak et al., 2009).

However, despite the need to increase footfall, from a UK TCM perspective, research (see for example, Page and Hardyman, 1996; Houghton, 1997; Pal and Sanders, 1997; Tomalin, 1997; Peel, 2003) suggested that despite the various iterations of UK retail planning policy guidance known as PPG6 (URBED, 1994; DoE, 1996; URBED, 1997) confusion in the selection and operationalisation of the performance measures was common. Reflecting a general finding from the PMM literature that standardising implementation is technically and socially difficult requiring active and engaged stakeholder participation (Neely, 2005; Franco-Santos et al., 2012). For example, there were difficulties comparing TCM schemes (Houghton, 1997) in part because as noted by Cox et al. (2000) and Ravenscroft (2000), local rather than universal measures were considered more important, and that a single construct of vitality and viability that could be applied to all town centres was unlikely to succeed - a view supported for performance measurement in general by Chenhall et al. (2017). In order to identify a national set of core indicators that provide a health check of UK towns, Cox et al. (2000) identified a number of issues with the use and capture of performance measurements:

- The performance indicators to be collected were not clearly defined or consistent in Government advice.

- Guidance on methods for the interpretation of information was limited.
- The importance of time-series data for monitoring was not sufficiently emphasised.
- There was no guidance on how to make comparisons between towns, or how to choose relevant places for comparison.
- A lack of nationally agreed benchmarks for time series data or inter-town comparisons undermined good practice guidance.
- The resource implications of town centre monitoring were not addressed. *PPG6* (DoE, 1996) did not provide sufficient guidance on interpretation of health check indicators or town centre monitoring.

The issues identified by Cox et al. (2000) are mitigated in part by the introduction of remote sensing techniques to capture footfall, such as those used by Springboard (Ozbay et al., 2010; Springboard, 2015). In addition, instead of the specific situations identified by URBED (1994) where footfall data was used to support TCM initiatives, the footfall data collected via these remote sensing techniques is a continuous time-series, with no need to sample specific periods due to resource constraints (Monheim, 1998). As a result, the objective of analysing footfall is able to change from one of proving an individual initiative was effective to becoming a standardised and comparable continual performance measure of environmental change as suggested by Koufteros et al. (2014).

Eventually, the voluntary participation and funding of the UK TCM approach led to questions as to whether schemes were sustainable in many locations despite a recognition from independent retailers that TCM had the potential to improve footfall via trading improvements (Medway et al., 1999; 2000). One cause for concern identified by Medway et al. (1999) was that only a small minority of the primary town centre stakeholder group (i.e., retailers) contributed to TCM funding (Cotterill et al., 2019). The UK Government, the private sector and the European Union were significant investors in TCM, but schemes were often set-up as short-term projects that had no way of ensuring the other businesses in the town centre that benefited from the activities funded by the project, contributed (Cotterill et al., 2019). Hence, alongside the TCM schemes, Business Improvement Districts were introduced into the UK in 2002/2003 and their adoption was linked to their ability to raise funds to invest in a locality (De Magalhães, 2012).

Business Improvement Districts (BID), with their conceptual origins in Toronto in the 1960s (to support revitalisation strategies and improve footfall), and their development in the US from the late 1970s and 1980s (to counter the impact of out-of-town malls and closer of downtown departure stores) (Ward, 2007) were introduced into the UK to overcome the perceived deficiencies of TCM (see Cotterill et al. (2019) for a chronology of their introduction, regional variations and supporting organisations). After a pilot project at 22 selected locations, the legislation required to enable BIDs in England and Wales was introduced in the Local Government Act 2003 (Sandford, 2014). In Scotland, the required legislation was introduced in 2007 and in Northern Ireland, this occurred in 2013 and 2014. BIDs were seen as a way of carrying on the positive work that the TCM movement had started, but in a more equitable and sustainable way (Cotterill et al., 2019).

Although academically, there is no single BID definition (Hoyt and Gopal-Agge, 2007; Ward, 2007; Grail et al., 2019), Ward (2007:658) summarises the general characteristics as:

> *“Business Improvement Districts are public–private partnerships, in which property and business owners in a defined geographic area elect to make a collective contribution to the maintenance, development and marketing/promotion of their commercial district.”*

De Magalhães (2012:145) adds that BIDs in the UK are: “a time-limited, flexible funding mechanism that aims to improve and manage a clearly defined commercial area”. The process of establishing a BID (see Figure 3.1) involves a bidding process and majority vote by all qualifying commercial taxpayers (Guimarães, 2013; Department for Communities and Local Government, 2015). In the UK, the funding contribution is compulsory for all businesses within the area once the Business Improvement District is established, setting it apart from predecessors such as town management schemes (Ward, 2007).

In general terms, Ward (2007) identified the strategies delivered by BIDs and these are summarised by Grail et al. (2019:75) as follows:

- Physical infrastructure – i.e., capital improvements, economic development, area maintenance.
- Promotional infrastructure – i.e., marketing to place users and other consumers and policy advocacy.
- Surveillance infrastructure – i.e., public space regulation and security.

However, in terms of having the autonomy to support business interests, Guimarães (2013) found that in the UK, BIDs are limited by the resources available and the nature of the relationship with the local authority - one of the key differences to previous TCM schemes is the formalised and contractual regime (Peel et al., 2009). As a result, BIDs were mostly focused on coordination, complementing, and enhancing services and activities already in place (Guimarães, 2013).

Cotterill et al. (2019) identified that by the end of 2018, there were 303 BIDs operating in the United Kingdom (in other words, at Stage 4 - see Figure 3.1 - of the above BID development process), spending approximately £108m of levy income between them on improving their local trading environments. The majority have a specific town or city centre remit, and most operate as independent organisations (as not-for-profit limited companies). Of these current BIDs, 55 are operating in their third or fourth term, making them at least ten years old, with 253 BIDs operating within their first or second term. By 2019, moves to initiate BIDs in a variety of locations across the UK were continuing (Cotterill et al., 2019).

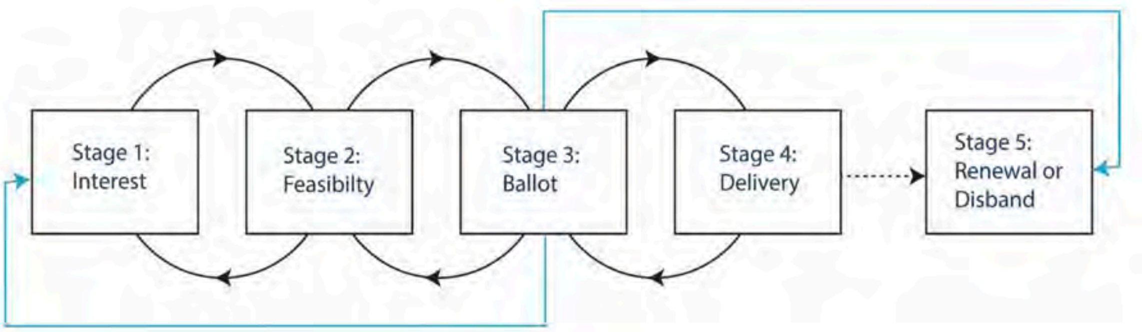


Figure 3.1. The five possible stages of a BID (Source:Grail et al., 2019:75)

There are concerns regarding the inequalities that BIDs may produce; for example, the unforeseen consequences of associated ‘indirect costs’ or ‘spill-over effects’ - in other words, the displacement of crime and other problems to areas outside their service boundaries (Hoyt and Gopal-Agge, 2007). In addition, Hoyt and Gopal-Agge (2007) also question to what extent BIDs create wealth-based inequalities in the delivery of public services, arising from the inevitable concentration of efforts and resources within their spatial boundaries (Cotterill et al., 2019). Whether BIDs increase spatial inequalities any more than other forms of place management, is untested. More BIDs have formed under the political economic environment of austerity, and BIDs are to be found in both strong and weak local economies, suggesting they do not just locate in more favourable trading environments, during more periods of economic growth (Cotterill et al., 2019).

It should be noted that TCM and BIDs are not the only initiatives in operation. Following the Portas Review (Portas, 2011), there were also UK government initiatives designed to promote innovative and multi-stakeholder approaches to town centre change, namely, the High Street Innovation Fund (Retail Week, 2012); the Portas Pilots (Portas, 2011); and the Town Team Partners (The Journal (Newcastle), 2012) (Parker et al., 2017).

Within TCM schemes and BIDs, the plurality of place management practices and organisational structures (Nikolaos Ntounis et al., 2020) and the diversity of stakeholders is one of the complexities that can cause conflict and debate when attempting to identify and define problems that need to be resolved (Le Feuvre et al., 2016; Peel and Parker, 2017). Yet as Bititci et al. (2006) and Ukko et al. (2007)

argue, PMM when performed in a participative and consultative manner, results in finding new and better ways of working within and between organisations. More professional governance (Cotterill et al., 2019) and the inclusion and cooperation of stakeholders (CLG, 2012; Theodoridis et al., 2017), are needed to understand a place's identity and to guide strategic vision (Ntounis and Kavaratzis, 2017) and facilitate performance management and evaluation (Cotterill et al., 2019:55).

To summarise, despite a set of measures (URBED, 1994; DCLG, 2006) that have been identified for use by TCM schemes and BIDs, the complexity and diversity of places and interactions (Coca-Stefaniak et al., 2009) mean that measuring and understanding place is still problematic (Millington and Ntounis, 2017). The ongoing evolution of places mean that whatever measures are used, they need to be able to evolve with the changes in strategy and the general environment influencing individual places. Thus, the performance measures need to be flexible and support the ongoing learning of place everyday experiences and the urban ecosystem (Coca-Stefaniak et al., 2009). The challenge of managing town centres, therefore, appears to be a perpetual issue of effectively understanding and addressing the current situation (Millington and Ntounis, 2017). A challenge because usually identification of local variations and the problems and challenges associated with the town centre was based on anecdotal evidence (Millington and Ntounis, 2017).

3.4.2 Performance Measurement in TCM schemes and BIDs

The most common performance measures employed in UK TCM were identified by Hogg et al. (2004) in a survey of eighty-seven TCM schemes and found to include, car park usage (90% of schemes), footfall (87%), vacant property rate (84%), and town centre theft (79%), with sixteen different types of KPI identified (Hogg et al., 2007). Hogg et al. (2007) found that whilst evaluating performance outcomes, the misinterpretation of causal influences was viewed as a problem. It was all too easy to accept recognition for a positive outcome that might have occurred without the intervention. Equally, however, this could be used as a useful excuse to `opt out' of blame for negative performance if outside forces could be held responsible (Hogg et al., 2007). Guimarães (2013) noted that even when considering the difficulties of an evaluation process, the lack of any kind of assessment can be the result of an absence of engagement with defined objectives (assuming they exist). Confirming this, Hogg et al. (2007) found little evidence that TCM performance management measures were linked to strategic objectives. Hogg et al. (2007) also identified that the scope of performance measurement for a TCM can be problematic – i.e., did the scope encompass the TCM scheme or the town centre as a whole. A problem identified by Donaghy et al. (2013) and the boundary effects of BIDs. Ownership of the performance data Carter (1991) also was an issue, and this resulted in various TCM stakeholders wanting to accept credit (Van Dooren et al., 2015) for performance improvements. Thus, an underlying factor here was the lack of clear ownership of urban performance (Hogg et al., 2007).

Nevertheless, in-line with the general PMM literature (Papalexandris et al., 2004; Mahama, 2006; Cousins et al., 2008; Kolehmainen, 2010), Hogg et al. (2007) found that where performance indicators were initiated by TCM managers, they were more confident in the capability of the indicators and felt more able to share data with TCM stakeholders. In contrast, managers who were told which performance indicators to employ, were less confident and put a lower emphasis upon their importance. Convenience also contributed to the selection of performance indicators as the time and money constraints under which most TCM schemes operate were an influence. Hogg et al. (2007) also identified trust and the release of performance indicators as a problem where to gain trust, TCM managers needed to build a rapport with the individual stakeholders to gain their support and involvement.

Donaghy et al. (2013) highlighted that the measurement of BIDs is conceptually and methodologically problematic in that, by definition, BIDs are seeking to change outcomes to which changes are difficult to attribute cause, especially as there are national trends, local circumstances and a range of ongoing initiatives all impacting each other. This ties in the need for performance measures such as footfall that can adjust to change and provide a measure of external change (Davenport, 2006; Bititci et al., 2012; Moxham, 2013; Koufteros et al., 2014; Melnyk et al., 2014; Canonico et al., 2015). Additionally, the assumption that place management partnerships were beneficial, led to a culture of inadequate monitoring and evaluation (Hogg et al., 2004). According to Cotterill et al. (2019), this weakness is also present with BIDs. Yet, feedback from businesses show that they do want information on impact and some form of independent validation of the BID that goes beyond the anecdotal (Donaghy et al., 2013).

With the issuing of the URBED (1994) report, a set of performance measures were identified that could be used to assess place viability and vitality.
Table 3.1, lists the factors and indicators that town centre management considered to be important noting that the measure selected for vitality of place was footfall. URBED (1994) provided a performance measurement framework and performance management template and has been very influential. For example, Millington and Ntounis (2017) provides examples from URBED (1994, 1997) and PPG6 (DoE, 1996) as suggestions for data to be captured.

Table 3.1 - Factors and indicators that can facilitate town centre management
(Source: URBED, 1997:13)

Factor	Indicator
Viability	Private investment in property
Vitality	Footfall
Diversity	Wider range of shops and services
Security	Reduced Crime
Vacancy	Easier lettings/fewer empty shops
Employment	New businesses/training opportunities
Accessibility	More shoppers/visitors
Retail Turnover	Increased transactions
Property Investment	Higher rentals/lower yield
Image	Favourable publicity

However, despite the publications of URBED (1994), DoE (1996) and BIS (2011) identifying the measures to be captured, provision of guidance on the analysis of the data and results interpretation is not covered by the toolset documentation. A problem for TCMs identified by Cox et al. (2000) where it was found that the methodology used by individual TCM schemes to collect footfall measures is rarely stated. Thus, Cox et al. (2000) found inconsistencies in the collection of data (e.g. from continuous monitoring using shopping centre automatic counts to one day specifically for the health check). This resulted in too many ways of collecting town data making comparisons difficult (Cox et al., 2000).

A more recent town management framework (see Figure 3.2), which includes a performance measurement toolset is that created by Coca-Stefaniak (2013); Coca-Stefaniak and Bagaeen (2013). This measurement framework suggests creating a strategy map, identifying the classification of a place according to a place ‘personality type’, evaluating the current state of a place and identifying how to monitor progress towards strategic objectives. Importantly, Coca-Stefaniak and Carroll (2015) also note the need for a sufficient period of time in order for places to understand the relationships and actions that can help facilitate TCM. However, like URBED (1994), DoE (1996) and BIS (2011), although measures are identified for the framework, how to interpret and analyse the results is not covered by the toolset documentation. Again, a problem for TCM schemes identified by Cox et al. (2000).

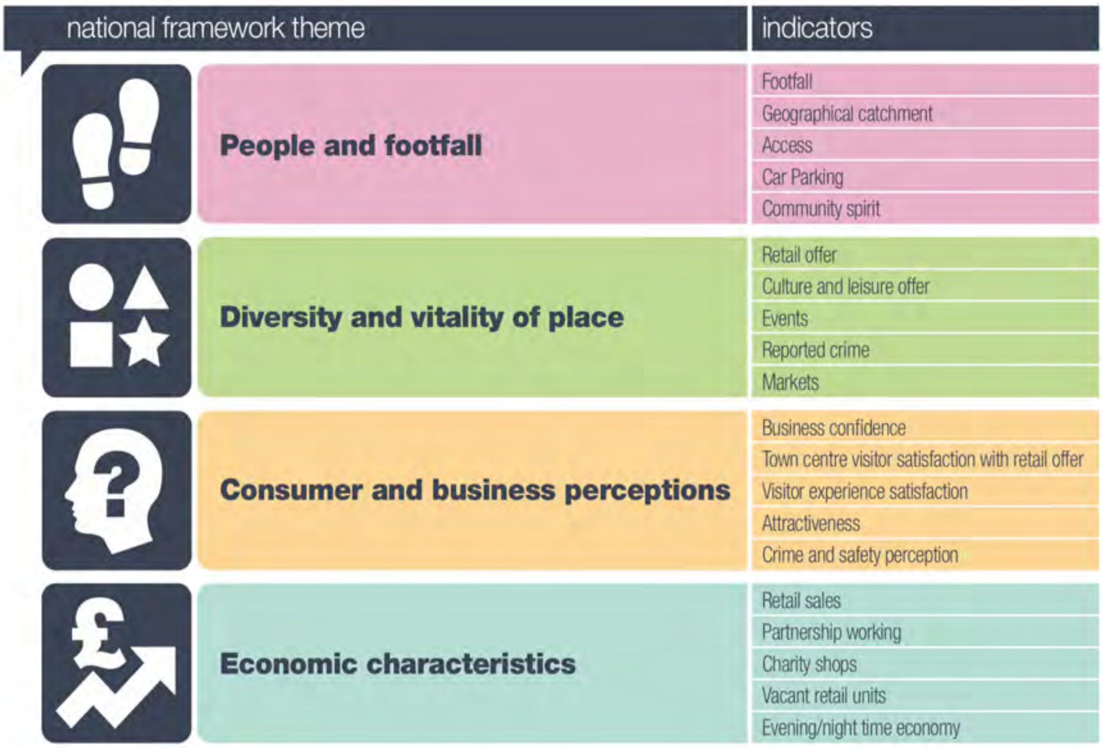


Figure 3.2 - An indicator-based performance toolkit
(Source: Coca-Stefaniak, 2013:23)

A potential toolset that could form a performance measurement framework for observing public life in the urban environment is provided by Gehl and Svarre (2013). Gehl and Svarre (2013) lists a variety of tools and how they can be used, such as counts (footfall) (Monheim, 1998), mapping behaviour (Kärrholm, 2016), tracing lines of movement (Traunmueller et al., 2018) (as suggested in time-geography), tracking (Hart et al., 2014), looking for traces (direct and indirect such as trampled shortcuts across grass squares), photography (Simpson, 2008), keeping a diary (Wunderlich, 2013, 2014), test walks (Kang et al., 2018) (noting hindrances and/or diversions). As noted by Gehl and Svarre (2013), purpose, budget, time and local conditions determine the tools chosen for a study. The choice of tools is dependent on whether the area studied is a delimited public space, a street, a quarter, or an entire city. Even for a delimited scope, it is necessary to consider the context of the study holistically, including the local physical, cultural and climate aspects. A single tool is rarely sufficient - it is necessary to combine various types of investigation (Gehl and Svarre, 2013). Unlike URBED (1994) and Coca-Stefaniak (2013), Gehl and Svarre (2013) also consider implementation of the framework by providing case study-based examples of how to use each technique, how they can be combined to aid investigations and how to communicate the results.

Another framework suggestion is provided by Balsas (2010), with a set of town centre liveability measures of an urban area and the use of quantitative and qualitative data to create a health check. Balsas (2010) suggests the importance of collecting from the start an agreed set of core indicators that can be built upon year after year. A question then would be how such a framework could adapt to strategy changes and changes in the environment of each place. Other examples are provided by:

- Davison Porter et al. (2017) - framework for world towns
- BIS (2011) High Street Performance of Retail focus.
- Houghton (1997) Town Planning Indicators
- Ravenscroft (2000) Health of Town Centres focus on vitality and viability
- Riviezzo et al. (2009) Importance-performance analysis

However, in all cases except Gehl and Svarre (2013), how such performance measures should be implemented and utilised by the stakeholders is hardly addressed.

Reviewing the literature regarding town centre management performance measures (e.g. URBED, 1994, 1997; BIS, 2011, 2012; CLG, 2012; DCLG, 2012; Digital High Street Advisory Board, 2015), a common theme is the mixing of terminology between performance measures and performance indicators. For example, although Hogg et al. (2004) identify a number of town management Key Performance Indicators (KPIs), there is no evidence of measurement performance targets nor what happens when a target is missed. This suggests than that the measures would not meet the performance metric criteria defined by Melnyk et al. (2014) - and therefore are performance measures, not performance indicators. For example, Page and Hardyman (1996), from a survey of TCM schemes in the UK, identified problems with TCMs struggling to define the correct performance indicators as the desired outcomes of schemes were continually debated and fluid.

A conclusion of Millington and Ntounis (2017) and Gehl and Svarre (2013) was that it was essential to complement local knowledge, basic metrics and “soft” data with more comprehensive data collection and data analysis approaches, as well as data sharing between partners (Millington and Ntounis, 2017). These approaches can include analysis of traditional performance measures, such as footfall, retailers’ representation and performance, car parking provision, vacancy rates, property rents, retail, and housing investments (Hogg et al., 2007). In addition, more sophisticated approaches that evaluate consumers’ perceptions and shopping behaviour (De Nisco and Warnaby, 2013) should also be considered to generate performance measures that together, provide a management tool that aids the increase of footfall in town centres (Millington and Ntounis, 2017).

3.4.3 Performance Management

Whereas the previous section was focused on performance measurement, this section considers performance *management* for town centre management. The same research that found inadequate monitoring for TCM and BID schemes also as a result, identified performance management as an issue (Hogg et al., 2004; Cotterill et al., 2019), notwithstanding the fact that feedback from businesses indicate they do want to understand the impact of BIDs beyond that which is anecdotal (Donaghy et al., 2013). Indeed, if there is a lack of literature regarding BID evaluation (Peel et al., 2009; Donaghy et al., 2013) then, arguably improvements, innovation and changes in behaviours is also going to be lacking.

Although town management frameworks such as URBED (1994) have been proposed, as already noted, problems with implementation of the performance measurement elements of these frameworks means that there is a distinct lack of information regarding performance management. Importantly, Theodoridis et al. (2017) emphasise the need to engage with local decision makers to support the reinvention of the High Street and town centres. This suggests that the processes of learning and collaboration are important in the process of understanding what town centre management can achieve. With cooperation between stakeholders and participation, then the development of understanding a place's identify and a strategic vision (Ntounis and Kavaratzis, 2017) are useful first steps to creating a PMM system. A recent example of such a framework is the 4Rs strategic framework (Parker et al., 2017).

Through collaboration between researchers and in-situ stakeholders, the 4Rs framework was found to bring a thorough but complicated evidence base to towns in a more coherent fashion (Parker et al., 2017). By having a simple framework, town stakeholders could start at any point and approach regeneration in a way that accommodated the path they had already started to take and being sensitive to how they had started to conceptualise the problem or reflect the amount of people and resources they had to hand (Parker et al., 2017). What the 4Rs framework research shows, is that in order to create an effective performance management system, the approach of Engaged Scholarship (Van De Ven and Johnson, 2006; Ntounis and Parker, 2017) that was taken, meant that implementation was not a matter of interpretation from a document such as URBED (1994) but one of collaboration amongst multiple stakeholders. This mirrors the findings of the general PMM literature in that successful PMMs are created via collaboration between stakeholders (Speckbacher et al., 2003; Kolehmainen, 2010; Franco-Santos et al., 2012).

The objective of this research with the 4Rs strategic framework was to continue with the validation of the framework in 2020 (Parker et al., 2017). However due to COVID-19, an adapted framework has been developed and implemented using the same process of Engaged Scholarship with stakeholders and partners. This is the High Streets Task Force Covid-19 Recovery Framework (HSTF, 2020) and provides a template to guide towns through the process of recovery from the impacts of COVID-19. Again, collaboration is a key to learning how best to use the framework and to judge success of measures taken within an individual location and to find out what is being done elsewhere.

To conclude, for town centre management to succeed, recent events suggest that when academia and place stakeholders work together (Theodoridis and Kayas, 2017), performance frameworks can be created that drive actions, and bring about improvements. As a part of these performance frameworks, a consistency found throughout the place performance management literature is that footfall is a ‘key’ performance measure. The next section is a review of the literature where footfall, or similar pedestrian activity measures were considered as a performance measure of place vitality.

3.5 Previous Footfall and Related Research

For the social sciences, the available statistical techniques assume the availability of high-quality data, obtained under experimental conditions (Wrigley, 1983). In reality, spatial and temporal data is gathered from non-experimental observations and is subject to collection errors, missing data, outliers, collinearity, the modifiable areal unit problem, temporal and spatial autocorrelations (Wrigley, 1983). For example, regarding the modifiable areal unit problem (Johnston et al., 2018; Wolf et al., 2020), where data such as resident or working population are aggregated for a territorial unit, investigations show that different conclusions can be drawn from the same data depending on the scale of the analysis and the nature of the aggregation (Johnston et al., 2018). Additionally, there is the spatial and temporal correlation of data, where proximity increases the likelihood of similarity of characteristics and behaviours between observations (Johnston et al., 2018). These are relevant considerations as data sources such as pedestrian movements are correlated against, for example, population data, transport facilities, distances to stores and entertainment facilities, vacancy rates and store density (Philp et al., 2021) – all representations of the key factors that can be held to characterise town centres and drive footfall, namely: economy (which integrates the various town centre employment types ones might expect to find); property (the density of the buildings); diversity of use, and visitor attractions. (Thurstain-Goodwin and Unwin, 2000).

Early examples of pedestrian count studies were those conducted by chain stores in the US, using footfall in a spatial context to assess the value of their sites for business. The underlying assumption of these studies, that more people equated to more business, resulted in footfall being used as a means of determining the maximum rental worth of property. This assumption was statistically proven, with good regression correlations if the area of study focused on the Central Business District area and not 'out-of-town' locations (Meserole, 1935). More recently, summary statistics which can be used for descriptive purposes, stratified by place, region, and town types, such as those provided by Springboard, based upon footfall sensor data as temporally based comparisons such as year-on-year and weekly percentage changes (Springboard, 2020). The use by practitioners (e.g., shopping centre managers) using similar descriptive measures is identified by Warnaby and Man Yip (2005), finding that footfall data is used in conjunction with sales data to measure the success of place marketing campaigns.

Using dynamic modelling approaches, place attractiveness has been modelled spatially using Gravity Models (Reilly, 1931) using the idea of a 'geographical trade area' (catchment area) (Applebaum, 1965; Rosenbloom, 1976) in which a store (place) derives its business potential. Such mathematical models, incorporate observations and surveys, customer segments, mapping techniques, driving times etc., with the objective to understand the geographical extent of market potential. Typically, gravity models provide generalised estimates (Timmermans et al., 1992; O'Kelly, 2009) of trade area potential and attractiveness where the bigger the centre, the greater the pull to attract customers from a specific catchment area (Carruthers, 1957; Dennis et al., 2002; Teller and Reutterer, 2008).

Originally used for transport flow modelling, spatial interaction models have further developed the gravity model by incorporating the entropy-maximising and multinominal logit models approaches (Ghosh and McLafferty, 1982; Craig et al., 1984; Arentze et al., 1993; Roy and Thill, 2004), using population data, per-capita expenditure, transport costs and centre size to model the flows of population to a location. The models are essentially statistical-averaging models and contribute to multiregional demographic models, to transport, and to location modeling, such as retail (Wilson, 2010). These models cannot be applied to pedestrian behaviour directly but rather the spatial estimation of potential and existing catchment areas (Timmermans et al., 1992).

However, spatial patterns of pedestrian movement and choice behaviour have been modelled using factor analysis and Markov chain models to simulate multi-purpose trips (Borgers and Timmermans, 1986; Timmermans et al., 1992). Typically, understanding the choice of consumers used by such models is gathered through questionnaires (Spiggle and Sewall, 1987; Borgers and Vosters, 2011; Das, 2014), which are then analysed using multiple regression techniques checking for collinearity, normality etc. Other approaches have looked at modelling pedestrian flows, using observations, customer diaries (Hart et al., 2014), and photographs of people to map and approximate the flow of pedestrians between junction intersections. Such approaches can have anomalies as people do not always walk from one intersection to the next and can use shops as means to move through a town (Thornton et al., 1991). More recently, using mobile telecommunications data, human motion has been investigated using random walk models (González et al., 2008; Hernando et al., 2014) to identify spatio-temporal pedestrian patterns in urban environments.

Whereas spatial interaction models focus on catchment area potential, Cooper et al. (2019) have created a model to evaluate and forecast the effect of major city centre changes, both spatially and temporally, using pedestrian flows. Their model incorporates changes in street layout in Cardiff city centre and through pedestrian layout mapping, empirical pedestrian flow observation and pedestrian route assignment, can model changes in pedestrian routing using spatial design network analysis modelling (Hossain and Cooper, 2021). D'Urso and Massari (2013) have used fuzzy cluster analyses to model the movement of shoppers, reflecting recent developments in the use of exploratory techniques associated with Data Science (Singleton and Arribas-Bel, 2019), where footfall data has been analysed using clustering algorithms (especially k-means) to identify and explore different temporal patterns apparent in the data across different locations in the UK (Mumford et al., 2017; Lugomer and Longley, 2018; Mumford et al., 2021; Philp et al., 2021). Finally, where vector data of footfall is derived from Wi-Fi or other similar data sources, graphical representations using network charts and frequency diagrams have plotted pedestrian movements (Traunmueller et al., 2018).

From this literature, the most closely related studies investigating pedestrian movements using footfall data and the most detailed are those of Monheim (1998) and Mumford et al. (2021). In the study by Monheim (1998), manually collected footfall counts and other qualitative information were combined for a select number of German cities and analysed to assess daily, monthly, and annual patterns of pedestrian activity. Monheim (1998) notes that although pedestrian counts appear a relatively simple measure, the footfall counts could reveal periodic cycles, processes of transformation, variations between locations in the same city and specific or random influences. The findings provided a useful reference to validate the results of this study as the annual and daily signatures identified by Monheim (1998) can be identified within the UK data as identified by Mumford et al. (2021). The study by Mumford et al. (2021) used the same data from Springboard as this research, to assess annual patterns in the footfall data; the difference being that monthly totals were used to diagnose annual patterns in the footfall data whereas this study choses a much finer resolution of hourly data. As with Monheim (1998), the findings of Mumford et al. (2021) provided a source of validation of the methods used by this study. Monheim (1998) points out the need to standardise the manual methods used for gathering of the footfall counts as making comparisons was made difficult where this was not the case, confirming findings by Cox et al. (2000). In addition, because of the manual techniques adopted, this presented a funding constraint on how much data could be gathered. However, Monheim (1998) does conclude that combined usage of footfall counts, and qualitative information gathered from surveys are useful information sources for retail research and town planning. Both studies have in common the use of footfall data based upon street pedestrian volumes, whereas most of the research identified below, has had to use other data sources.

Taylor and Parkes (1975) found that previous research analysing pedestrian behaviour and the dynamics of everyday place movements of people revealed the paucity of data available for analysis. Taylor and Parkes (1975) used data from the UK population census and concluded that all that could be understood was the night-time distribution of the population. Hidden from the census data (at that time) were the places of work and the daily commutes of the population. As a result, they theorised how the rhythms of people could identify employment cycles over several years, plus annual, weekly, and daily cycles, concluding that time was just as important as space in the organisation of the modern city and that the different rhythms and patterns that exist could provide an important way of understanding places better. Highlighting the daily activities of people rather than a focus upon the place of residence, as the areal units of a census measures (Kwan, 2018).

To test the theory of Taylor and Parkes (1975), Goodchild and Janelle (1984) collected space-time diaries from around 1500 people in Halifax, Canada, over a period of ten months. A key finding of the study was that the traditional models of urban social structure, derived mostly inductively from standard census data, have neglected significant elements of diurnal variation in the population compositions of urban subregions. Goodchild and Janelle (1984) noted that the use of diary data provided the opportunity to create census like information for designated times of the day that identified diurnal variations in population distributions and to temporal changes in concentrations of the elderly, children, working mothers and others. However, an impediment to using the technique was expense and the lack of experience of analysing the data (Goodchild and Janelle, 1984). Yet, by employing the technique in different types of cities, the suggestion was that the diurnal variations in populations could provide a means of comparing urban centres (Goodchild and Janelle, 1984).

Research studies of city entry points and pedestrian trip behaviours (Borgers and Timmermans, 1986), pedestrian street usage (Rapoport, 1987), the behaviours of shoppers and their circulation patterns in shopping centres (Brown, 1991b), the impact of pedestrianisation on retailing (Hass-Klau, 1993), space use, movement, and urban design (Hillier et al., 1993), all provide insights into aspects of pedestrian behaviour. With a focus on retailers, Kirkup (1999) provided a review of the potential of electronic monitoring of footfall in and out of stores, noting the technological problems with installing such systems and integrating them into supply chain operations. Pedestrian modelling (Haklay et al., 2001; Antonini et al., 2006), pedestrian route choice (Hoogendoorn and Bovy, 2004), walkability (Frank et al., 2010; Alfonzo, 2016), mobility patterns (González et al., 2008), provide ways to model and categorise pedestrian environments. However, the representative models and methods used, which are largely based upon the individual (micro-level) provide few clues as to how footfall data might be used and interpreted. The first specific reference appears to be that provided by Monheim (1998).

With a focus on everyday practice, Bromley et al. (2003) gathered evidence from residents of Swansea, UK using questionnaires to understand better the temporal usages of the city, in particular, the contrast between the working day, evening and night-time. From the data, a distinct temporal division between a frequently visited daytime city and a much less frequently visited evening and night-time city, was identified. Again, the data used was restricted by cost and limited to Fridays and Saturdays between February and March. From these findings, daytime attractions in Swansea during the day were shopping and refreshments - 51% shopping, 21% eating out and only 10% working. The newest shopping facilities offered the greatest appeal to the young whereas for the older population, the traditional facilities such as the market appealed more. The newer shopping facilities had a stronger fashion clothing or leisure function whereas the market had a bias towards household provisions. In the evening and night-time, pubs and nightclubs were the most frequently visited activities, restaurants and cafes had a lower intensity. The majority of visitor arrivals to the evening and night-time city were in the time period 5.50pm to 9pm. The departure pattern was more distinctive, late-night shoppers left before 9pm, other low intensity activities such as theatre goers left by 11pm. For pub and club visitors, most left after 11pm, the majority clubbers remained in the night-time city beyond 2am. By 4am, the city centre was devoid of activity. This study provides insight into the kind of social activity patterns that over the period of a day, that the footfall data should capture as found by Monheim (1998) and Lugomer and Longley (2018). It also reflects the types of users proposed by Gehl (2010), where necessary activities dominate the day and social activities dominate the evening and night-time periods.

Both Wunderlich (2014) and Hart et al. (2014) use diaries to study the movements of people in the urban environment. Wunderlich (2014) aimed to identify place specific rhythms using the diaries but also audio, video, and interviews. Hart et al. (2014) were able to track where people visited at different times of day when visiting a town. Again, both studies were limited by the sample size that can be achieved using manual methods. Thus, a pattern emerges of the collection of data being a major limitation on studies using footfall data captured through manual means. However, with today's availability of mobile communication and social media generated geospatial data, other routes to discovering everyday patterns and pedestrian movements have been explored through data exploration techniques using data-mining techniques (Kitchin, 2014a).

For example, Agryzkov et al. (2016) use Foursquare Data, Singh et al. (2018) uses wavelet analysis to look at impacts upon footfall in conjunction with USA economic performance indices. Although not pedestrian movements, vehicle trajectories have also been used to identify patterns, classify trajectories, and predict the location of vehicles in real-time using video surveillance vehicle trackers (Wu et al., 2017). Digital footprints have been extracted from Wi-Fi probe data in Lower Manhattan (Traunmueller et al., 2018) to model street use intensity and paths of travel. Using the ideas of Hägerstrand and time-geography, patterns from people's movements show peaks in the morning, lunchtime, and early evening, reflecting the commercial land use and associated workplace mobilities during the week. At weekends, morning peaks are later with different afternoon patterns, reflecting the mobility patterns of visitors and tourists at landmarks and retail establishments (Traunmueller et al., 2018). However, identifying individual tracks from Wi-Fi data is complicated and like manual methods, there are budget constraints on accessing the data. Hence for this study, the sample period was one week.

Sulis and Manley (2018) and Sulis et al. (2018) explore the rhythms of places and people in London to assess place vitality with particular reference to Jacobs (1961). Sulis et al. (2018) highlight that Jacobs (1961) considered the trait of vitality to mean the spatiotemporal continuity of human presence and activities in a place. Hence Sulis et al. (2018) view temporal variations, in terms of intensity and duration of flows that result from different place activities as important when evaluating urban vitality. The study makes used of three forms of data:

- ‘Smart card’ data (Oyster card) of one month of journeys on the underground rail and bus networks within the Transport for London area
- Three months of Twitter data using geo-tagging information.
- Points of Interest as mapped by OpenStreet Map

Using cluster analysis, Sulis and Manley (2018) perform a quantitative evaluation of vitality for places in London based upon intensity, variability, and consistency of mobility flows at different temporal scales. Noting that the locations are transport nodes, specific patterns would be expected. For central London, Sulis and Manley (2018) finds that where most workplaces, businesses, leisure and entertainment, and tourist attractions are located, also unsurprisingly are the highest values of vitality. The higher values of vitality during weekdays were strongly influenced by the magnitude of flows related to the home-work commute. At weekends, areas such as the City of London appeared less vital as this is an area dominated by workplaces and offices. Other locations such as Old Street which have high vitality scores during the week had even higher scores at weekends. So, this was a London focused study and again, although using different sources of data other than footfall, the availability of data was still limited to one month. The findings are useful as the findings of Sulis and Manley (2018) mirror the patterns identified from the footfall data for locations such as Leicester Square, London that has a very evident intensification of vitality in the evening and night-time (Sulis and Manley, 2018).

Like Traunmueller et al. (2018), Lugomer and Longley (2018) use Wi-Fi data from towns and cities in the UK. From their cluster analysis, eight daily cluster patterns (Figure 3.3) were identified and labelled using descriptions of the cluster centroid shapes. Like the findings of Sulis et al. (2018), the shapes identified for the daily patterns are evident in the results for this study. Unlike the other studies identified, this study is based upon three years data and therefore provides a valuable validation check for the daily results of this study.

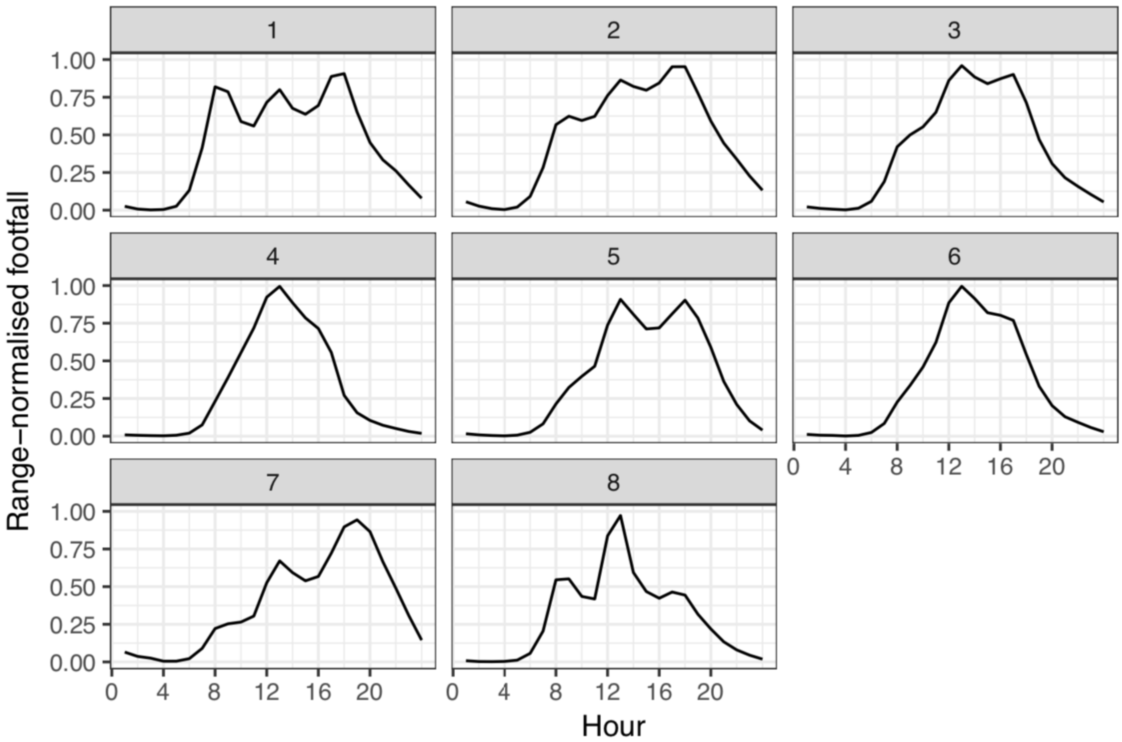


Figure 3.3. Temporal profiles of microsite locations [Data Source: Local Data Company (2015-2017)]
(Source:Lugomer and Longley, 2018:43:4)

Arellana et al. (2019) focus on looking at meso-scale and micro-scale environmental characteristics and their impact upon the walkability index (Frank et al., 2010) - the walkability concept referring to the extent to which the built environment is friendly to the presence of people walking, living, shopping, visiting, enjoying, or simply spending time in an area. Meso-scale variables included factors such as housing density, job density, land use diversity, street connectivity and proximity to destinations. Micro-scale variables captured street-level characteristics such as trees, the quality and width of pavements and the quality of streets (Kim et al., 2014). Arellana et al. (2019) suggest micro-scale variables are seldom considered in Walking Index studies. From their study (based in Barranquilla, Colombia), inspired by the walking needs proposed by Alfonzo (2016) they focus on the condition and problems with walkability of pavements due to cleanliness, obstructions etc.

A common theme for all the research identified, whether footfall or pedestrian movement data is gathered manually or derived from secondary data sources, is the limited sample sizes. In only two studies (Lugomer and Longley, 2018; Traunmueller et al., 2018) was more than a continuous year of data available for the research. Hence using pedestrian count data to analyse the changes to social activity patterns over time makes this study unique. Table 3.2 provides a summary of other studies not already discussed where the same issues of sample size remain an issue. As a result, findings are limited to patterns within the timeframes of the data. Another issue with using secondary data sources such as communication technologies and social media, is the assumed presence of individuals having smartphones or at least, mobile phones. Those people without either are excluded from the data and therefore not represented (Mumford et al., 2021).

Following on from the findings of Mumford et al. (2021), this makes the availability of over ten years hourly footfall data for this study unique. In addition, footfall is an inclusive measure that is not dependent upon smartphone technology. Thus, it provides the means to measure vitality for <u>all users</u> of a town or city and to explore the assemblages that represent the changes in intensity of place territorialisation over the time periods of years, weeks, and days. With over ten years of data, this study can discover these assemblages, to see how they change over time for all places and individual towns and cities.

Table 3.2. Other related literature

Author	Concept(s)	Data	Method	Sample Period	Where
Osman and Mulíček (2017)	Rhythmanalysis	Questionnaires	Narrative and Graphical Analysis	18 locations, each sampled for at least 24 hours between April and May 2015.	CZ, Brno
Manley and Dennett (2018)	Data Driven	Secondary Data Phone location data Land Use Type data	Cluster Analysis (k-means)	7 Months Phone Records Data	Dakar, Senegal
Giglio et al. (2019)	Data Driven	Secondary Data - Flickr metadata	Machine Learning and Cluster Analysis	3 years from Milan, Florence, Rome, Naples, Venice, and Palermo	Italy - Six Cities
Martínez Plumé et al. (2019)	Data Driven	Secondary Data - Bluetooth sensors	Algorithm development - to enable distinction between vehicles and pedestrians to track journeys	18 Days	Spain, Valencia
Nemeškal et al. (2020)	Data Driven	Secondary Data - Phone location data	Classification scheme based upon location and codes. Time series plots	1 Day – limited by cost	CZ, Prague

3.6 Summary

As a performance measure, footfall is viewed by this study as a measure of persistent patterns of social activity, not at the level of the individual - the micro-level, but at the meso-level - the convergences of shared everyday practices of many individuals (De Certeau, 1984; Schatzki, 2009). These persistent patterns of social activity exist at different temporal periods, as suggested by Duffy and Stojanovic (2017) and Escobar (2007) and it is these periodic meso-level assemblages that this study focuses upon. The previous chapter considered that the analysis of the footfall can apply the analytical perspective of territorology (Brighenti, 2010a) which is then grounded within the ontology of assemblage theory (DeLanda, 2016). This then provides the theoretical framework for the study. However, there is also the need to understand how footfall can be considered as a performance measure, how it frames movement-space within the epistemological framework of territorology (Merriman, 2012).

As an observation of place, counting pedestrians, or footfall, is a means to measure city life. The ability to answer the question, *how many* or *how few* provides the means to evaluate and compare different days, weeks, years etc (Gehl and Svarre, 2013). Furthermore, Mumford et al. (2021) demonstrate that patterns of monthly social activity over the period of a year can also be identified and used to distinguish different place types. However, the epistemological framework of territorology that is used by this study needs to be set in the context of what the quantification process of counting pedestrians obscures. In fact, the discussion below helps reinforce that this is a study focused upon the meso-level of collective social activities.

According to Lamont (2012), quantification is often considered the dominant means for valuation and evaluation in sociology, and measurements and evaluations are pervasive in our day-to-day lives (Hesselmann and Schendzielorz, 2019). Measurement is always an act of value discovery or creation and re-creation, insofar as it rests on the assertion that something is potentially of value or valuable (Hesselmann and Schendzielorz, 2019). In modern science, value is usually associated with a numerical determination (Brighenti, 2019). In other words, measures are associated with dealing only with quantitative aspects of existence and discard (as a reductionism) all qualitative qualities (Brighenti, 2019). Ingold (2007) provides a good example of this reductionism when he compares the idea of a walk to that of an assembly of point-to-point connectors. Whereas a walk is a trace of a continuous gesture, the line is fragmented, and provides destinations. With the line, the multiple and interlaced strands of movement, interactions and the inhabitation of the environment are lost. Instead, all that remains is a static network of connectors.

The predicament in all measurement systems and all measurement apparatuses can thus be traced back to the epistemological disappearance, or in-visibilisation, of *virtus* (worth) from modern measure. Such disappearance has left magnitude as the only legitimate, visible reference (Brighenti, 2019) - and this limits the value of the quantitative for the social scientist. Brighenti (2018) notes that measures are not simply tools they are also environments in which we live. While our awareness focus is upon measures as technical devices and formal procedures, from the moment measures become infrastructural, they also become an ‘air’ we breathe, an atmospheric component of society (Brighenti, 2018), or have the potential to be part of a sentient city (Thrift, 2014). The relation between measure and value is circular, entangled - where value exists before and after measurement and can be conceptualised as territorialising devices; that is, as social territory-making acts, they appear to be part of territories and their encounters (Brighenti, 2010b). For Brighenti (2018), special attention should be paid to the case n = 1. In this case, the unit is not just a quantitative happening but has a qualitative meaning as well. The tendency to treat data in the aggregate and to break down entities to extract data, hides the significance of the unit of the element (Brighenti, 2018). For example, Brighenti (2018) provides the example of a city that can be measured many ways to compare it to other cities - but each city has a uniqueness, a singularity that resists decomposition into a bunch of traits and aggregation across other comparable urban entities.

To expand upon this, Brighenti (2018) argues n = 1 is not just a quantitative happening but also qualitatively distinct event, where the unit is like a monad or eigenstate that directly and immediately condenses its environment. Brighenti

(2018) adds that measures are simultaneously technological-material, legal-political and cultural. Every technical measurement system functions not only as an epistemic model but also, inevitably as a power tool. Severed from the measure-value environments in which they are produced, numeric and metrical measurements are devoid of sense. Measures help turn what we want into what we believe - made possible by the fact measures return to us values in a homogenous medium, namely the visible (Brighenti, 2016). In realist terms, this is the empirical domain (Bhaskar, 2008).

Other examples of discussions regarding how values can be understood is that of utility vs experience discussed by (Kahneman et al., 1977; Kahneman and Thaler, 2006; Read, 2007; De Vos et al., 2015). Or, how values can be used to promote initiative and risk within cities, or simply to enforce the security-entertainment complex (Thrift, 2014). Within the field of measurement, Micheli and Mari (2014) note that there has been a shift from error to uncertainty (BIPM, 2012). This has required a shift from ontology (measurement as a means to know how reality is) to epistemology (measurement as a means to acquire and consistently express information on reality). This position maintains that measurement can only claim to act as a representational tool - where measurement relates to the available knowledge on the state of an object. So uncertainty is the lack of complete certainty on the value that should be assigned to describe the object being measured (Micheli and Mari, 2014).

Taking the reasoning from Brighenti (2018) mentioned above, a single count of a person, n = 1, measures the (de)territorialisation of a person passing through the boundaries measured by the footfall sensor. This measure is a reductionism from the plurality of economic, political, cultural, phenomenological, ecological, and non-representative everyday factors embodied within that person as to why that person was at that point, at a specific time. By registering this as a single count, clearly all that information is lost. Consequently, the factors identified by Ntounis and Parker (2017) can no longer be attributed directly back to that person (the micro-level) and the plurality of methods used to study and manage places (Ntounis, 2018) mean that attribution back to motivations, place management decisions etc can only be inferred at best. In other words, through the process of quantification, footfall can be viewed as a meso-level performance measure as even when n=1, the qualitative meaning of the individual is invisible.

However, despite this reductionism (Brighenti, 2018) and uncertainty (Micheli and Mari, 2014) inherent in the data, the notion of rhythmanalysis (Lefebvre, 2004) is an important and helpful research technique in the social and spatial sciences (Brighenti and Kärrholm, 2018). Based upon work of Deleuze and Guattari (1988) the life of territories can be said to be not only rhythmic but also melodic (Brighenti and Kärrholm, 2018). In this case, territories can be seen as refrains and melodies joined together, but just as refrains cannot exist without some melody and rhythm, so lived rhythms are constituted of melodies and refrains (McCormack, 2013). By aggregating the data, even though this is reductive, there are still rhythms evident and from these rhythms, individual melodies can still be identified that signify individual places. More specifically, for Brighenti and Kärrholm (2018:2), “the nexus between rhythm and territory lies not only in the coming together of spaces and times, but more specifically in the *investments of energy*, or *intensities* that accompany it.” Footfall data is well placed as a performance measure to summarise such intensities within the limited time-space of the sensor territory.

Yet Brighenti and Kärrholm (2018), with a vitalistic approach to both rhythms and territories, suggest that rhythm could be explored not only in terms of the recurrent patterns of association it defines, but also with essential reference to the qualitative singular intensive situations to which it corresponds. Thus, their project consists of the intensification of rhythmanalysis to the point of pushing it beyond itself, to capture the peculiar *eigenstates* created by specific rhythmic steps and melodic lines in social life. Ultimately, the footfall data falls short of the completeness of measurement suggested by Brighenti and Kärrholm (2018). In their theory of territorology Brighenti and Kärrholm (2018) theorise how rhythmic production interweaves with territorialisation processes at large in *all their dimensions*. The aggregated nature of the footfall data results in many of the phenomenal components being obscured in the reduction of the data to a count. On the other hand, the aggregated intensities of these phenomenon can still be identified, permitting the study of rhythms through investigations of spatial-temporal intensities and presences (Brighenti and Kärrholm, 2018) at the meso-level. Thus, this research study follows a territorological perspective for the analysis of the footfall data allowing the uncovering of meso-level assemblages that are associated with the rhythmic intensifications of the territorialisation processes.

3.7 A Conceptual Model

Territorology and the changing intensities of footfall over different periods of time provide the framework for analysing the footfall data of this study as represented in Figure 2.6. What is missing though from Figure 2.6 is a means of categorising the different types of pedestrian (social) activities that represent the intensification of territorialisation processes. Gehl (2010:20-21) and Gehl and Svarre (2013:16-17) suggest a framework based upon the quality of the urban physical environment and social activities which are identified as:

- **Necessary activities -** these take place under all conditions of the physical environment. Activities include those that people must do, such as going to work, school, waiting for the bus, bringing goods to customers, and working as a postman or police officer and so on.

- **Optional activities -** these are largely recreational such as walking along a street, stopping to look around, or sitting down. Most of the most attractive and popular city activities belong to this group and so is a measure of place quality. Such actives are sensitive to the weather, where a snowstorm can prevent anything from happening whereas the sun can bring people out onto the streets.

- **Social activities** include all types of communication between people in city space and require the presence of people. A wide spectrum of activities exists, such as passively watching people, or more active activities such as a chance meeting, or the gathering of large groups e.g., markets, street parties, meetings, demonstrations etc.

Gehl and Svarre (2013) notes that necessary activities for some people could be optional for others, such as people that can telework no longer needing to commute to an office because of the COVID-19 pandemic. Hence for Gehl and Svarre (2013), there is sliding scale between optional activities which take place in good external conditions and can be viewed as increasing in their degree of necessity to become ‘necessary activities’ that take place under all conditions. Gehl (2010) also reasons that just as climate is an important factor for the extent and character of outdoor activities, so is the quality of the outdoor environment. As urban quality increases, so do optional activities and therefore, the increase in activity level invites a substantial increase in social activities. Whereas necessary activities remain roughly the same, no matter the quality of the physical environment. As a framework for analysing the footfall results of this study, thinking in terms of the social activity types that the footfall data suggests was considered a useful descriptor for the analysis. Therefore, Figure 2.6 is modified to include these activity categories in the consideration of territorialisation intensity – see Figure 3.4 below.

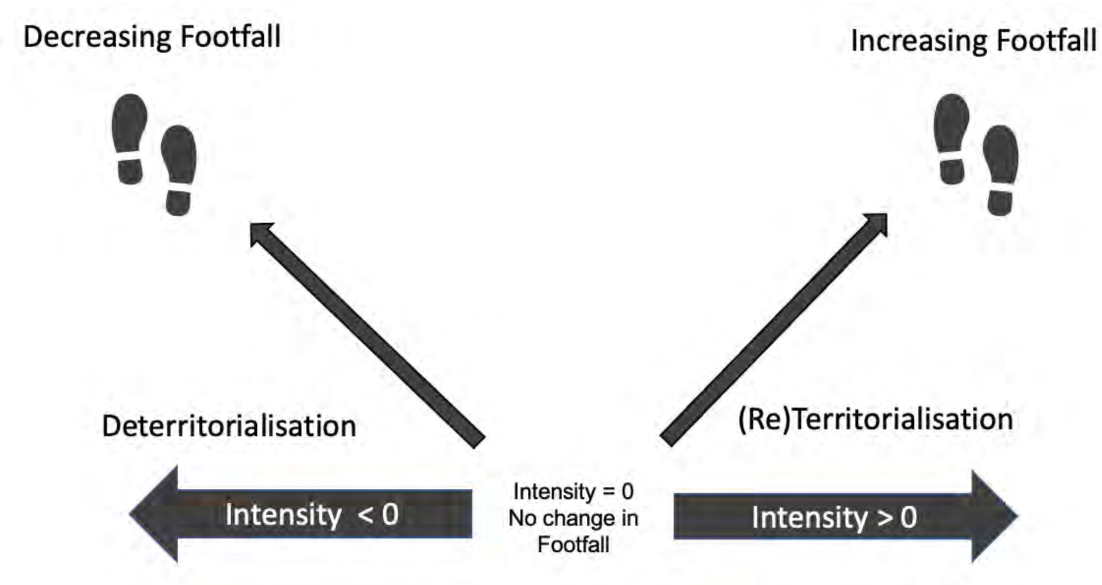


Figure 3.4. Intensity of Summed Activity Types versus Territorialisation and Footfall

The degree of intensity in Figure 3.4 is represented by Equation 3.1 below noting that factors such as climate, pandemics, and the urban environment impact elements of the individual activity types.

Equation 3.1. Intensity of Activity Types

$$Intensity_{ijk} = \sum_{i=0}^{n} necessary_i + \sum_{j=0}^{n} optional_j + \sum_{k=0}^{n} social_k$$

Where the sum of each activity is the contribution of the individual rhythms associated with each activity type, where each activity type may have none or many concurrent rhythms, which account for the period of territorial intensity. The equation expresses an idea, not a mathematical certainty so is not intended to be interpreted literally. Principally, this is because footfall counts cannot differentiate between the different types of social activity since, as already identified, each count is a reductionism that obscures the motivations of individuals such as going to work, meeting a friend, shopping, or simply going for a walk. The equation attempts to identify complexity based upon the number of summed activity types that account for differences in footfall intensity. Thus, the more complex the activity types, the more polyrhythmic the footfall becomes as opposed to being isorhythmic and dominated by single activities. Note that whichever activity type is the dominant cause of territorialisation intensity, for example necessary activities, will dictate whether the intensity is negative or positive thus masking lesser changes in other activities. A further reductionism to be considered during the analysis.

Both Figure 3.4 and Equation 3.1 provided a useful tool for determining the research design approach and the interpretation of the results. For the research design, an analytical technique was required that could identify the daily, weekly, and annual footfall rhythms in a manner that could be readily interpreted in terms of the changes of territorialisation intensity for the different periodicities. For the interpretation of the results, the conceptual model also facilitated the evaluation of how social activity types evolve over time and, how changes to the processes of territorialisation intensification could be assessed and presented. The next chapter discusses the research design and the approach taken to support the conceptual model and, how this was operationalised.

4 Research Design

The research design chosen is positioned within the theoretical frameworks of territorology (Kärrholm, 2008; Brighenti, 2010a, 2013) and assemblage theory (DeLanda, 2016); that is, capturing the meso-level assemblages of social activity through identifiable rhythms and intensities within the footfall data that form part of the continually shifting territorial landscape (Brighenti and Kärrholm, 2018) of each sensor location and place. Although Brighenti and Kärrholm (2018) argue that territorology is grounded in phenomenology, it can also encompass other approaches. This then is a quantitative exploratory study, using a secondary data source of footfall data where the unit of analysis is not the individual, but instead the interwoven social activity timespaces that form where human activities gather and aggregate (Batty, 2002; Schatzki, 2009).

The Chapter begins by considering the philosophical issues of ontology, epistemology, and research strategy. The sources of data are then discussed followed by a justification for choosing time-series fuzzy cluster methods to discover the rhythms in the footfall data. The final section focuses on the operationalisation of the research design using an iterative (Agile) process (Cohn, 2005; Leffingwell, 2011) for implementation. In this section, the individual elements of the research design implementation are discussed such as the processing of missing data (Moritz and Bartz-Beielstein, 2017; Demirhan and Renwick, 2018; Little and Rubin, 2020), the seasonal decomposition of the time-series (Cleveland et al., 1990; Shim and Eastlick, 1998; Sanchez-Vazquez et al., 2012; Rojo et al., 2017) and the parameterisations needed for the fuzzy cluster analysis (Bezdek, 1981; Ratanamahatana and Keogh, 2005; Wang and Zhang, 2007; Sardá-Espinosa, 2019). The research design includes specific technical details, and these are provided in Appendix B with the intention of enabling reproducibility and replicability (Wolf et al., 2020).

As identified by Ntounis (2018), place management knowledge is derived from a plurality of disciplines, and no single paradigm or research programme is capable of fully addressing the relational complexity of place management. In addition, multiple theoretical lenses can be used as part of the methodology to inform research, theory, and practice. With hourly footfall counts as the source of data, this is a quantitative study that narrows the theoretical lens options and so the study informs a small part of the totality that is the theory and practice of place management. In exploring the footfall data through data exploratory techniques (Kitchin, 2014a, 2014b; Brunsdon, 2016) and by adopting assemblage theory, a realist stance is applied - as discussed below.

As discussed in the literature review, if places can be considered in terms of their everyday rhythms, then patterns of territorialisation should be apparent in the footfall data. By identifying these patterns, it should be possible to analyse similarities and dissimilarities in the intensities of territorialisation at different sensor locations. Thus, it should be possible to identify the assemblages at each location, those that are common across locations and assess how the assemblages change over time. As a performance measure, the analysis of the data should enable the identification of rhythms and intensities of the common and shared social activities and how they have changed over time, an insight that aids learning for town managers.

4.1 Ontological Considerations

Ontology, the nature of social reality, identifies assumptions regarding the kinds of social phenomenon that do or can exist, the conditions for their existence and the ways they are related (Blaikie, 2007:13; 2009:92). Epistemology, the theory of knowledge, provides a grounding for establishing what kinds of knowledge are possible and the criteria for justifying legitimacy and adequateness (Blaikie, 2007:18). This section is focused on ontological considerations for this investigation and as already discussed, much of that thinking is provided by Assemblage Theory.

Assemblage theory, the composition of heterogeneous elements that may be human, non-human, organic, non-organic, technical, and natural (Anderson and McFarlane, 2011), has a commitment to a relational ontology (Dittmer, 2014b) . Dittmer (2014b) adds that relational ontologies are particularly important to scholars of non-representational theory who posit bodies always in relation not only to each other but to other things. Assemblage thinking therefore is not just concerned with social/political processes that are happening at a site, but also concerns itself with those external to a site (Featherstone, 2011:140). Assemblages emphasise spatiality and temporality and therefore involve an orientation of assembling and disassembling as relations form, take hold, endure or might change or be disrupted (Anderson and McFarlane, 2011).

However, Harvey (1996) cautions, whilst adopting a process of relational dialectics (Ollman, 2003), that the reduction of everything to fluxes and flows, and the consequent emphasis upon the transitoriness of all forms and positions has its limits. Harvey (1996) accepts the general argument that process, flux and flow should be given a certain ontological priority in understanding the world, but that attention needs to be also given towards ‘the permeances that surround us too which we construct to help solidify and give meaning to our lives’ (Harvey, 1996:7). MacFarlane (2017) reiterates the criticism of Harvey (1996) in that an relational ontology of pure flux denies any stable point at which a decision could be made to affirm or reject any relations. DeLanda and Harman (2017) agree with MacFarlane (2017) adding that realist ontologies that are all process and no product are to be rejected since, what is the point of suggesting the existence of genesis and maintenance if there is no product that possesses that identity (DeLanda and Harman, 2017:77).

Assemblage theory has been applied to urbanism and the relationships within and between urban sites (McFarlane, 2011; McFarlane and Anderson, 2011). Thinking of the city as a gathering process, McFarlane (2011) views the concept of assemblages as particularly useful for understanding the processual, relationship and generative nature of the city, in reference to both the momentum of historical processes and political economics and the eventful, disruptive, atmospheric, and random juxtapositions that characterise urban space. McFarlane (2011) adds that the urban assemblage is structured with hierarchies and narratives via the relations of power, resource and knowledge and so suggests that there is more to assemblages than just process. Anderson et al. (2012) also confirm this, adding that assemblage thinking is based upon an experimental realism. More generally, assemblage theory has been deployed as an alternative to paradigms that rely on ideas of identity, structure, and system in explaining how social and material orders take form (Kinkaid, 2019).

Assemblage theory operates within a (neo-)realist ontology (DeLanda, 2016). Easton (2010) points out that critical realists accept the world is socially constructed and that critical realism (Bhaskar, 2008) is stratified between the empirical and the actual and the real. The empirical domain is where observations are made and experienced by observers and our senses (Blaikie, 2007). Events occur in the actual domain and may not be observed or may be understood quite differently by observers. The real refers to the structures and powers of objects, whereas the actual refers to what happens when these powers are activated Sayer (2000). There is a process of interpretation that intervenes between the two domains though it is not true to say that the real and actual cannot be observed, but simply that they might not be capable of being observed (Easton, 2010; Jagosh, 2020). The aim of science (social sciences) is therefore to explain observable phenomenon with reference to underlying structures and mechanisms (Jagosh, 2020). Hence the assemblages identified by this study are created via this process of interpretation.

One of the distinctive features of realism (Sayer, 2000:13-14) is the analysis of causation, which rejects the standard Humean ‘successionist’ view that it involves regularities among sequences of events (Bhaskar, 2008). For neo-realists, causation is not understood using the model of regular successions of events, and hence explanation need not depend upon on finding them. What causes something to happen has nothing to do with the number of times we have observed it happen. Explanation depends upon identifying causal mechanisms and how they work and discovering if they have been activated and under what conditions. In other words, there is a distinction between the real and actual, where we introduced the concept of causal powers. In the social world, where systems are open, the same causal power can produce different outcomes according to how the conditions for closure are broken; for example, economic competition can prompt firms to restructure, innovate, or close. Sometimes different causal mechanisms can create the same result, for example reasons for losing a job. Thus, events are not pre-determined before they happen but depend upon contingent conditions; the future is open - many outcomes are possible (Sayer, 2000) and so there is ontological depth. Events rise from the workings of mechanisms which derive from the structures of objects, and they take place within geo-historical contexts (Sayer, 2000). Thus, although assemblage patterns in the footfall data might be shared between different locations, that does not imply common causal mechanisms.

Harman (2008) finds that the assemblage structure of DeLanda (2006) has two dimensions - from one of material vs expression, the other defining processes involved that stabilise or destabilise the boundaries of an assemblage by a process of territorialisation and deterritorialisation. Harman (2008) however, criticises the assemblage approach due to a lack of development of the properties of an assemblage, thus making it difficult to know how to define. This investigation chooses to think of the world in neo-realist terms and to take from both territorialisation and assemblage theory the ideas of de/territorialisation, intensities, and structure.

4.2 Epistemological Considerations

Epistemology is the theory of knowledge. It is the theory of how we come to have knowledge of the world around us, of how we know what we know (Blaikie, 2007:18). Epistemologies can be distinguished by the status of the knowledge that they claim to produce. For example, adherents of empirical epistemology believe it produces absolute knowledge whereas that of neo-realism, more aligned to this study, accept that knowledge of structures and mechanisms is always tentative (Blaikie, 2007:24). Thus, Micheli and Mari (2014) identify the shift from error to uncertainty (BIPM, 2012) with respect measurement systems, a shift from ontology (measurement as a means to know how reality is) to epistemology (measurement as a means to acquire and consistently express information on reality). A position that therefore maintains that measurement can only claim to act as a representational tool - where measurement relates to the available knowledge on the state of an object. So, uncertainty is the lack of complete certainty on the value that should be assigned to describe the object being measured (Micheli and Mari, 2014).

Taking a territorological perspective, it makes sense to advance the study of rhythms through in-depth investigations of space-temporal intensities and presences (Brighenti and Kärrholm, 2018). Brighenti (2010a) highlights the need for territorology to include an epistemology that accommodates the fact that territories are interactional. Territories result from encounters and from the affects developed during those encounters. Territories are also the effect of the material inscription of social relationships, where actors inscribe an ensemble of cognitive and normative plans into given material supports. For example, procedures (e.g., procedures for navigating a certain space), ways of doing things conveniently (proper behaviour, efficient action, etc.), expectations about mutual recognition (interaction rituals, reparations, etc.), power claims and hierarchies (both personal and impersonal), and so on.

By employing a territorological approach (as this investigation does), the difficulty in conceptualising the interplay between physical space and the organisation of relations and functions that comes with it, within and throughout a territory, is an epistemological difficulty (Brighenti, 2010a). Brighenti (2010c) points out that epistemological choices are not matters of mere intellectual fashion trends. Rather they stem from immediate and concrete problems. Concepts are never created for their own sake; on the contrary, they are introduced to face the puzzles we engage with during our research into the social, its configurations and its dynamics (Brighenti, 2010c).

With respect to place management, in order to solve the epistemological difficulty identified by Brighenti (2010a), there is a need for epistemological plurality as place management needs to embrace the incompleteness, openness, and situatedness of place knowledge (Ntounis, 2018). Supporting this, (Pierce and Martin, 2015:1294) state: “Importantly, relational places cannot be completely known through any one epistemic approach: incompleteness is inevitable.” Just as place management then has a need for multiple epistemologies, Merriman (2012) also notes the need for a range of epistemological devices and technologies for thinking, measuring and framing movement-space which can be worked into ontological assemblages.

Therefore, to examine relational place (assemblages), the epistemological and methodological investigation of the assemblages (processes) involved in place production, demands acknowledgment of the partialness, and uncertainty, of any methodological engagement with place (Pierce and Martin, 2015). Pierce and Martin (2015:1294) adds that: “examining place in its constituent parts is not merely possible but methodologically necessary. It is in the analytical process that relational place-making and (socio-)spatial production again converge, as researchers identify the assemblages which various place-frames produce.”

Methodologically, this is a quantitatively focused study, so it is important to acknowledge the flattened vision of the social phenomenon (Brighenti, 2010c) provided by the footfall measurements, resulting in the incompleteness of place understanding identified by both Ntounis (2018) and Pierce and Martin (2015). Consequently, this is one part, a view through an individual theoretical lens, for example, within the part of place making practice that focuses on understanding the patterns of everyday life that is identified by (Ntounis, 2018). In other words, the empirical findings of this investigation is a single bundle of all the bundles of knowledge (Pierce and Martin, 2015) needed to support our understanding of place.

In conclusion, although place management suggests a pluralist standpoint both ontologically and epistemologically, this study is viewed as a single lens view into the place management field. Ontologically, by positioning the study using the concept of assemblages, the theory of territorology and the quantitative nature of this investigation, a neo-realist understanding of places is achieved. Epistemologically, recognising the incompleteness, openness and situatedness of place knowledge (Ntounis, 2018), this study looks to understand how social practices can be identified using the analytical framework provided by territorology theory (Brighenti, 2010a; Brighenti and Kärrholm, 2018).

4.3 Research Strategy - An Abductive, Retroductive Approach

The research approach taken was that of exploratory data-driven science (Kitchin, 2014a) which seeks to hold onto the tenets of the scientific method but is more open to using a hybrid combination of abductive, inductive, and deductive approaches (Kitchin, 2014b). It differs from the traditional, experimental deductive design in that it seeks to generate hypotheses and insights ‘from the data’ rather than ‘born from the theory’ (Kelling et al., 2009:614). Such decision-making with respect to methods of data analysis are based on abductive reasoning (Kitchin, 2014b). Abduction is the logic used to construct descriptions and explanations that are grounded in everyday activities of social life (Blaikie, 2004).

Abductive reasoning, articulated by astronomer and mathematician Peirce (1839–1914), is a form of inference that starts with data describing something and ends with a hypothesis that best explains the data. Whereas deduction proves that something *must be*, induction shows that something *is*, conclusions based on abductive reasoning are more tentative (that something *may be*) than those based on deduction and induction (Miller, 2010; Kitchin, 2014b). As an approach, it is more suited to exploring, extracting value, and making sense of data sets (especially big data) (Kelling et al., 2009). It also has the potential to produce studies with much greater scale and timeliness, that are inherently longitudinal, in contrast to existing social sciences research (Lazer et al., 2009; Batty et al., 2012; Kitchin, 2014b). Hence, the research strategy adopted within data-driven science is to use knowledge discovery techniques to identify potential questions (hypotheses) worthy of further examination and testing (Kitchin, 2014b).

At the start of this study, although the footfall data was available to process and investigate, the theoretical background to this research was unknown and initially, this ambiguity meant that defining the theoretical framework for the research and defining the objectives took time. The search for theory was initially (to a large degree) an abductive (hunch-driven) process (Jagosh, 2020). With rhythms apparent in the data, relating these back to everyday life and social patterns became more and more appealing. From the review of the literature, and supervisor discussions, eventually it was possible to infer that territorialisation

(Brighenti, 2010a, 2013, 2014) provided a basis for investigation of the footfall data. As Jagosh (2020) states, abduction requires creativity to reframe a phenomenon of interest into a conceptualisation that leads the researcher to explore the empirical world in different and innovative ways. For example, conceptualising the footfall signatures as a collection of assemblages that de-territorialised and re-territorialised a location.

Using the territorology concept (Brighenti, 2010a), exploratory data analysis techniques were used to uncover the assemblages in the footfall data, and this was more a retroductive process, where retroduction is inference that generates possible explanations and the testing of ideas (Blaikie, 2009; Jagosh, 2020). Thus, the study has employed a blend of abductive and retroductive approaches as is suggested by Saenz et al. (2011); Jagosh (2020).

4.4 Data Sources

The footfall data used for this study is provided by Springboard (www.spring-board.info), a leading supplier (UK and USA) of technology used to measure customer activity such as footfall, vehicle counting and Wi-Fi tracking. This study is therefore dependent upon a secondary data source.

The Springboard technology monitors pedestrian movements continuously 24 hours a day, 7 days a week. A small counting device is mounted on either a building or lighting/ CCTV column and a virtual zone is defined where pedestrians that pass through the zone are recorded. Footfall numbers are recorded using counting software based on “target specific tracking”, which via independent audits has a degree of accuracy of between 95% and 98% (Springboard, 2015).

Site selection for Springboard counters follows a site survey in collaboration with town centre stakeholders. In addition to walking through a location to understand visitor usage, the Springboard team consider what the place stakeholders aim to achieve. Whereas in the past there was a predominant retail focus, this is now changing to include considerations relating to events and the night-time economy. It is also important to avoid overlap with existing data capture capabilities, for example, Springboard footfall sensors used by Transport for London at tube stations (Mumford et al., 2021).

With respect to the representativeness of the data, the footfall sensors provide a partial sample of urban reality regardless of their extensiveness (Sulis et al., 2018). By focusing on a single source of data, there is the additional concern about reliability of the results (Sulis et al., 2018). It was therefore a useful validation process to review other research where different data sources or methods were used and signatures identified (Monheim, 1998; Lugomer and Longley, 2018; Sulis and Manley, 2018; Sulis et al., 2018; Martínez Plumé et al., 2019).

The sensor data available to this study covers the period 2006 to 2019. However, neither 2006 nor 2019 contained a full year of data (this was needed for the annual cluster analyses) so the study is limited to the period 2007 to 2018 as a result. The map plots (Figure 4.1, Figure 4.2 and Figure 4.3) show how the distribution of the sensor network has expanded during this time. The geographical location of the sensors includes the UK, Channel Islands and Northern Ireland. In 2007, there were initially 74 sensors available and by 2018, this had increased to 538. Figure 4.4 below plots the roughly constant increase in sensor numbers over the study period.

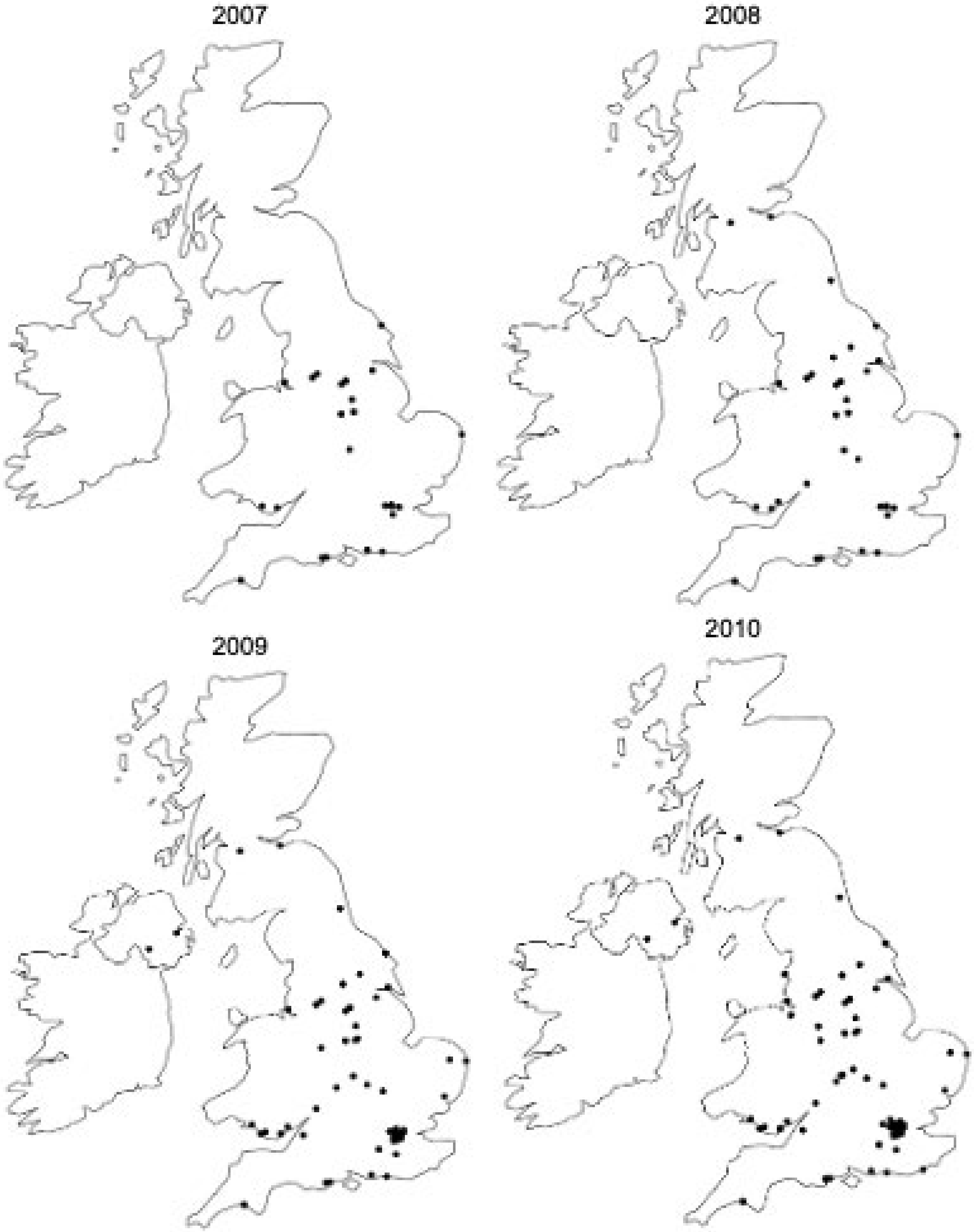


Figure 4.1 - The location of footfall sensors 2007 - 2010

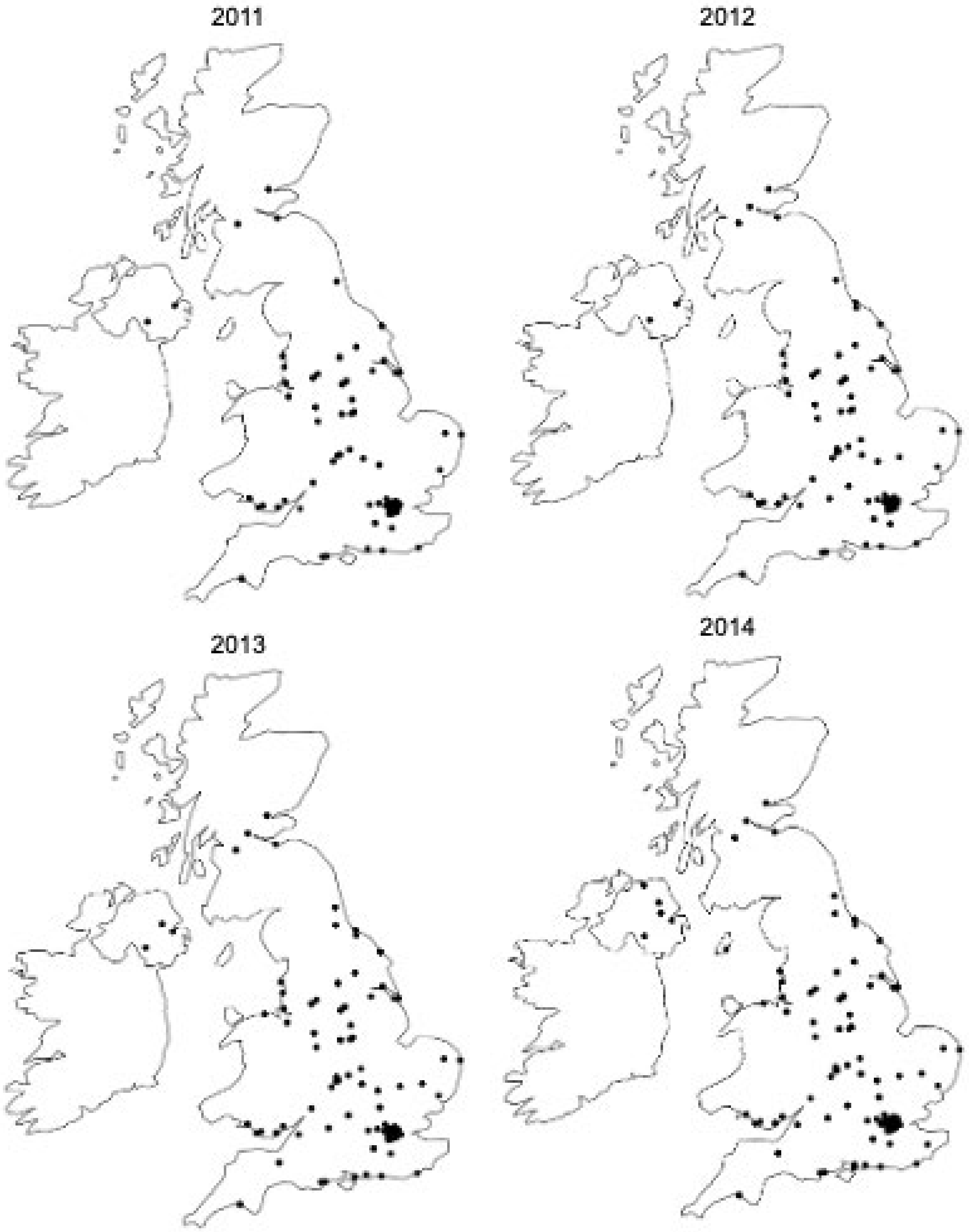


Figure 4.2 - The location of footfall sensors 2011 - 2014

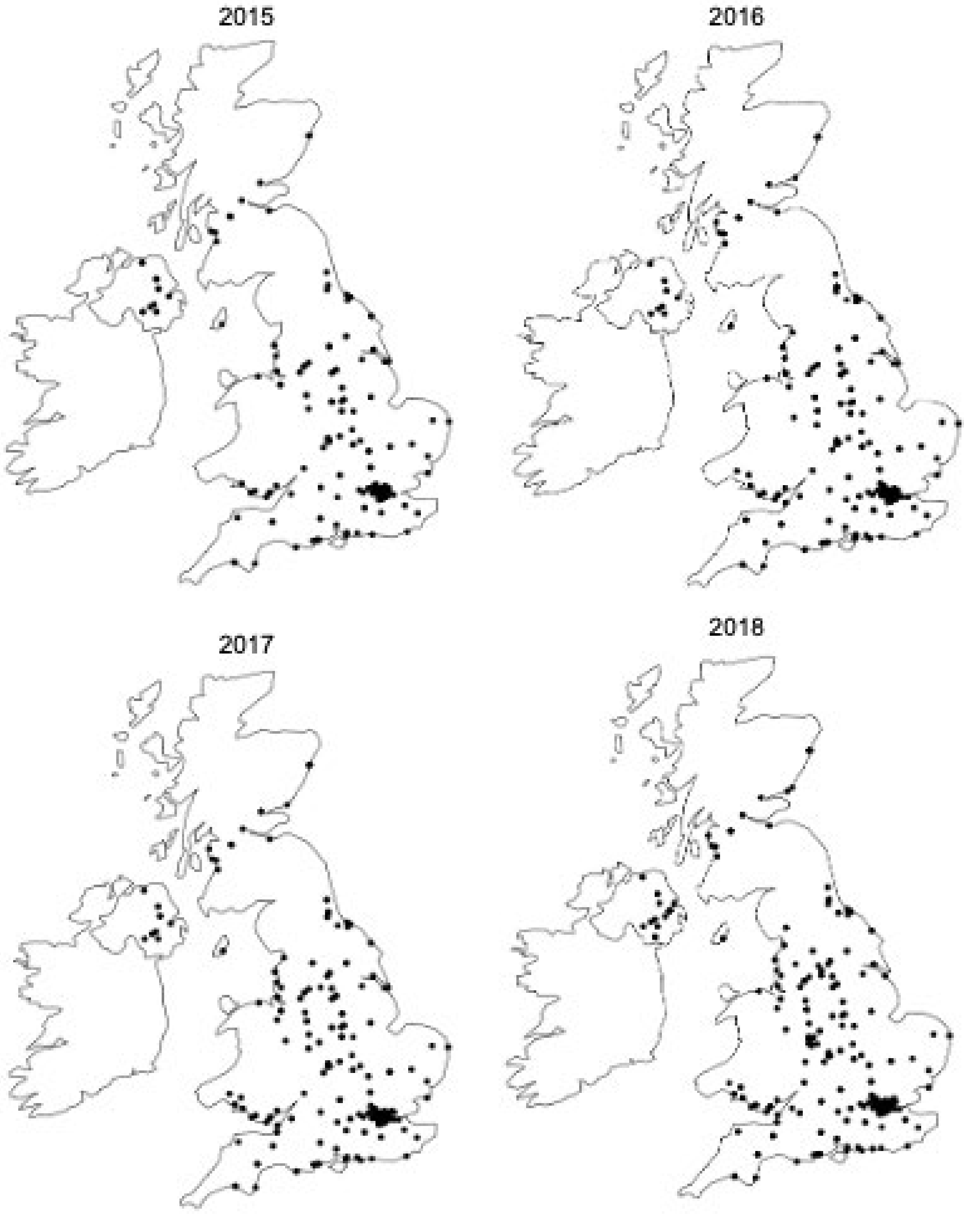


Figure 4.3 - The location of footfall sensors 2015 - 2018

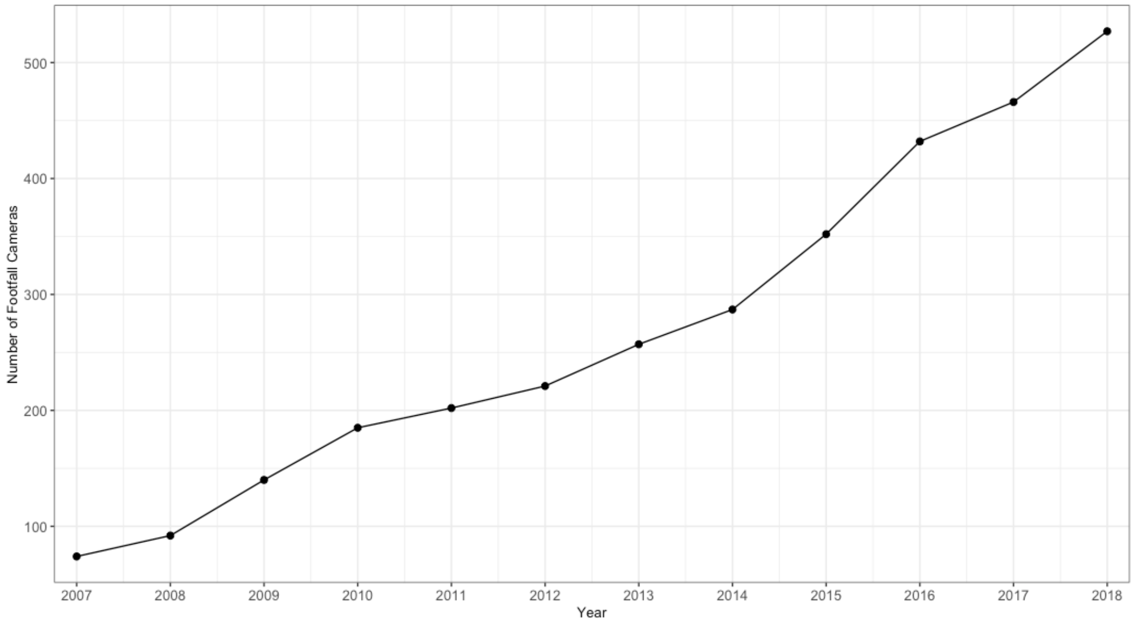


Figure 4.4 - The annual increase in sensor numbers for all locations

The footfall data was provided by Springboard as CSV (comma separated variable) files where each file contained all the data for each individual year. A significant part of the implementation of the research design, required the development of software to load this data into a database and enable the data analysis phase. An example of the CSV contents is provided below in Table 4.1.

Table 4.1 –Footfall CSV file example

Region	Place	Sensor Location	Date Time	Hourly Count
East	Great Yarmouth Town Centre	King Street	2007-01-01 02:00:00	1
East	Great Yarmouth Town Centre	King Street	2007-01-01 22:00:00	4
East	Great Yarmouth Town Centre	King Street	2007-01-02 19:00:00	4

To help categorise some of the results of this study, the planning authority centre designations (CLG, 2008, 2009, 2012) of major city, regional centre, sub-regional centre, major town, town and district were used as provided in the supplementary materials of Mumford et al. (2021). The updated values needed for this study are available in Appendix A - Section 12.3 Data Sources. As noted by Mumford et al. (2021), this was a manual task of searching through online planning documentation available for each relevant council authority.

Table 4.2 and Figure 4.5 below show that as the number of sensors increases over time, so the distribution of sensors assigned to different urban classification types (see Appendix A) also changes. As is evident, the relative contribution of footfall data from places identified as major cities reduces over the sample period whereas for the other urban classification types, increases. This change in representation of the sample data needs to be noted when identifying trends and changes in the results and reflects a limitation in the study in that, the analysis that follows does not apply the full statistical rigour - for example performing cross validation using k-nearest neighbour analysis (Rhys, 2020) - needed to differentiate between trends and changes in sensor representation.

Table 4.2 - Percentage of footfall sensors assigned to each planning authority urban hierarchy classification, by year

Year	Major City	Regional Centre	Sub-Regional Centre	Major Town	Town
2007	58.1%	6.8%	23.0%	10.8%	1.4%
2008	54.3%	8.7%	25.0%	10.9%	1.1%
2009	56.4%	12.9%	19.3%	7.9%	3.6%
2010	51.9%	13.0%	25.9%	5.9%	3.2%
2011	49.3%	12.9%	28.4%	6.5%	3.0%
2012	45.2%	14.6%	28.3%	6.8%	5.0%
2013	41.9%	15.8%	30.0%	7.1%	5.1%
2014	37.5%	15.9%	32.5%	7.4%	6.7%
2015	31.2%	18.2%	34.4%	7.2%	9.0%
2016	26.6%	19.5%	37.4%	8.0%	8.5%
2017	24.8%	20.0%	36.2%	9.8%	9.2%
2018	23.4%	20.3%	36.7%	10.2%	9.3%

For example, to account for the changing representation of the sensors as highlighted in Table 4.2, a possible approach would have been to compare a control set of sensors available from 2006 with findings from subsequent years. Then by comparing the general findings from the control set, this might have helped distinguish between changes in sensor representation versus actual changes in footfall patterns. As mentioned, it is a limitation of the study in that this was not performed. However, the approach adopted was considered because the representation of sensors, especially in Towns was very limited compared to City-based locations, so comparing results between the control set and subsequent years would also have had limitations. Although not validated, the rationale was that the control would be dominated by city located signatures so that any differences identified would be city biased making interpretation of the control comparison complicated.

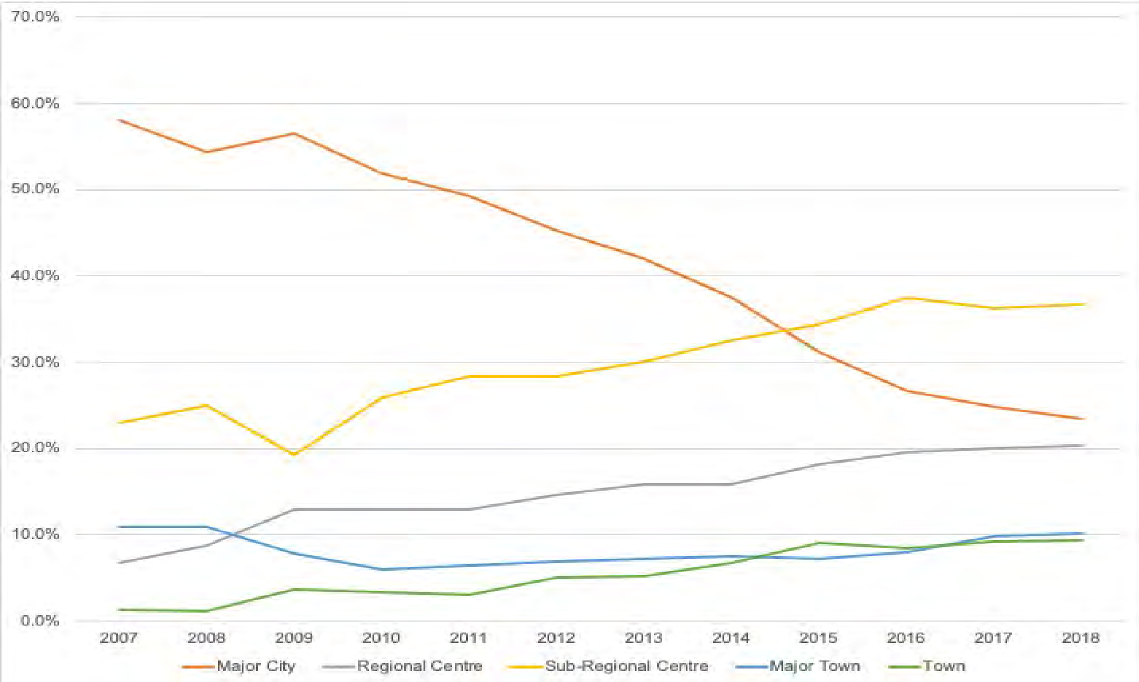


Figure 4.5 - Plot of the proportion of footfall sensors assigned to each urban classification type by year

4.5 Adopting a Time-Series Fuzzy Cluster Analysis Approach

The following section provides the background and thinking as to why a time-series fuzzy cluster analysis approach was adopted to identify rhythms in the time series data – see Appendix A Section 12.5 for a detailed review of time-series clustering.

Different techniques for pattern recognition exist for the classification of objects into several categories or classes derived from images, signal waveforms or any type of measurement (Theodoridis and Koutroumbas, 2009). Although not an exhaustive list, Theodoridis and Koutroumbas (2009) list research areas and business applications that pattern recognition can be used for:

- Machine vision - for example, defect tracking during manufacture using images
- Character recognition - for example optical character recognition (OCR)
- Computer-aided diagnosis - aiding medical diagnosis
- Speech recognition
- Data mining and knowledge discovery - the retrieval of information and turning it into knowledge

A time-series is essentially classified as dynamic data (Antunes and Olivera, 2001) because its feature values change as a function of time, which means that the value of each point is an observation made chronologically (Aghabozorgi et al., 2015). A univariate time-series is the simplest form of temporal data being a collection of observations collected regularly in time, where each observation represents a value that is numeric (Wang et al., 2004; Aghabozorgi et al., 2015). The footfall data is therefore a series of univariate time-series for each sensor location. With a focus on exploring the time dimension of the sensor time-series, the study limits itself by not considering the additional spatial dimensions that could have been explored. This was, in part, because of not having direct access to other sources of data but primarily due to time constraints as the creation of the analysis framework, the software programming and data analysis, took a significant amount of time.

Initially, approaches that enable the reduction of dimensional complexity in time-series data (Ali et al., 2019) including ARIMA (Autoregressive Integrated Moving Average) (McCleary and Hay, 1980; Box et al., 2008), Discrete Wave Analysis (Percival and Walden, 2000; Abuadbba and Khalil, 2015; Aldrich, 2020) and change point analysis (Killick and Eckley, 2014) were considered. Additionally, Discrete Fourier Transforms (DFT) and Wavelet Transform methods were reviewed as these can detect periodicity, yet neither technique can reveal long-term trends or anomalies (Zhu and Guo, 2017). Although for all the above there were elements of each that were relevant, each was mathematically complex, especially Discrete Wave Analysis, and it was unclear how to use the techniques to compare sensor locations.

Hence, various domains of knowledge were reviewed where time-series analysis is common, for example, seismology (Hadiloo et al., 2018), image matching (Parastar and Bazrafshan, 2016), traffic patterns (Liu et al., 2012; Wu et al., 2017), satellite image processing (Verbesselt et al., 2010a; Verbesselt et al., 2010b), meteorological observations (Kyriakidis et al., 2004) and previous footfall studies (Mumford et al., 2017; Lugomer and Longley, 2018). Across all these knowledge domains, the use of cluster analysis was found to be a common technique for discovering patterns in time-series. Time-series clustering (Warren Liao, 2005; Fu, 2011; Aghabozorgi et al., 2015) is mostly utilised to discover patterns that appear frequently (Verbesselt et al., 2010b; Copeland, 2012; Chanda et al., 2015), or, to discover patterns that happen surprisingly (D'Urso and Massari, 2013; Rasheed and Alhajj, 2014; Zhu and Guo, 2017). The objective of the clustering is to recognise dynamic changes in time-series; provide the ability to predict and recommend; or to discover patterns in the data (Aghabozorgi et al., 2015). However, time-series classification/clustering problems are differentiated from traditional classification/clustering problems because the attributes are ordered (Bagnall et al., 2016). The approach taken by this study is focused on clustering a set of individual time-series with respect to their similarity.

In data science, many of the techniques employed to discover patterns in data come from machine learning, a branch of computational statistics (Singleton and Arribas-Bel, 2019). Within machine learning, the methods adopted are usually separated into two categories, supervised and unsupervised (Rhys, 2020). In supervised learning, the aim of the analysis is to assess membership to an existing classification (Everitt et al., 2011) whereas unsupervised learning – or cluster analysis (Theodoridis and Koutroumbas, 2009:7), is essentially about discovering groups in data that are not known *a priori*. With the footfall data, no *a priori* data was available, so the approach considered by this study was to use cluster analysis (i.e., unsupervised learning). However, for a researcher with a greater understanding of statistics and their formulation, there is the opportunity to use supervised techniques such as k-nearest neighbour (Martínez et al., 2017; Rhys, 2020) or supervised fuzzy pattern matching techniques (Angstenberger, 2001) – and some of the limitations of this study could potentially have been resolved if techniques such as these had been used.

Influential in deciding to use a fuzzy clustering approach was the work of D'Urso and Massari (2013), where the technique was used to analyse patterns of human activity. For D'Urso and Massari (2013), because fuzzy clustering calculates the degree of membership to clusters as probabilities - a phenomenon that crisp membership techniques hide (Everitt et al., 2011) - this provides the ability to compare how the degree of membership varies over time – thus enabling the changes in footfall activity patterns to be diagnosed and providing a very useful analysis tool.

The objective of this study was not to build statistically valid predictive models of footfall patterns (a limitation in part due to a lack of statistical and mathematical specialism), but instead aimed to perform a diagnosis of historic data. For this reason, although the algorithms used by this study can be applied to generate statistically valid machine learning models (Rhys, 2020), this was not done primarily due to a lack of statistical specialism. Hence, there is no attempt at cross-validation of the footfall data, where data is split into training and testing data sets and used to statistically validate algorithm generated models (Rhys, 2020). This is another limitation of the study as such an approach might have been used to differentiate between changes in the sensor representativeness versus actual changes in the footfall data.

To perform the fuzzy cluster analysis, the dtwclust R package (Sardá-Espinosa, 2019) was used. A key reason for choosing this package was the clarity of the documentation and the ability to perform the data analysis process in a single programme execution. This highlights a limitation of the study in that the analysis was very dependent upon pre-packaged functions that required no mathematical reconfiguration. In addition, the final choice of time-series cluster analysis was influenced by Parker et al. (2016); Mumford et al. (2017); (Hadiloo et al., 2018); Pavlis et al. (2018) and Theodoridis and Koutroumbas (2009). Although the approach taken is not a machine learning methodology as adopted by Soomro et al. (2019), that was an approach that could have been considered especially as packages available in both R and Python continue to be developed.

This study therefore takes a time series fuzzy cluster analysis approach and from the raw time-series, extracts the periodic vectors for annual, weekly, and daily intervals. For the distance measure, dynamic time warping is used although the R package used, dtwclust (Sardá-Espinosa, 2019) provided the ability to force the distance similarity measure to be Euclidian via parameterisation settings (as was required). For the clustering prototypes, k-Medoids were used due to their robustness in the presence of outliers and noise (D'Urso and Massari, 2013; D'Urso et al., 2016; 2018). Fuzzy clustering using Fuzzy C-Medoids (FCMdd) (Krishnapuram et al., 2001) was implemented to take advantage of the capabilities of human activity pattern analysis (D'Urso and Massari, 2013). Fuzzy clustering provides a means to view how membership between the medoids changes over time and, aids the identification of the contribution of the next best fit medoids (D'Urso and Massari, 2013; Wang, 2014; Khoo-Lattimore et al., 2019). For this reason, fuzzy clustering was the chosen clustering analytical method as the interplay between the medoids was considered a useful diagnostic of place rhythms and how they change over time.

The internal indices used (as no ground truth existed) are those implemented by Sardá-Espinosa (2019) which are based upon the findings of Wang and Zhang (2007). Wang and Zhang (2007) review a wide range of validation indices with respect to fuzzy clustering and internal unsupervised cluster identification. In practical terms, a mixture of validation indices was required as no single index, could consistently identify the optimal cluster number. Finally, all the options to perform the fuzzy clustering analysis were available via the R package dtwclust (Sardá-Espinosa, 2019). The next section details the operationalisation of these clustering techniques.

4.6 Operationalisation of the Research Design

To operationalise the research design, the knowledge discovery process (see Figure 4.6) suggested by Frawley et al. (1992) and adapted by Fayyad et al. (1996) and Angstenberger (2001), was followed. These stages were:

1. **Selection:** selecting target data and identifying where it is stored
2. **Pre-processing:** applying basic operations to clean the data, removing noise, outliers, resolving missing data etc.
3. **Transformation:** selecting relevant features to represent the data using dimensionality reduction, projection, or transformational techniques
4. **Data Mining**: extracting patterns from the data in a particular representational form relating to the chosen data mining algorithm.
5. **Interpretation/Evaluation**: translating discovered patterns into knowledge to support the human decision-making process

In following the process displayed in Figure 4.6, a significant effort was required to develop the software needed to store, process, analyse and display the data. Thus, an incremental development process in the manner of Agile Software Development (Cohn, 2005; Leffingwell, 2011) was followed, primarily to de-risk the project by ensuring that considered options were viable for the computer resources available (see Appendix A: 12.1 System Configuration). To help with remembering things of interest in the data, a journal was kept so that a record of data processing was kept and not forgotten (Brinkmann and Kvale, 2015).

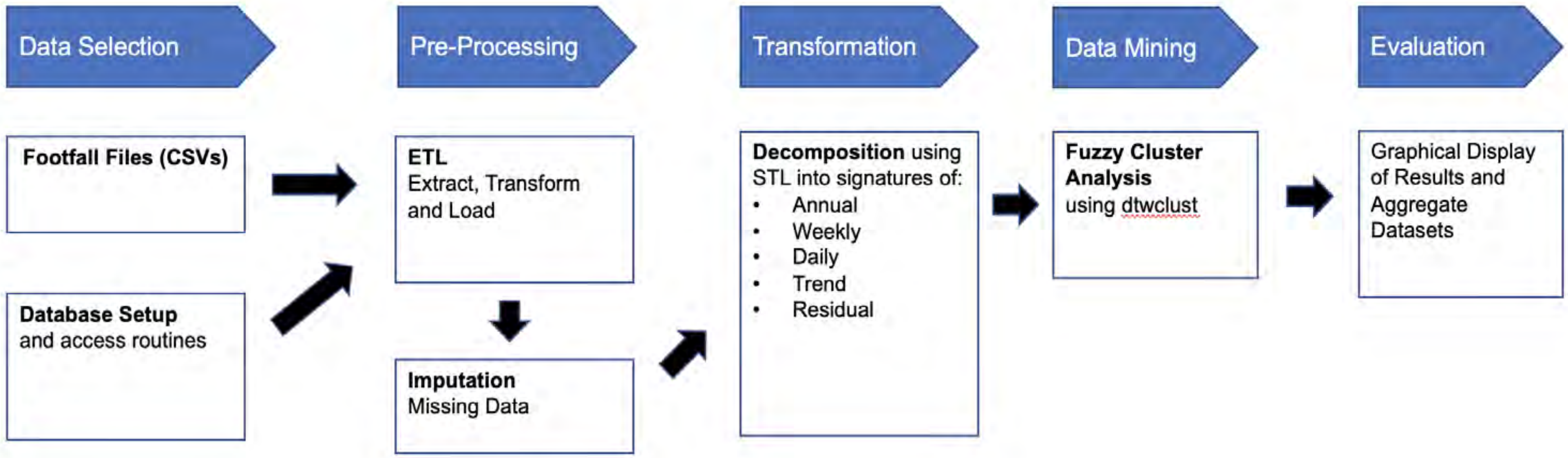


Figure 4.6 - The research design stages taken to analyse the footfall data

Also beneficial was the logging of executed commands by RStudio (RStudio Team, 2018) providing a history of previous work. The following sections provide details of the research design stages and the final section provides details of the iteration phases needed to create the complete data analysis toolset and generate the results.

4.6.1 Data Selection

The footfall data provided by Springboard was provided as CSV files. To analyse this data, a means of storing the data was needed to enabled access to multiple record sets for any required period. As the data was structured, and because the technology was familiar, the decision to store the data in a relational database was taken.

Relational databases are still the most used storage mechanism (Soomro et al., 2019) and provide a structure that allows access to data through related tables via a query language called structured query language (SQL). The database chosen, was the open-source (free) community edition of MySQL (https://www.mysql.com/products/community/). The intention of using the database was to store the data in a form that allowed access to various data subsets. Note that no production considerations were made such as how data could be continually updated on a regular basis, and nor was security an issue. Using some of the principles for data warehouse design proposed by Kimball and Ross (2013), a schema was created, see Figure 4.7, to ensure that data could be extracted for any combinations of required data. Further details of the database are provided in Appendix A: Section 12.4 Database Details. With the database schema in place, the process of extracting, transforming, and loading, known as ETL (Kimball and Ross, 2013), the footfall data could proceed.

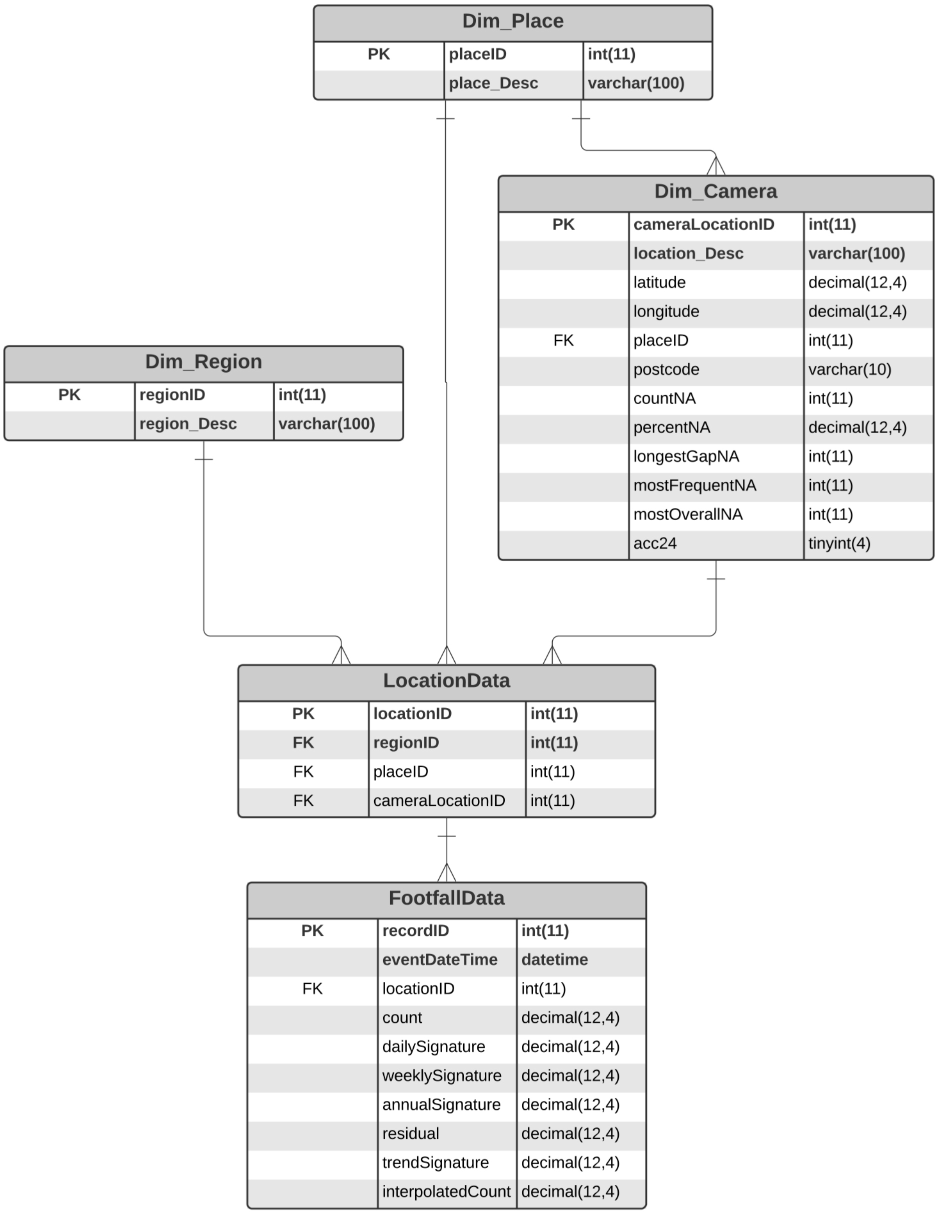


Figure 4.7 - Database schema for the footfall data

4.6.2 Pre-Processing

To load the CSV files provided by Springboard into the database, the pre-processing steps of loading the data into the database and resolving missing data issues was required as detailed below.

4.6.2.1 Extract, Transform and Load Process (ETL)

The programming language Python with the addition of the Panda and NumPy data manipulation and processing libraries (McKinney, 2012) and SQL stored procedures (Harrison and Feuerstein, 2009), was chosen as the language to perform the CSV file extract, transform and load (ETL) processes. ETL is a familiar term in Business Intelligence (BI) and is associated with the management of large business volumes, diverse and distributed data sources (Theodorou et al., 2016). Unlike large BI systems, this study only considered the initial loading of the footfall data rather than its continual updating.

Initial thinking was that Python would be the preferred language for all the data loading and statistical processing. Although the ETL processes were completed using Python, problems with package version compatibility issues resulted in R being the chosen platform for subsequent data analysis. For more information regarding Python vs R, see Appendix A: Section 12.2 Python vs R.

Figure 4.8 presents the processes used to read, transform, and store the footfall data into the database. Most processing involved checking data quality issues. For example, for some sensors, there were occasional missing hourly data records. So, these needed to be identified and a data record created with the footfall count set to missing data due to a constraint with the data mining algorithms that required a complete 24 hours of data or else the programmes failed. Duplicate records were identified and resolved, and issues with place names or sensor location names corrected. Further details of the extract, process and load processes can be found at Appendix A: Section 12.6 Pre-Processing.

Having completed the initial data checks, then the data pre-processing missing data phase switched to using R (R Core Team, 2019) via RStudio (RStudio Team, 2018) and with R programming guidance using Kabacoff (2015).

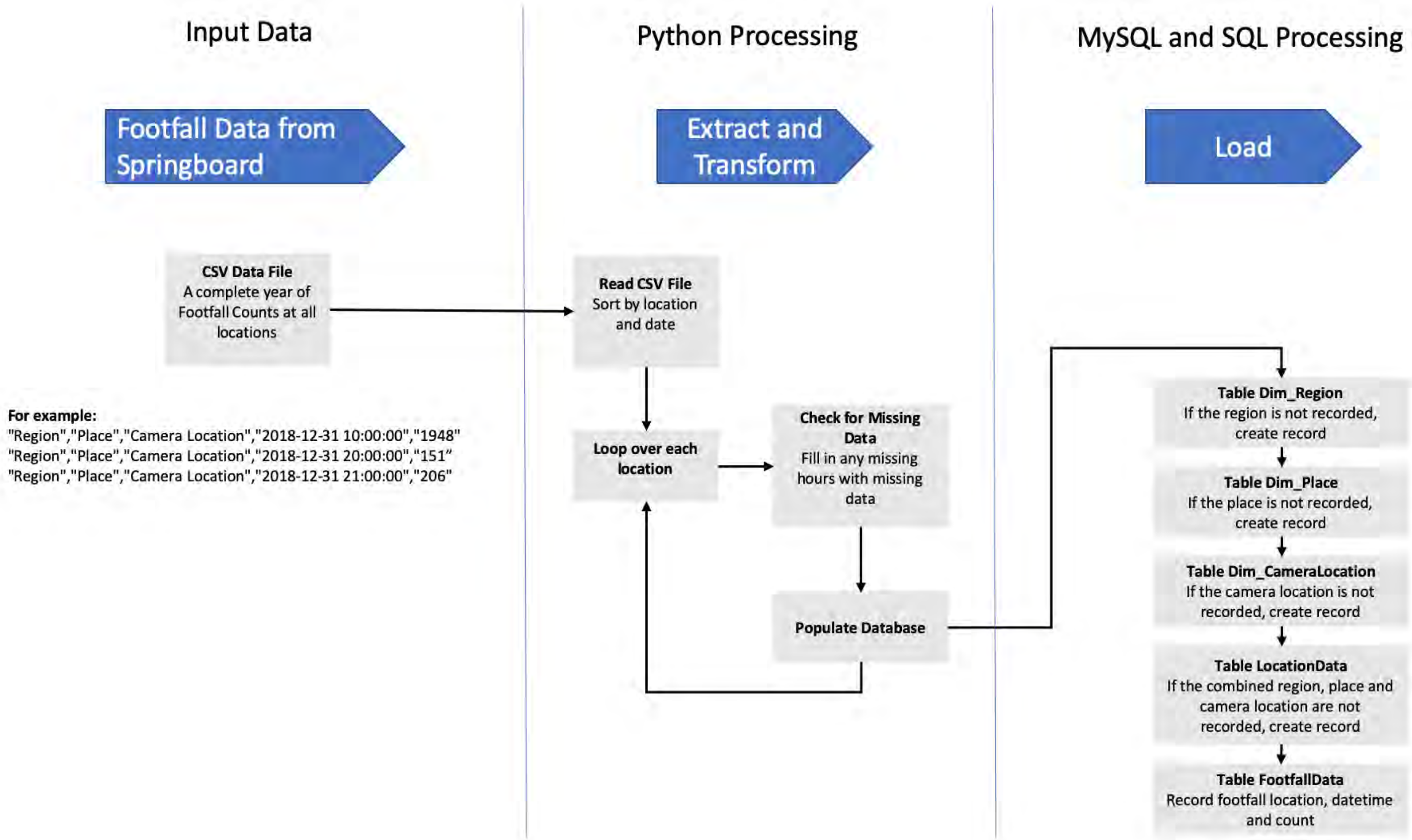


Figure 4.8 - Process for the initial load and pre-processing of the footfall data.

4.6.2.2 Missing Data - Imputation

The process of replacing missing data (Little and Rubin, 2020) with reasonable values is known as imputation (Moritz and Bartz-Beielstein, 2017). For time-series, the common approach (Andiojaya and Demirhan, 2019) to deal with missing data is to fill in the gaps by imputation methods, and then apply methods for further analysis (Dempster et al., 1977; Moritz and Bartz-Beielstein, 2017; Phan et al., 2017; Demirhan and Renwick, 2018). As Lepot et al. (2017) note, gaps in the data occur for many reasons such as irregular time recording steps, removal of outlier data values, sensor calibration and so on. Lepot et al. (2017) also identify that numerous methods of imputation are available and that deciding which method to use, for non-mathematicians, is not easy. Lepot et al. (2017) writes that, according to Beveridge (1992), a useful interpolation technique should meet four criteria: (i) not a lot of data is required to fill missing values; (ii) estimation of parameters of the model and missing values are permitted at the same time; (iii) computation of large series must be efficient and fast, and (iv) the technique should be applicable to stationary and non-stationary time-series. The selected method should also be accurate and robust. In reviewing interpolation methods, Lepot et al. (2017) concluded for the numerous methods available, the criteria used for assessing the quality of interpolation methods was lacking.

For the footfall data, data from every sensor was extracted from the database and the missing data values identified and imputed. Once complete, the imputed values were then written back to the database although the raw data values were not overwritten. One complication with the footfall data was that missing data was not only indicated by a missing data indicator but also by having an hourly footfall count of zero as shown below in Figure 4.9.

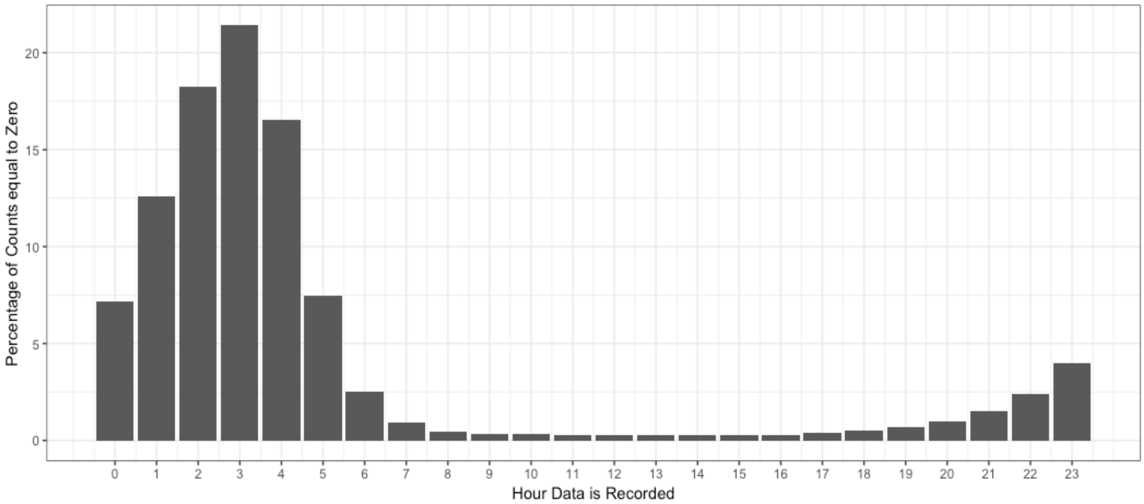


Figure 4.9 - The distribution of missing values and zero hourly footfall counts.

Figure 4.9 shows that as expected, in the early hours of the morning are the highest count of zero footfall counts occurs but, there are also periods during the day when missing or zero counts also are recorded. However, in most cases, the missing data was for a single hour only as displayed in Table 4.3. From the zero-count total, only 8 sensors were identified having no missing data present.

Table 4.3 - Frequency of consecutive missing data values and zero footfall counts.

Number of Consecutive Missing Data Values	Count	Percentage
0	8	1.44%
1	517	92.82%
2	11	1.97%
3	9	1.62%
4	1	0.18%
5	1	0.18%
10	1	0.18%
18	1	0.18%
21	8	1.44%
Totals	**557**	**100%**

The imputeTS R package (Moritz and Bartz-Beielstein, 2017) is used in this study and is an easy-to-use package that offers several utilities for ’univariate, equi-spaced, numeric time-series’ (Moritz and Bartz-Beielstein, 2017:207), like the footfall data. Demirhan and Renwick (2018) investigated the different imputation functions available via ImputeTS to assess the imputed values for the estimation of hourly, daily and weekly irradiance forecasts (used for solar irradiance forecasting). Demirhan and Renwick (2018) found that the linear and Stineman interpolation (Stineman, 1980) approaches within imputeTS and their seasonal versions worked accurately for the imputation of missing values in minutely solar irradiance series. For this study, the Stineman function provided the best results and satisfied the requirements of Beveridge (1992), an example of the original and imputed results is provided below in Figure 4.10 below.

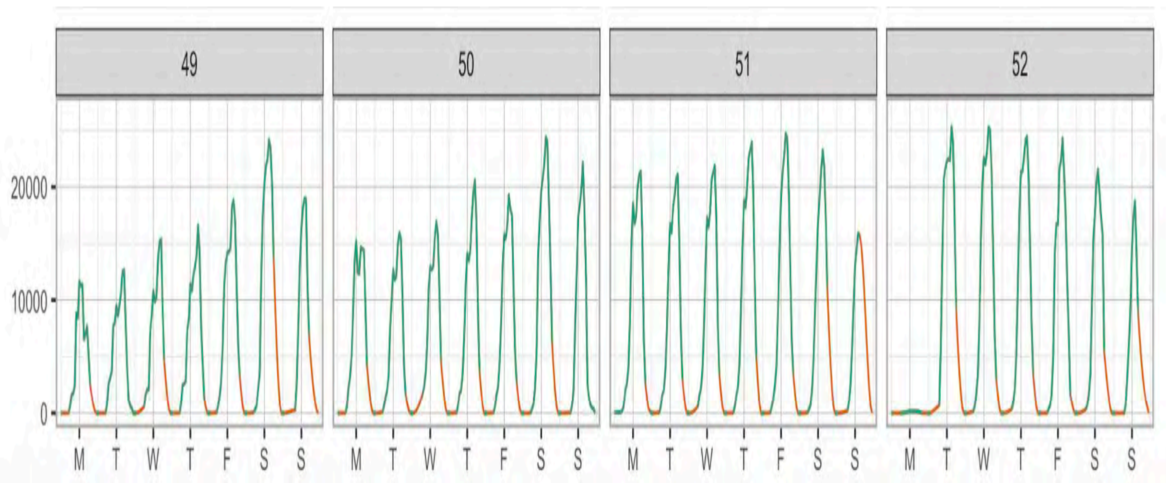


Figure 4.10 - Imputed footfall values (red) and original values (green)

As most missing values were for very short periods, the Stineman impute function was used to fill in the missing values. However, what was not established was the spatial distribution of the missing data values, nor was the missing data checked to see if the spatial distributions were random. This then reflects a limitation of the study in that the process of imputation was primarily used to prepare the data for the cluster analysis using reasonably fitting values, rather than establishing an understanding of the distribution and causes of missing data. In fact, this is an example where machine learning can provide missing data techniques that provide more statistically accurate fitting of imputed values (Rhys, 2020).

Further details of all the missing data processes and results are available in Appendix A: Section 12.7 Missing Data - Imputation. Only when the missing data issues were resolved, could the next phase, data transformation proceed as the routines used all required the presence of non-missing data.

4.6.3 Transformation

In this section, the process of decomposing the footfall data into the periodic components of annual, weekly, and daily values is discussed. The overall process is illustrated in Figure 4.11.

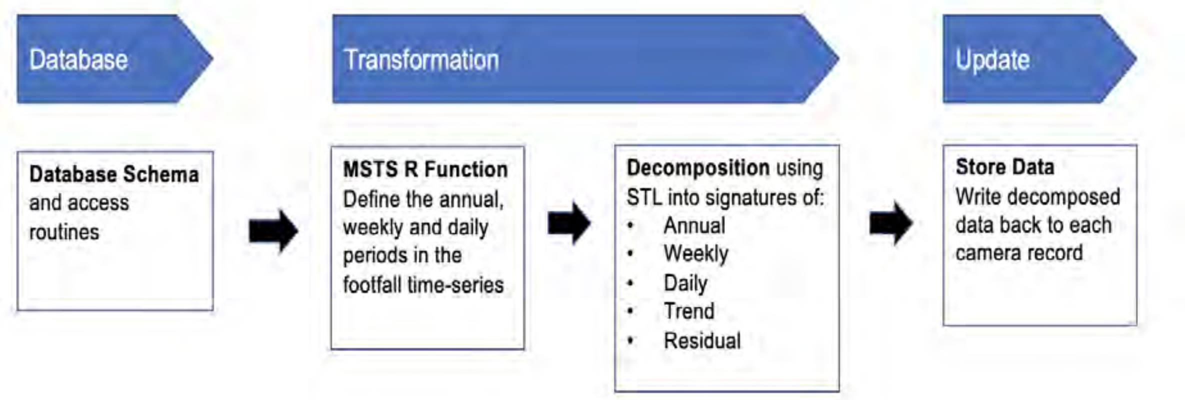


Figure 4.11. The transformation steps needed to extract periodic components

The decomposition of time-series is an important task in all national statistical agencies and in other contexts where seasonal variation in time-series data is observed (Dokumentov and Hyndman, 2015). Various decomposition methods exist, for example X-11-ARIMA (Dagum, 1980), X-12-ARIMA (Findley et al., 1998) and X-13-ARIMA-SEATS (Sax and Eddelbuettel, 2018). In addition to seasonal effects, monthly time-series are totals ("flows") of daily economic activity that are often influenced by the month, trading days, holidays and so on. Comparing these movements between one series and another is why many of these methods exist due to the difficulty of comparing results; for example, like for like sales, values across different months etc. as time-series need to be adjusted to help them align with previous seasons, trading days etc (Findley et al., 1998).

A issue with using these above techniques, however is their complexity and their limited seasonal periods, for example, X-11 allows for seasonal periods of only 4 and 12 months (Cleveland et al., 1990). A different approach was adopted by Cleveland et al. (1990) who developed STL - seasonal trend decomposition using Loess (locally weighted scatterplot smoothing) (Sanchez-Vazquez et al., 2012; Zhou et al., 2015; Rojo et al., 2017; Fernández-Morales and Cisneros-Martínez, 2019).

STL (*Seasonal-Trend decomposition based on Loess*) (Sanchez-Vazquez et al., 2012; Zhou et al., 2015; Rojo et al., 2017; Fernández-Morales and Cisneros-Martínez, 2019) was proposed by (Cleveland et al., 1990) at Bell Laboratories. The general idea of STL is to provide non-parametric regression based on locally weighted averaging of the data. Estimate and smoothing of trend and seasonality are obtained by fitting a polynomial by weighted least squares using a tri-cube weight function, more robust to outliers. Note that a linear or quadratic adjustment is used for the trend, while it is a constant or linear one for the seasonal component. The technique takes working days into account, while the management of holidays effects is not possible (Eurostat, 2018:73).

Zhu and Guo (2017) used STL as a data-driven exploratory technique to detect and map urban events and their impact upon taxi journeys. Other techniques reviewed by Zhu and Guo (2017) included:

- The use of a moving average window to smooth the time-series and to detect long-term trends. This however failed to recognise periodicity patterns and anomalies
- The use of Discrete Fourier Transforms (DFT) or Wavelet Transform methods to detect periodicity. However, neither technique can reveal long-term trends or anomalies.

Other examples of the use of STL have also been the decomposition of satellite image data into trend and seasonal components. However, these studies suggest that the smoothing technique used can reduce the capability to detect changes within time-series (Verbesselt et al., 2010a; Verbesselt et al., 2010b; Zhu and Guo, 2017). Hafen et al. (2009) however found that the STL method was sensitive enough to detect unusual health events such as disease outbreaks modelled over annual and weekly periods. Also important to note in using STL is that the method assumes a fixed seasonality (Wang et al., 2007). In other words, the decomposition of the data assumes that the daily, weekly, and annual signatures extracted for each camera assume these periodicities are valid through the whole period of each time-series. STL is an additive process, where the individual components can be summed to match the value of the original data as shown in Equation 4.1 below.

$$Y_v = T_v + S_v + R_v,$$

Equation 4.1 - STL additive components.
Where Yv, Tv, Sv and Rv represent the original data, trend, seasonality, and residual respectively (Source: Cleveland et al., 1990:3)

Hyndman and Athanasopoulos (2018) note that STL has several advantages over classical SEATS and X11:

- STL will handle any type of seasonality, not just monthly and quarterly data
- The seasonal component is allowed to change over time, and the rate of change can be controlled by the user.
- It is robust to outliers so that usual observations will not affect the estimates of the trend-cycle and seasonal components. They do however impact the residual component, which is an additional advantage.

However, Hyndman and Athanasopoulos (2018) also note that STL does not handle trading day or calendar variation automatically so events and holiday periods like Easter are decomposed but not matched across periods. As the STL function is widely available in R (R Core Team, 2019), it has become very popular outside the national statistics agencies (Dokumentov and Hyndman, 2015). Decomposition of the data was therefore performed using STL and other functions available via the R Forecast package (Hyndman and Khandakar, 2008; Hyndman et al., 2019a; Hyndman et al., 2019b).

The first step of the decomposition process was a validation that the footfall data had a 24-hour periodic cycle. This was checked as there was no point in trying to decompose the data for a 24-hour periodicity if none (or partially none) existed. Using the findfrequency function in the R forecast package, the autocorrelation significance was tested to ensure a 24-hour cycle existed. In all, only 8 cameras failed this test, and pursuing the reason for the failed test was not followed up. It would be interesting to do so but a very quick check of two of the cameras that failed this check suggested the reason might not be obvious. The other check that took place was to ensure there was at least two years annual data available for decomposition as this is the minimum requirement needed for the MSTL function. In those cases where less data was available, the decomposition for daily and weekly periods was still processed.

The MSTL function (Hyndman et al., 2019b) provides a convenient automated STL decomposition where parameters are automatically chosen unless defaults are overridden. The default function parameterisation usually provides a good balance between overfitting the seasonality and allowing it to slowly change over time. For the MSTL function (Hyndman et al., 2019b) to process the timeseries, the seasonal periods to be extracted are defined using the MSTS function, the output of which is then used by MSTL. Using the MSTS function enables multiple seasonal components to be extracted from each footfall camera time-series. Since the data was hourly, the seasonal periods were defined as hourly totals, namely:

- 24 - daily periods
- 168 - weekly periods
- 8766 - annual period (averaged over 4 years to include leap years as suggested by (Hyndman and Athanasopoulos, 2018))

R code used by this study:

```
msts.ts <- msts(footfall.data, start = start date of data, seasonal.periods =
c(24,168,8766))
```

Where start equals:

Initial Year + initial day / number of days in that year

The MTSL function (Hyndman et al., 2019b) provides default values for the processing of the data, and these are discussed in Appendix A: Section 12.8.2 Decomposition Process and Parameterisations.

For each sensor where decomposition was performed, the hourly decomposed results were written back to the database so that no regeneration of this data would be required for the subsequent data mining and cluster analysis phases. Equation 4.2 below shows how Equation 4.1 has been modified and that instead of identifying one seasonal component, the annual, weekly, and daily signatures are extracted.

$$Y_v = T_v + S_{annual} + S_{weekly} + S_{daily} + R_v,$$

Equation 4.2 - The implemented version of STL.
Where S_{annual}, S_{weekly}, S_{daily} are the periodic components extracted from the data.

Whilst reviewing the decomposition outputs, when autocorrelation and partial correlations were run against the residuals, the autocorrelations for different time lags exceeded the 95% significance identifying that the residual values cannot be attributed to white noise only (OU, 2007). An option for this study would have been to investigate these residuals to see how they matched to unique events in the same way Zhu and Guo (2017) used this technique to study how events and location effected taxi journeys; however, the focus of this study is on the regular patterns, so the seasonal components were the elements of interest.

Confirming that the residual values are not insignificant, Figure 4.12 displays the relative contribution of each periodic component derived using the STL algorithm.

The graph displays the daily root mean square (RMS) values for each component averaged over each year of footfall data. As is shown, proportionally, there is no indication of any significant change over the years. The residual component shares a greater contribution than the annual component but that probably reflects the fact that the residual values have greater variability and therefore a greater RMS value. As the RMS value will highlight variability, the daily component has the greatest contribution and reflects the importance of the daily signatures to overall footfall totals. The much smaller contribution of the annual component also reflects its smaller influence on overall footfall levels as determined by the STL algorithm.

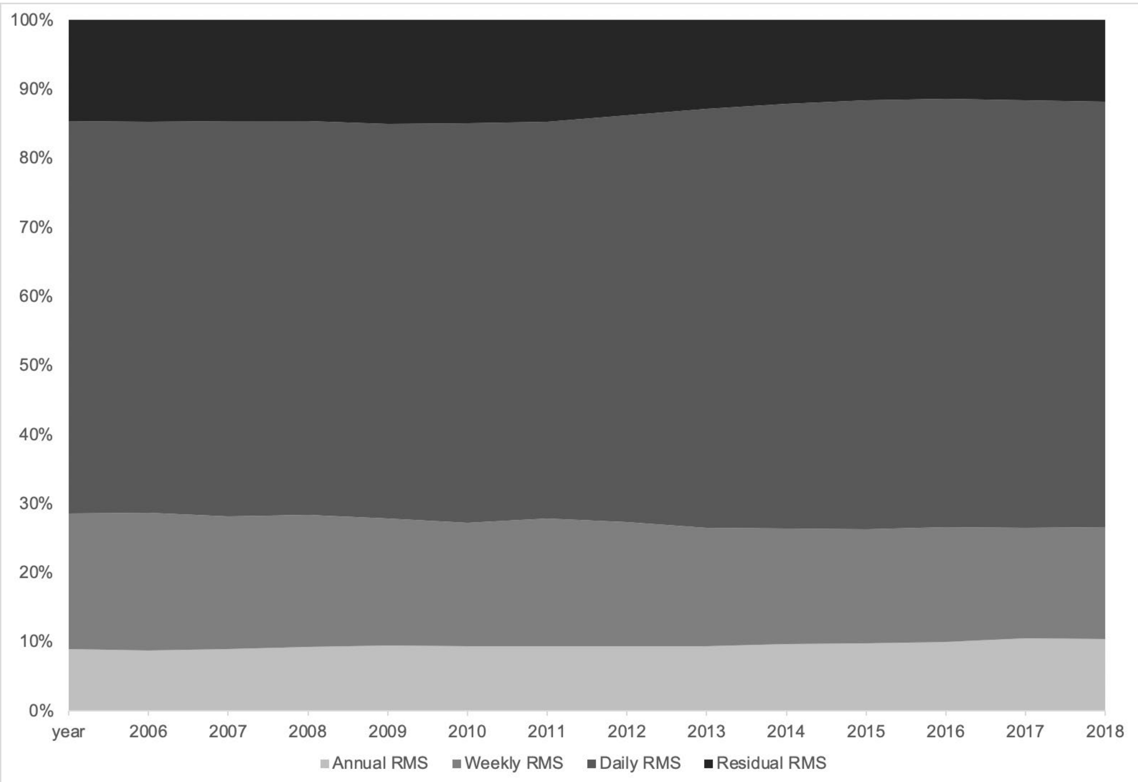


Figure 4.12. Proportional contribution of each STL derived periodic component

4.6.4 Data Mining

The dtwclust R package (Sardá-Espinosa, 2018, 2019) was chosen to perform the fuzzy cluster analysis (see Appendix A: Section 12.9.2 Code Example for dtwclust for an example of the R code employed). This package, developed for R statistical software (R Core Team, 2019) brings together all the algorithms that need to be combined to perform time-series fuzzy cluster analysis. That said, the package is not limited to fuzzy clustering and other cluster algorithms are also available. As Sardá-Espinosa (2019) intended, the package provides a user-friendly way of performing the time-series cluster analysis. An interactive version exists that provides a graphical display of the results and in the initial stages, was very useful for understanding the different cluster options, parameterisations, and outputs. To deploy dtwclust, the individual components needed to be setup and parametrised as shown in Figure 4.13.

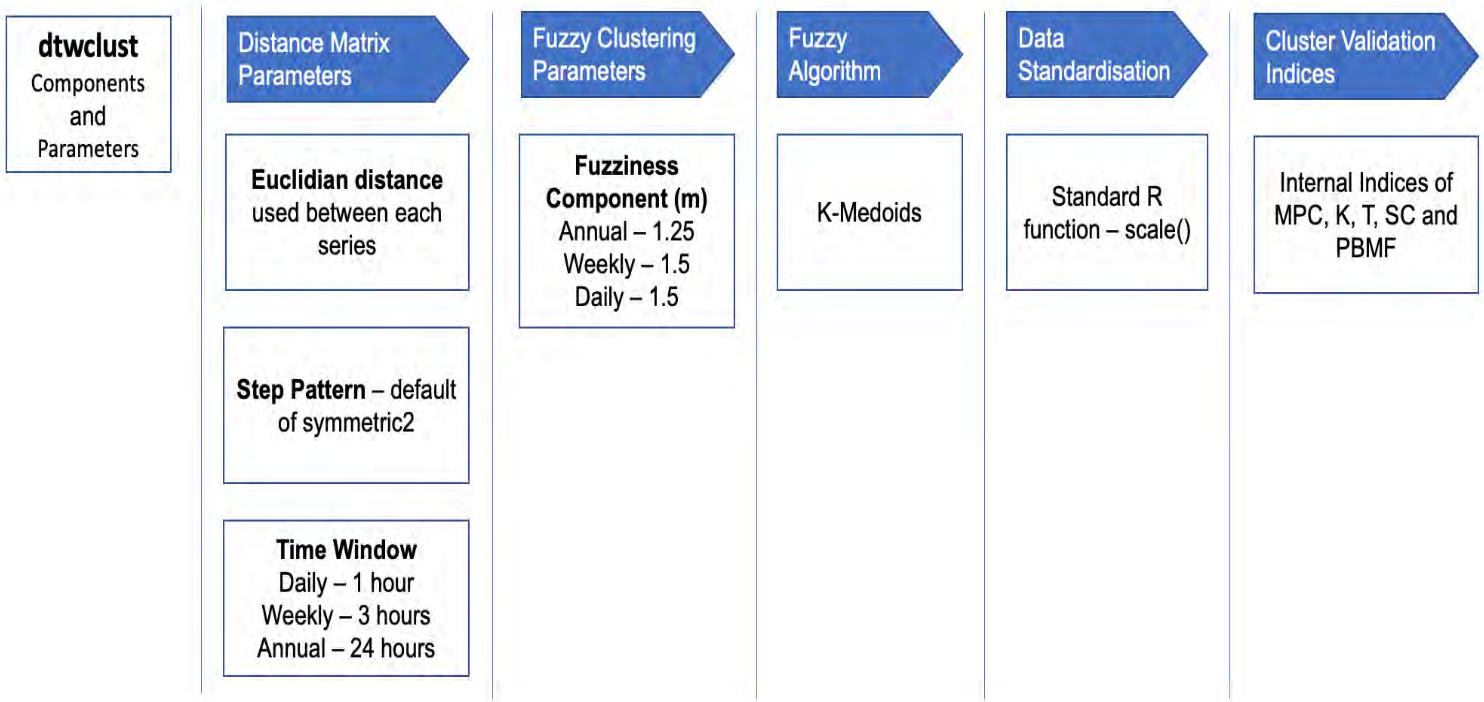


Figure 4.13 - dtwClust components and parameters.

4.6.4.1 Distance Matrix Parameters

The distance matrix parameterisations provided the means to compare individual sensor time-series with each other and to create a distance matrix from which similarities between the sensor data could then be clustered. This was done using both distance time warping (DTW) and Euclidean distance.

The first step performed by DTW is to create a low-cost matrix (LCM) - a distance matrix - which must be created for every series pair compared and can require significant amounts of memory. The distance measure between points was the Euclidean. In dtwclust - experiments using the DTW package for testing univariate series indicated no differences in the distance measures between Euclidean and Manhattan distance - which were the option available in dtwclust. (Sardá-Espinosa, 2018:6). Both dtwclust and dtw (Giorgino, 2009:2) identify that most common choice is Euclidean distance whereas default for dtwclust is Manhattan. In all cases for this study, the distance used was Euclidean as this is the most used measure (Chen et al., 2012; Aghabozorgi et al., 2015).

How the DTW algorithm traverses the LCM (distance matrix) is dictated by the chosen step pattern. The default pattern in dtw_basic, which is the symmetric2 pattern was the one used for this study. Sardá-Espinosa (2018) notes that few studies specify which pattern is used, so the default was chosen. Initial testing using the symmetric1 pattern via the DTW package (Giorgino, 2018) and dtwclust (Sardá-Espinosa, 2019) resulted in similar cluster results hence the decision to use the default.

Global constraints are added to DTW to partly help speed up computational speed but mainly, to stop pathological warping (Sardá-Espinosa, 2018). The constraint employed by this study was a window constraint that limits the area of the LCM that can be reached by the algorithm. For example, when comparing daily signatures to each other, a window constraint to limit warping to an hour either side of the reference point is employed. Although there is a suggestion that a window constraint of 10% is common (Sardá-Espinosa, 2018), Ratanamahatana and Keogh (2005) suggest that smaller window constraints are valid and desirable for different data types.

The graphs below indicate the results of different window sizes for the daily, weekly, and annual signatures. The outcome of which the decision was made to use the following window sizes:

- Annual - 24 (hours) – see Figure 4.14
- Weekly - 3 (hours) – see Figure 4.15
- Daily - 1 (hour) – see Figure 4.16

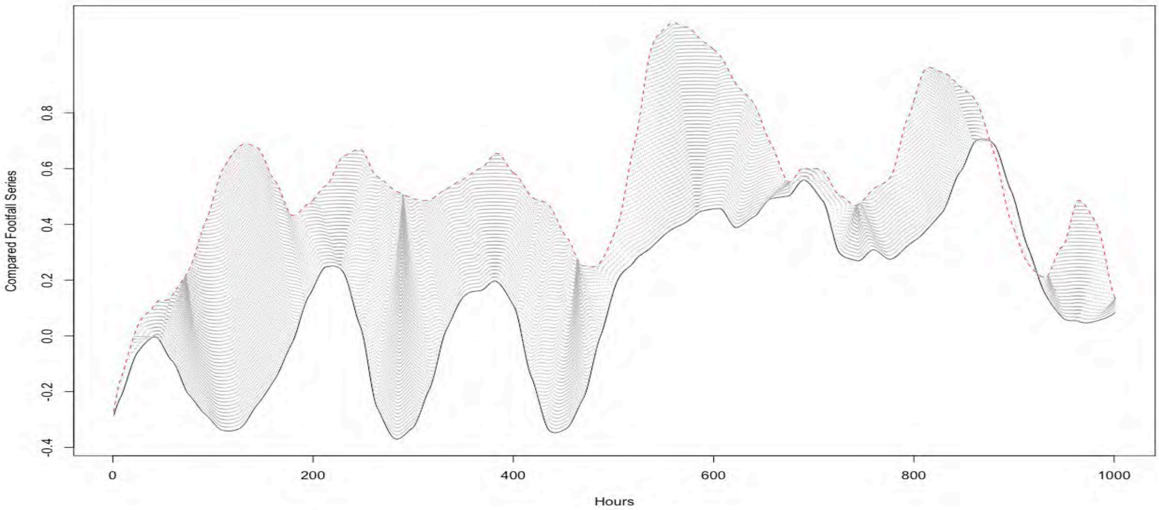


Figure 4.14 - Example alignment of two annual time series with a window size = 24.

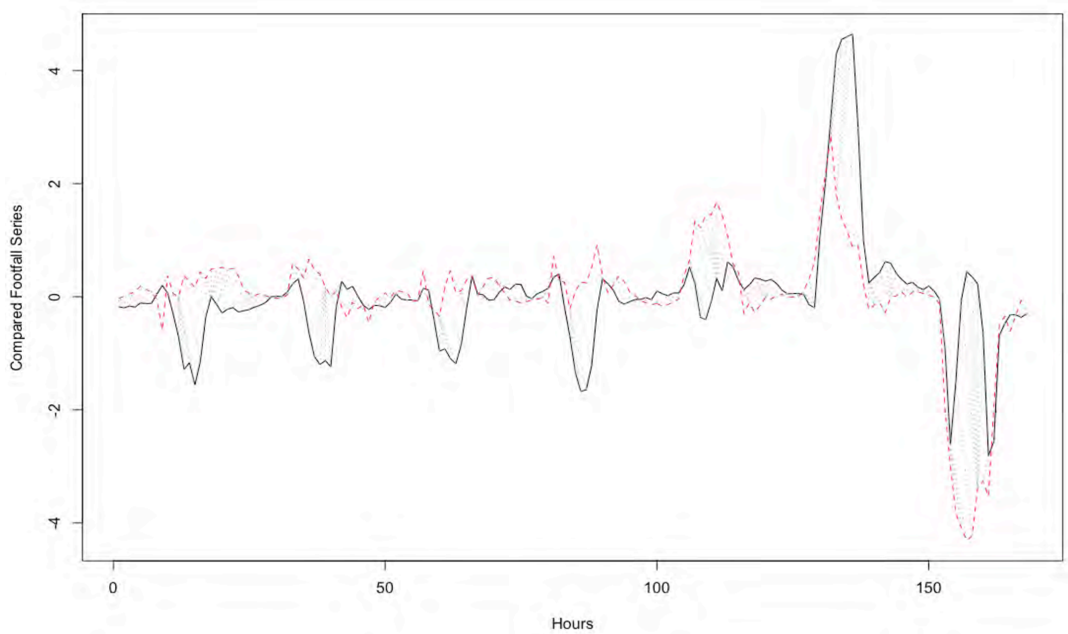


Figure 4.15 -Example alignment of two weekly time series with a window size = 3. Suggestion that window size = 3 is the preferred option.

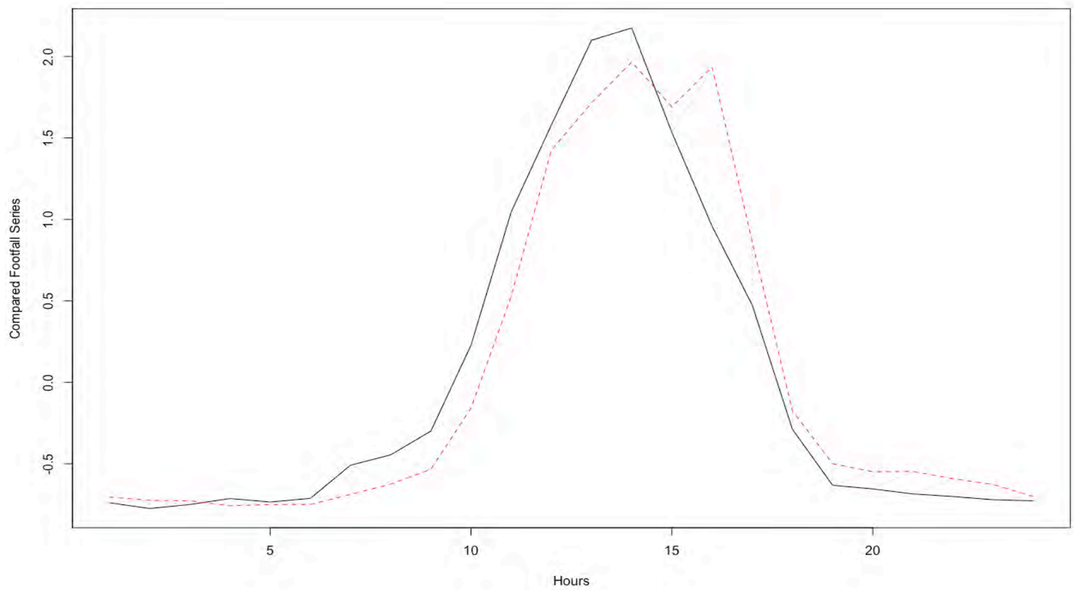


Figure 4.16 - Example alignment of two daily time series with a window size = 1.

4.6.4.2 Fuzzy clustering component

The fuzzy clustering component determines the ‘crispness’ for the distinction between the fuzzy clusters. Fuzzy clustering algorithms assign objects based upon their strength of membership across all the available clusters. This is calculated as a membership value ranging from 0 to 1 where one of the parameters required by this membership distribution is the fuzziness ‘crispness’ component (Everitt et al., 2011:245). This fuzziness component, that is usually designated by the letter *m* (see Equation 4.3), is a parameter in the various algorithms suggested for fuzzy clustering, such as fuzzy k-Mean or fuzzy k-Medoid (Bezdek, 1981; Krishnapuram et al., 2001; Izakian et al., 2015; Sardá-Espinosa, 2018). As identified by Bezdek (1981), the larger the value of *m*, the “fuzzier” are the assigned memberships whereas as m approaches a minimum of 1, then the memberships become hard partitions.

Equation 4.3. Fuzzy c-medoids (FCMdd) centroid function

$$q = \arg\ \min\ \sum_{p=1}^{N} u_{p,c}^{m} d_{p,c}^{2}$$

(Source:Krishnapuram et al., 2001; Izakian et al., 2015; Sardá-Espinosa, 2018:21)

Typically, and the default value for the dtwclust R package (Sardá-Espinosa, 2019), this value is set to a value of 2 (Everitt et al., 2011:245). However, Kroll (2011) suggest that the fuzziness exponent needs to be considered for each given problem and that values less than 2 should be considered as these can have a significant effect upon the quality and tightness of cluster membership assignments. Examples of values include Khoo-Lattimore et al. (2019) using a range of values [1, 1.5], the same as was also used by D’Urso and Massari (2013) in their study of fuzzy clustering of human activity

Chen and Wang (1999) suggest a means for determining the value of m, for this study however a heuristic method is used reflecting the findings of Bezdek (1981). From the literature, the need to check this parameter is clearly signposted and so during the implementation phase, the impact of this value was assessed, and the values used are provided below in Table 4.4.

Table 4.4 - The values assigned to the Fuzzy Parameter (*m*) used to determine the degree of fuzziness.

Signature Type	Fuzziness Parameter Value (m)
Annual	1.25
Weekly	1.5
Daily	1.5

In all cases, the default value of 2 was found not to discriminate enough the different clusters. Reviewing the Radviz diagrams, the cluster validation indices results and Medoids assigned to each cluster, the values in Table 4.4 were chosen as the most appropriate. Note, this selection process was subjective, there was no readily available deterministic test in R to check these values.

4.6.4.3 Data Standardisation

K-Medoids was the clustering algorithm chosen and to ensure that clustering was focused on comparing the different signature shapes, not the range of values, the data was standardised.

There are two reasons to standardise data. The first, standardising attributes removes arbitrary affects whilst looking for similarities between objects. The second, standardisation allows attributes to contribute more equally to the similarities among objects (Romesburg, 1984:78). Although the unit of measure, counts per hour, for the footfall data is the same for all the cameras, the ranges of the values varied significantly. To compare the patterns between one camera and another, it was necessary to standardise the data. Without standardisation, the clusters that were identified were often identical in shape but different in the range of values - an outcome that made analysis of the results difficult.

One of the techniques that can be used is by using the standard deviations calculated for the complete set of data, a technique often referred to as *autoscaling*, *standard scoring or z-scoring* (Everitt et al., 2011). However, this technique has been found to be less effective than using the ranges of values for many clustering applications (Milligan and Copper, 1988). As (Everitt et al., 2011:68) point out, one option is to use a clustering technique unaffected by the changes in the unit of measurements. The **scale** function provided by R (R Core Team, 2019) was used by this study. This core package function provides two scaling options, either to centre using the mean value or to perform no centring. For this study, the option not to centre the values was chosen (this had already been done by the decomposition process) so that the scaling was therefore performed using the formula below:

$$\sqrt{\sum(x^2)/(n-1)}$$

Equation 4.4 – Scaling function

Where ***x*** is a vector of the non-missing values and ***n*** is the number of non-missing values (Source: R Core Team, 2020)

4.6.4.4 Random Start Seeding

Technically, fuzzy clustering can be repeated several times using different random starts. However, comparing the results is difficult as the medoids allocated can be different. However, the overall fuzzy grouping remains the same, or almost the same, once the algorithms converge (Sardá-Espinosa, 2018). For this reason, a constant seed value of 1 was used therefore ensuring that repeated runs of the clustering software can generate the same results each time.

4.6.4.5 Cluster Validation Indices (CVIs)

Finally, the cluster validation indices needed to validate the optimal number of clusters that were implemented according to the recommendations of Sardá-Espinosa (2019) and Wang and Zhang (2007). An example plot of the validation indices is provided in Figure 4.17 which indicates that the optimal number of clusters was found where k = 3, where k represents the number of clusters.

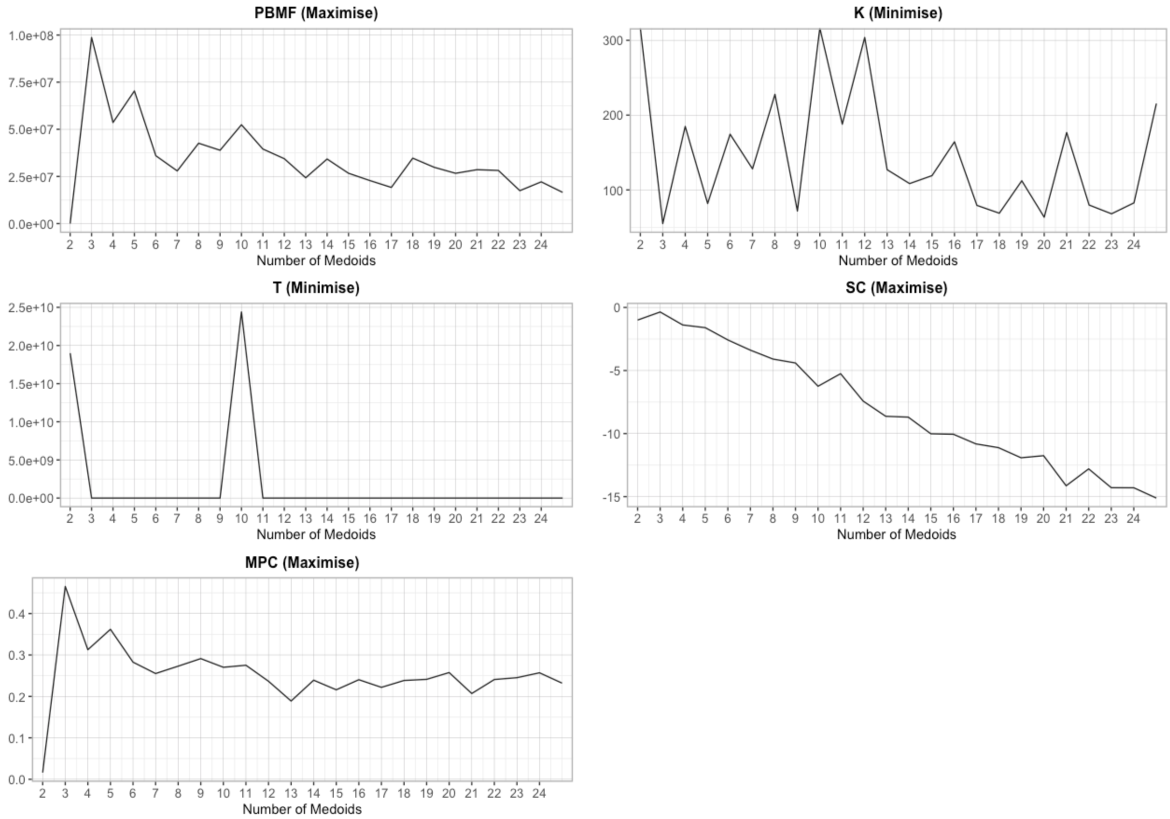


Figure 4.17 - Example Plot of Cluster Validation Indices (CVIs) for 2010 Annual Fuzzy Analysis.

Cluster validation indices |(CVIs) provide a means to evaluate (albeit subjectively) the optimum number of clusters within a dataset (Rousseeuw, 1987; Lei et al., 2017; Masud et al., 2018; Azhar et al., 2020). To validate the fuzzy clusters generated, the dtwclust package provides a set of five internal cluster validation indices (internal indices were required since there was no external truth to compare the clusters to) cluster validation indices as defined by (Wang and Zhang, 2007).

Table 4.5 - Cluster validity indices included in dtwclust for fuzzy clustering (Source: Sardá-Espinosa, 2019:24)

CVI Type (Wang and Zhang, 2007)	**Internal or External**	**Crisp or Fuzzy Partition**	**Minimised or Maximised**	**Considerations**
MPC	Internal	Fuzzy	Maximised	-
K	Internal	Fuzzy	Minimised	Calculates a global centroid
T	Internal	Fuzzy	Minimised	-
SC	Internal	Fuzzy	Maximised	Calculates a global centroid
PBMF	Internal	Fuzzy	Maximised	Calculates a global centroid

Of the 5 CVIs used, both MPC and T were found to be more useful (except for PBMF at times) presumably because of the need not to be based upon a global centroid. This however identifies that the choice of cluster number was not always clear and was a subjective process. As Sardá-Espinosa (2019) points out, knowing which CVI will work best cannot be determined *a priori*, so all the indices available should be tested to see if there is a majority consensus across all. This was generally the approach taken although not all cases were so clear. This could have been due to sub-optimal parameterisation of the dtw and fuzzy cluster algorithms for that case.

4.6.5 Interpretation and Evaluation

In all cases, R (R Core Team, 2019) and Microsoft Excel were used as the platforms of choice for displaying results of the analysis. In particular, the following R packages were used:

- ggplot2 (Wickham, 2016) - for all bespoke graphics creation
- ggmap (Kahle and Wickham, 2013) - for the specific location UK sensor plots
- Radviz (Abraham, 2016) - for the Radviz plots
- maps (Brownrigg et al., 2018) - for the UK sensor map plots
- qicharts2 (Anhoej, 2020) - from which the run charts were derived using ggplot2

To create aggregated sets of results for daily, weekly and annual summaries, R (R Core Team, 2019) was used with the R package dplyr (Wickham et al., 2019) - a data manipulation library provided via tidyverse (Wickham et al., 2020).

4.6.5.1 Process for Selecting the Number of Medoids (k)

Once a cluster analysis was performed, the next task was to choose the optimal number of medoids that best represented the data. This process consisted of the following steps:

- Viewing the Cluster Validation Indices (CVI) plot for all the cluster options processed (where usually $k>1$ and $k<26$).
- Reviewing and validating the CVI outputs using Radviz and Boxplot outputs
- Reviewing the medoid plots
- Final decision

Below, the processes is provided by way of example using the 2007 annual cluster analysis results.

After performing the cluster analysis for each year, the first step was to check the cluster validation indices, to identify the best fitting number of medoids
as shown below in were displayed as shown below in Figure 4.18.

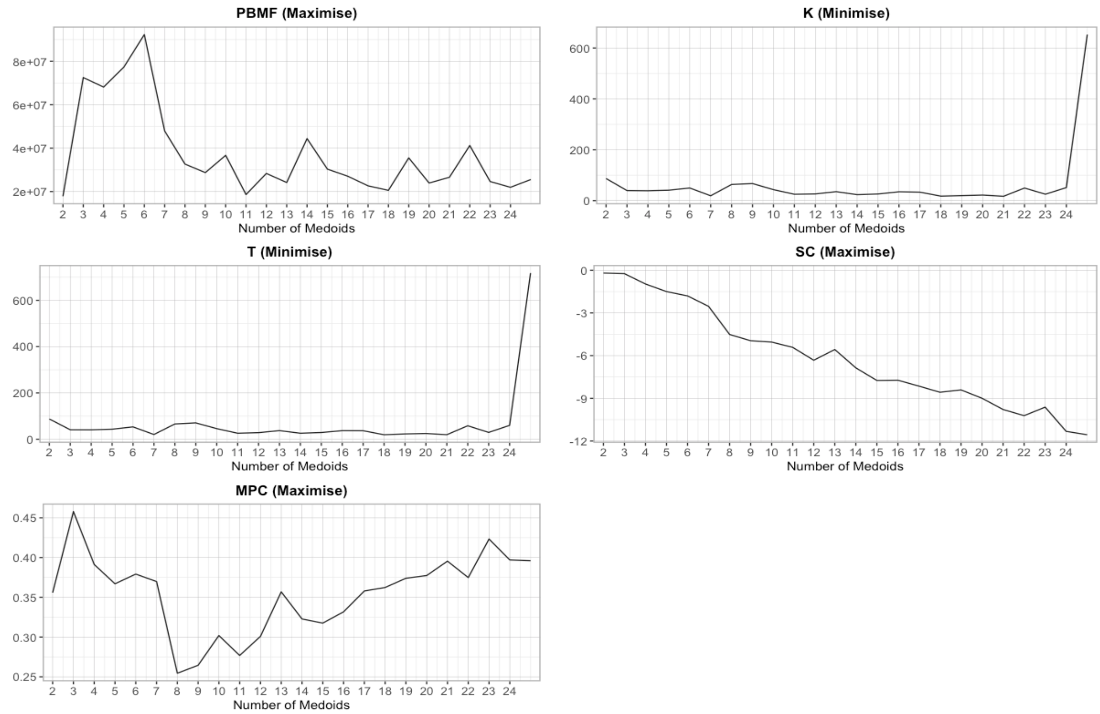


Figure 4.18 - Cluster Validation Indices (CVIs) for 2007 Annual Fuzzy Analysis

From Figure 4.18, it is clear that the validation indices are not all consistent, a known issue with the indices and why multiple indices are recommended (Sardá-Espinosa, 2019). Thus, the process of selection of the best match was heuristic rather than deterministic (Rousseeuw, 1987; Wang and Zhang, 2007; Azhar et al., 2020). This process was applied to all the cluster analyses performed, not just the annual results. For the annual, weekly, and daily results, the choice of medoid number was found to be usually informed most consistently by the MPC and T indices (Wang and Zhang, 2007), maybe because neither index required the use of a global centroid (Sardá-Espinosa, 2019:24).

For this example, the following steps were taken (and repeated for all subsequent years) to determine the number of medoids. From Figure 4.18, the smallest number of valid medoids is suggested by the MPC and T indices at k = 3 (where k is the number of medoids). The PBMF index suggests k = 6 but this is not supported by the other indices.

To verify the number of medoids, the Radviz plot (see Figure 4.19) and boxplot (see Figure 4.20) of the fuzzy scores were checked to make sure nothing unusual was evident in the data. From Figure 4.19, medoid 1 (labelled cluster_1) can be seen to be a dominant cluster, medoids 2 and 3 have a lesser significance. However, between medoid 3 and medoid 2, there is a greater contribution from medoid 2 although medoid 3 appears to have a ‘pull’ upon some medoid 1 locations. Importantly, there is no clustering in the middle of the plot identifying that the fuzzy parameterisation and the number of clusters chosen have been able to discriminate between the medoids. For other years, two medoids might have been selected that were very similar to each other (especially for higher values of k) which resulted in an easily identifiable mid-point cluster between the two medoids. Where this happened, a different value of k was selected.

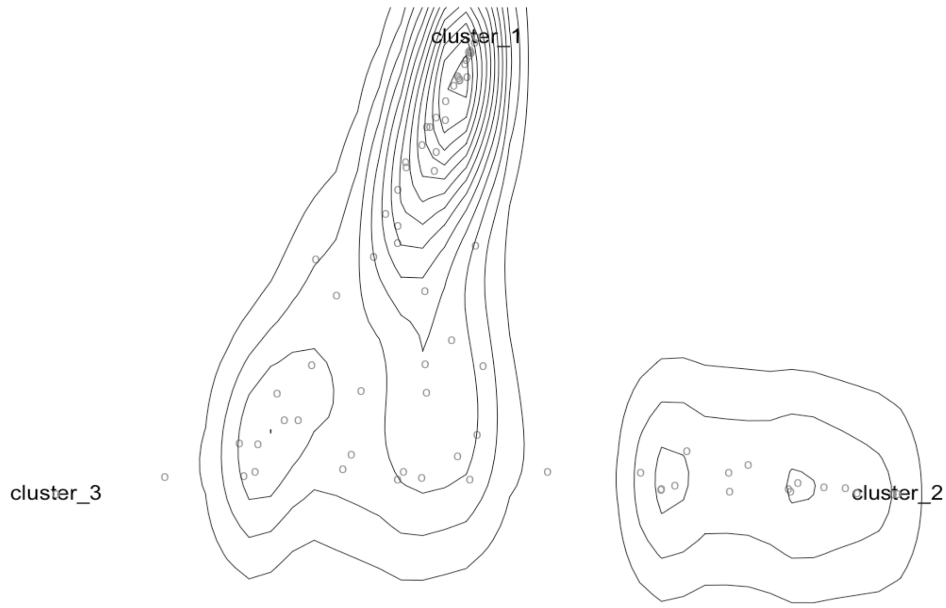


Figure 4.19. Radviz plot of the 2007 Annual Results for k = 3

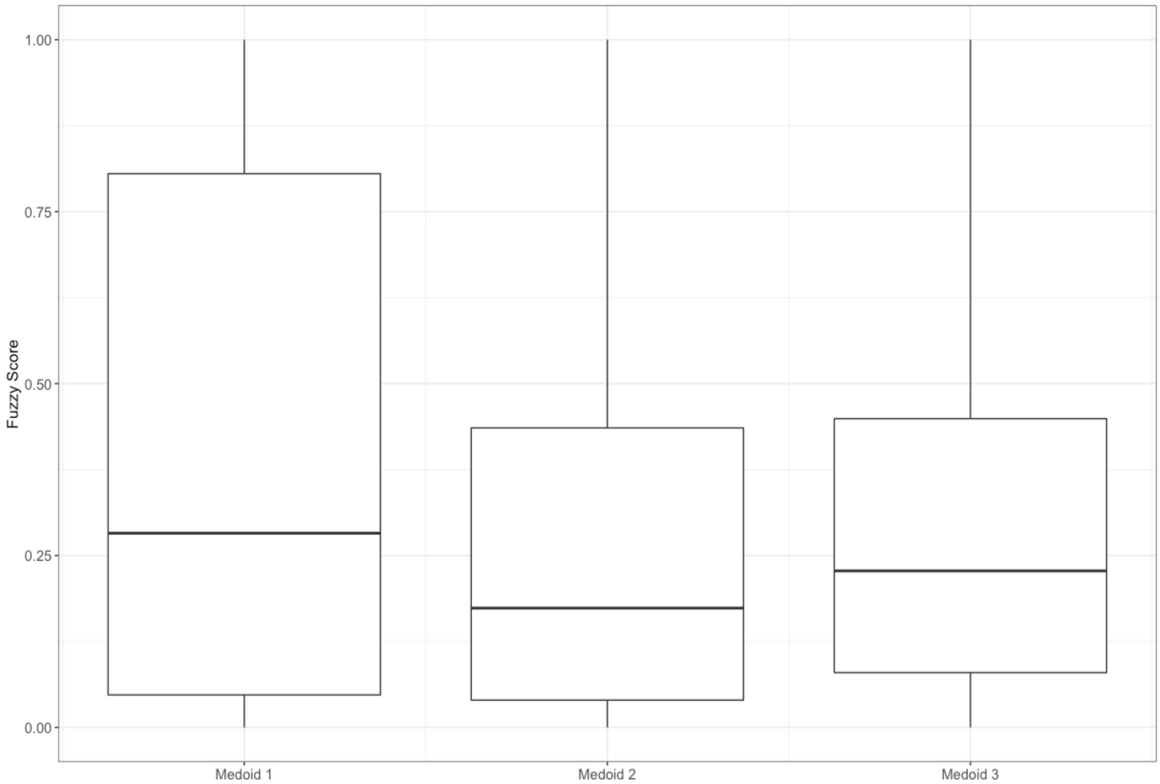


Figure 4.20. Boxplot plot of the 2007 Annual Results for k = 3

In Figure 4.20, the boxplot helps identify which of the medoids are more significant than others and how well distributed the fuzzy matching values are. In the case of 2007, although the Radviz diagram indicated medoid 2 was a more distinct cluster, medoid 3 can be seen to have more ‘influence’.

Finally, as shown in Figure 4.21 the annual signature medoids are plotted. This provided a final check and helped identify if duplicate medoids had been assigned or were very similar.

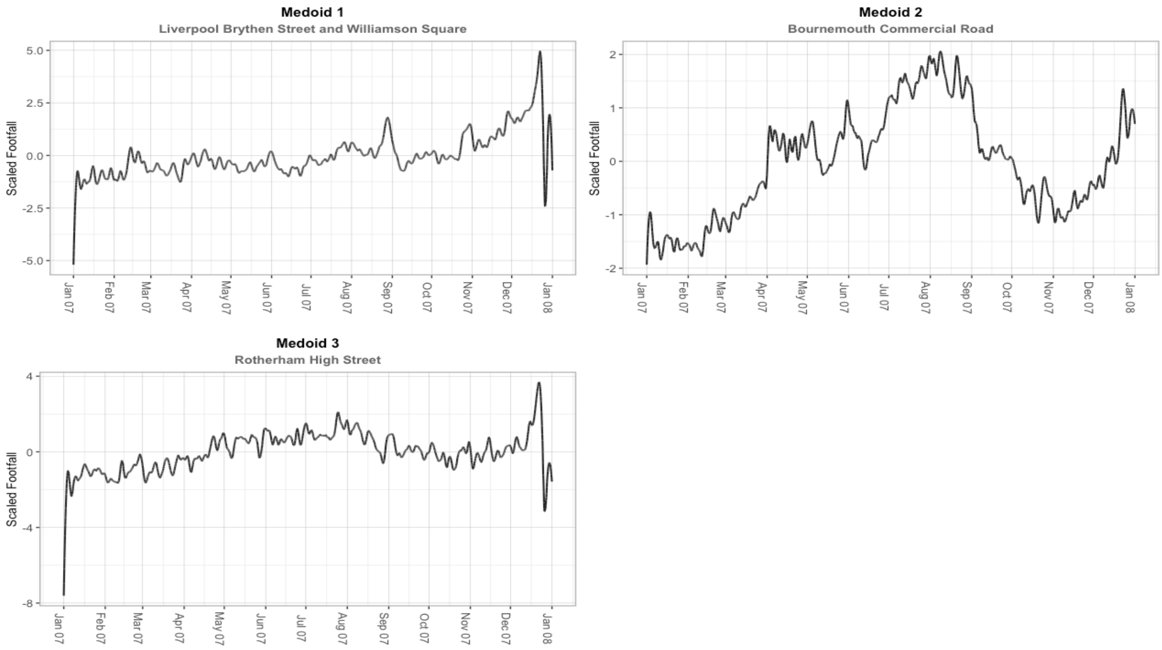


Figure 4.21. Medoid Annual Signatures for 2007 where k = 3

In most cases, the final decision was reasonably clear but where two possibilities seemed appropriate, the lower value of k (the number of medoids) was always selected.

4.6.5.2 Displaying Results

In several cases, the analysis packages, such as dtwclust provided very useful plot functions to display results. For the analysis phase, these were used extensively but in order to display the results for presentational purposes, these routines were recreated using ggplot2 (Wickham, 2016). Exceptions were the outputs from the imputation missing data phase (Moritz and Bartz-Beielstein, 2017) and the tuning of the DWT function (Giorgino, 2018) where the output was considered good enough and, the effort to rewrite these functions was not considered worthwhile.

Some of the packages provided specialised output formats required for the display of the fuzzy cluster results, in particular, the generation of Radial Coordinate Visualisation (Radviz) diagrams using the Radviz package (Abraham, 2016). Presenting the results of fuzzy clusters is problematic as the resulting clusters are high-dimensional geometrical objects, which are difficult to analyse and interpret (Pedrycz, 2005; Feil et al., 2006; Sato-Ilic and Ilic, 2016). Abraham (2020) identifies several tools such as principal component analysis (PCA) but notes that these do not allow for the direct interpretation of the position of points in space. However, Radial Coordinate Visualisation (Radviz) aims to solve this problem by projecting data of N-dimensions onto a simple 2D space where the influence of each dimension can be interpreted as a balance between the influence of all dimensions (Abraham, 2020). The Radviz package implements the concept of dimensional anchors to visualize multivariate datasets in a 2D projection (Abraham, 2016). This was originally defined by Hoffman et al. (1999) and improved upon to provide ordering of the dimensional anchors (Di Caro et al., 2010). An example of the Radviz diagrams used by this study is provided below in Figure 4.22 where there are four medoids and the relative location of each daily signature to each of the medoids is plotted.

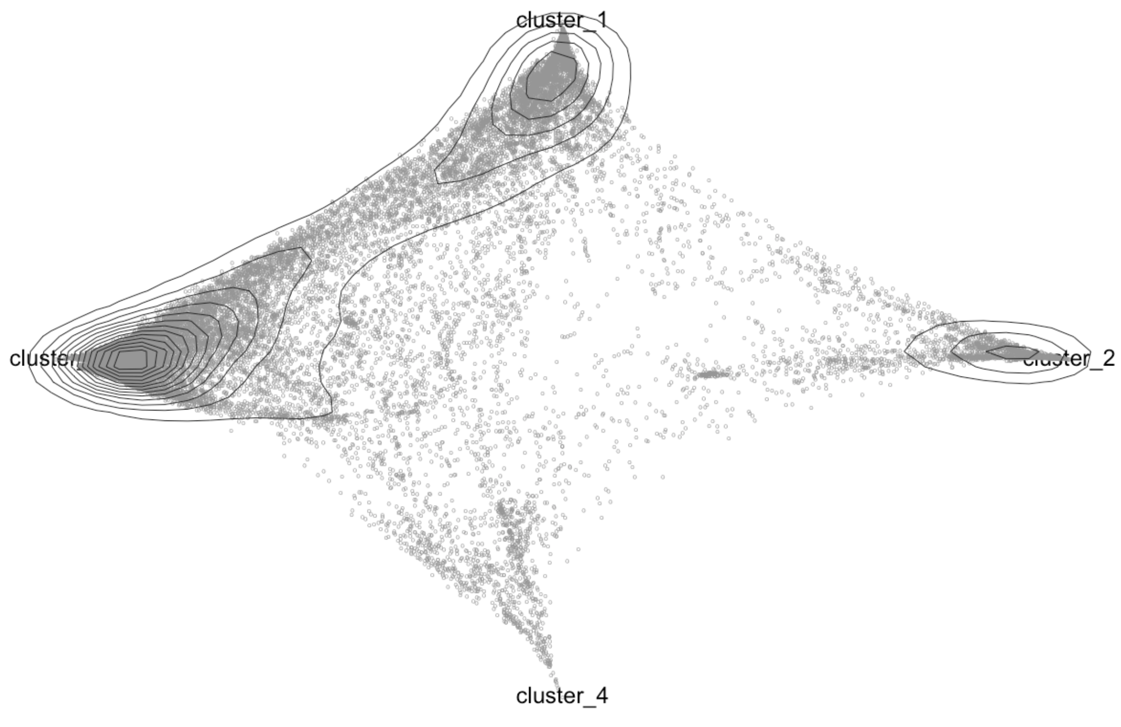


Figure 4.22 - Example Radviz diagram showing daily clusters for 2007

In Figure 4.22, note the general dominance of medoids 1 and 3 (labelled cluster_1 and cluster_3 as no option to change the name from cluster to medoid was identified in the software). An important aspect of using the Radviz diagrams was

to check the quality of the fuzzy clustering outputs. For example, should all the points be in the middle of the plot, then the fuzzy analysis had failed to distinguish between the medoids, and hence the analysis was of no value.
Further details of the diagramming packages used is available in Appendix A: Section 12.10 Interpretation and Analysis.

4.6.6 Phases of Operationalisation

Three phases of software development and data analysis were required before the final phase of analysis.

4.6.6.1 Phase 1 - Technical Feasibility

This phase involved the consideration of removing technical risk, determining how to store the footfall data and which technologies would be used for data processing and analysis. Wherever possible, open-source software was used. Based upon previous experience, the Community Edition of MySQL was used to store the data. To load the footfall data from the raw file inputs into the database, the software language Python was chosen. The objectives for the initial phase were:

- Provide an initial view of the raw data.
- Confirm the best approach for storing and manipulating the data. (Python and MySQL)
- Identify problems in the data and what would be needed to resolve any issues
- Assess data analysis tools and techniques

The outcomes of this phase were:

- The creation of a database and the software needed to process and store the footfall data into the database.
- Accounting for missing data in the input data. Imputing the missing data was performed using an R package - ImputeTS.
- Options to decompose the footfall data into daily, weekly, annual signatures

were explored and STL Loess (Cleveland et al., 1990) was tested and selected.

- Options for analysing and displaying the results in R were assessed. For flexibility, ggplot2 (Wickham, 2016) was chosen as the main display package.
- Data mining options were explored, including ARIMA, Discrete Signal Analysis and various clustering packages. At this point, no real decision was made though apart from the fact that R would be the data analysis platform.

The overall conclusion from the phase was that MySQL was a good option for storing the data. Python would remain the language used for the extraction and loading of the footfall files into the database. R was the platform of choice for analysis and presenting results.

4.6.6.2 Phase 2 - Scalability, Debugging, Visualisation and Testing

Following on from Phase 1, the key objectives were:

- Reloading the database - with additional footfall data to test the scalability of the database
- Ensuring that bugs and errors in the data were being identified and resolved.
- Creation of a graphical library of individual plots for each sensor to aid with data visualisation and validation.
- Validation of the selected clustering approach and a check for technical feasibility.

The outcomes for this phase were:

- The codebase was retested to eliminate bugs in the programming and problems caused by the data. Issues such as DST switching was checked for, missing hours in the data checked, duplications, spurious characters and missing data imputation were all tested, and the code improved to eliminate these problems.

- The dtwclust package in R (Sardá-Espinosa, 2019) was explored more fully and the clustering capabilities to process annual, weekly, and daily footfall signatures verified. This flagged up a system limitation with RAM memory capacity being exceeded. To overcome this, a sampling strategy was explored and tested.
- Further enhancements of all the tools needed to display the data and, a library of the plots for each place and sensor was created so that raw, imputed, and decomposed time series could be viewed for each sensor.

4.6.6.3 Phase 3 - Final Data Load and Analysis

The key objectives for this phase were:

- Final checking for bugs in the software.
- Reloading, cleansing and decomposition all the footfall data.
- Final tuning of all parameterisations using for processing the data.
- Regeneration of individual sensor reference plots.
- Checking each of the sensor plots to ensure validity of the original and decomposed time-series.
- Performing the cluster analyses and tuning parameterisations.

Outcomes from the phase were:

- For the seasonal decomposition, parameters were tuned and tested before final decomposition of the data and storage of the results was performed (see 4.6.1 Data Selection). Annual signature results were limited to sensors having a full year of data running from 1st Jan to 31st Dec and only where there was at least 2 consecutive years - this was a minimum requirement of the STL decomposition algorithm.

- The Cluster Analysis algorithm required tuning of DWT and fuzzy clustering algorithms the results of which are found in section 4.6.4 Data Mining. Ideally, the analysis would have followed the process suggested by (Angstenberger, 2001) in using the fuzzy analysis results of a previous period and comparing these to the current results to compare what has changed. This proved difficult to implement and with a dataset where the number of sensors and medoids were not constant, the results that were generated were confusing, so the approach was abandoned. As an approach though, research suggests it is doable and this is a recommendation from this research that it should at least be attempted.

The final presentation of the results was performed using R but also Excel which offered the chance to rapidly explore and display results. Presentational bugs were identified and resolved.

4.6.6.4 Phase 4 - Generating the Results

To answer the research questions, the fuzzy cluster analysis was performed with the annual, weekly, and daily decomposed footfall time-series. To identify how the combined set of places and their footfall sensor counts change over time, individual years were processed for all the available sensors, the details of which are provided in the relevant result sections. For the annual results, no complications arose but for the weekly and daily analysis, computer memory limits meant that sampling of the sensor data was required. Details of the amount of sampling required are provided alongside the results in the next chapter.

To analyse how individual places, change over time, the exemplar places chosen had multiple sensors in operation for at least ten years – a sufficient period to ensure identified changes are not simply random (Richard et al., 2009). To single out exemplars for investigation, the two places investigated, Manchester and Rotherham presented contrasting results from the collective analysis. For Manchester, the footfall sensors all demonstrated differences in their daily and weekly cluster patterns, whereas Rotherham indicated very few differences. Manchester therefore presented an opportunity to investigate the different social activity patterns and how these change over time, whereas for Rotherham, the challenge was to see how sensitive the analysis framework could be to identify any differences at all. However, it is noted that by using exemplars to evaluate intra-place variation, there is still much to investigate for those places not selected (Lamont, 2012). The exemplar analyses were not limited to individual years so provided the opportunity to see how the fuzzy clusters changed over much longer periods of time. As a result, the exemplar results required different presentational tools to the combined results although the fuzzy analysis toolset remained the same. Both the above sets of analyses used the same R toolkit which offered the analysis framework a lot of flexibility.

A particular concern with using the clustering techniques is that clusters are identified even though the data is essentially randomly distributed (Keogh and Lin, 2004). To ensure the results were valid, the clusters identified were firstly compared to footfall patterns already identified in the literature (Monheim, 1998; Lugomer and Longley, 2018; Mumford et al., 2021). Additionally, the results were validated against the original data using time-series plots to ensure the patterns identified were real.

4.6.7 Reflections and Limitations

The development of the research design, deciding upon a theoretical framework and defining the research questions was a very iterative process. The setting up of the database and being able to access and visualise basic time-series of the footfall data was an important first step for this study.

An attempt to use pattern matching techniques to compare year-on-year annual clustering results was attempted but the results were confusing and reluctantly, the option was dropped. However, there must be an opportunity to pursue this as it would provide the ability to continually monitor the combined footfall sensor data. In the end, the research design has allowed the research questions to be answered, but there is further work to be done to create a comprehensive means of monitoring the footfall patterns for the combined footfall sensors.

Software development skills were a very useful asset for this project especially as the use of basic design patterns allowed repeated use of code modules without the need for continual rewriting. Both R and Python had to be learnt and, because this was a part-time study, there were long periods where the created codebases went unused. By keeping a journal of what had been done, either as a written document or via the history feature within R, the time taken to relearn how to run existing code, to remember code sequences and how to process data etc was reduced significantly.

The study includes the following limitations:

- The footfall data used for this study precedes the COVID-19 pandemic period.
- This is not a study of statistical and mathematical methods, rather it employs freely available resources for the analysis phase. No underlying change to the code base of any function or algorithm is made.
- The study focuses upon time rather than spatial dimensions apparent in the footfall data.
- As an exercise in exploring the data, the methods used lack the rigour that a statistician or mathematician would apply and for this reason, the findings could be viewed as ideas for further research, rather than, for example, proven models of social activity movements. The original intention having been to provide a practical tool for place managers which in the end, was not really realised.
- The analysis does not include the residual values. The focus of the study is on the representative and regular patterns extracted from the data rather than the exceptions. This though is not to dismiss the value of the data - it was simply a matter of research scope. One of the suggestions of this study is that the residual values need to be investigated more.
- The data analysis processes were limited by the capabilities of the computer platform used. See Appendix A: Section 12.1 System Configuration for details.

4.6.8 Summary

The first part of the research design discusses the approaches chosen to process the footfall time-series to uncover the periodic rhythms within the data. The process of finding how best to analyse the data took time, especially that taken exploring ARIMA and discrete wave analysis. The conclusion arising from this initial exploration was that there was merit in taking a simple approach. There is probably an optimal way of discovering the rhythms in the footfall data, but for this study, data mining via cluster analysis techniques provided an established research approach (Romesburg, 1984; Warren Liao, 2005; Chiş et al., 2009; Everitt et al., 2011; D'Urso and Massari, 2013; Aghabozorgi et al., 2015). For the data mining of human activity, the research also suggested the use of fuzzy cluster analysis (D'Urso and Massari, 2013).

Pragmatically, the R package dtwclust (Sardá-Espinosa, 2019) provided all the components needed to perform the fuzzy cluster analysis and therefore, this was the option chosen. A reflection that all the results were generated using the R statistical platform (R Core Team, 2019) and this then enabled the presentation of the results used predominately, the R ggplot2 package (Wickham, 2016).

The implementation phase of the research design was technology orientated and required the use of database, data manipulation, statistical processing, and presentational technologies. Broadly, through an iterative process, the implementation steps were:

- **Data Preparation and Storage** – creating a database of the footfall data where the original values were processed to account for errors and missing data. The cleaned data was then decomposed into different seasonal components (annual, weekly, and daily) and stored back into the database. By storing all the data in the database, the analysis phase was then able to extract all the footfall decompositions and imputed values for any location(s) and any period.

- **Analysis and Results Presentation** – extracting from the database, the footfall seasonal components and processed values to perform the cluster analysis and presentation of the results. In addition, the ability to extract and manipulate the footfall data into summary forms that aided the interpretation of the cluster results.

The implementation of the research design provided the analysis framework needed to assess the footfall data to answer the research questions. The results chapters that follow are therefore based upon the statistical and presentational outputs produced via this framework.

5 Results - Combined Annual Rhythms

The next three chapters present the results for the combined footfall sensors; that is, the collective of all the footfall sensors from which generic rhythms and the patterns of territorialisation can be identified across all locations. This Chapter focuses on the annual rhythms, Chapter 8 considers the daily rhythms and Chapter 9 completes the analysis considering weekly rhythms. The objective of all three chapters is to answer the following research question:

> *“As a performance measure, what insights can footfall offer to identify how collectively, places change over time?”*

In each chapter, the key results are identified, and additional detail is provided in the Appendices. Appendix B – Combined Sensor Annual Results supplements the annual results by providing addition details of the fuzzy cluster outputs for each year.

Taking a very general view using the Springboard footfall data, Figure 5.1 displays how mean hourly footfall has reduced over the period of the study. The fall in mean footfall is clear, but not very helpful as a performance measure, as this does not account for the increase in footfall sensors nor the different types of places they represent.

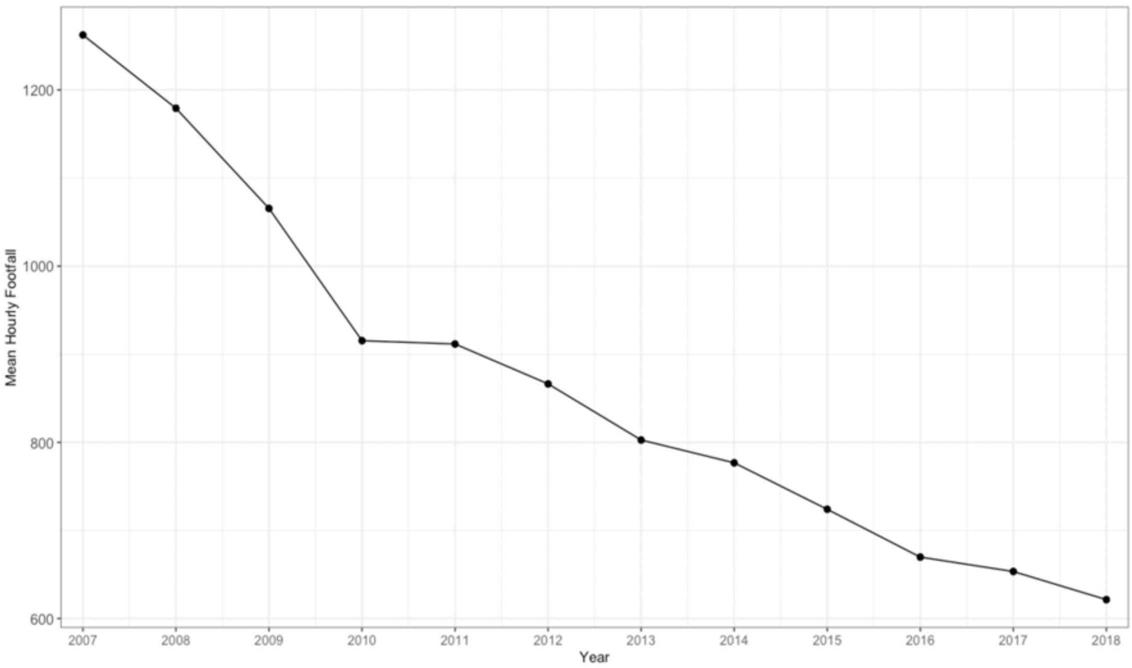


Figure 5.1. Annual changes to mean hourly footfall for all footfall sensors

Therefore, Figure 5.2 segments the annual mean footfall into the planning based urban classifications used by this study (see Appendix A: Section 12.3 Data Sources). This provides a different view of the decrease in footfall and reflects better the increased contribution of sensors from locations other than Major Cities over the period of study (see Figure 4.5 p130). It also suggests that the urban classifications used, although manually derived from various planning documents, provide a meaningful way of segmenting the footfall results.

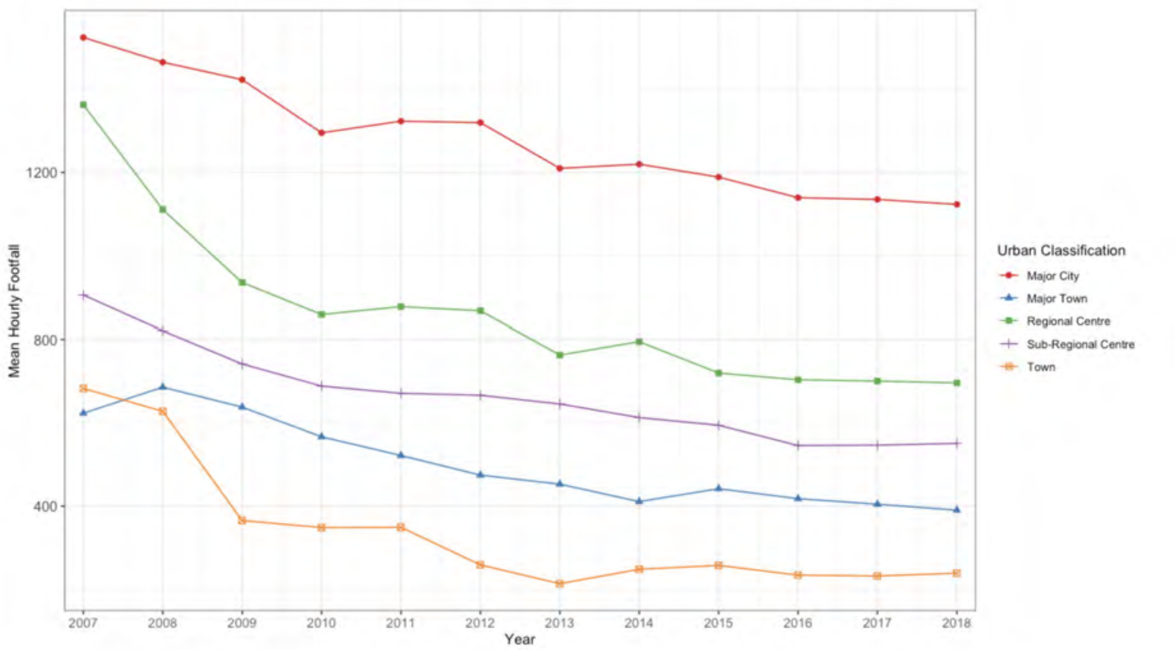


Figure 5.2. Annual changes to mean hourly footfall and urban classification type

Figure 5.2 presents a much less dramatic fall in footfall, a result of more footfall sensors becoming operational in places other than the major cities over time. However, there is still a reduction in the mean values although the decrease appears to tail off around 2016. This sets the background for the study, one where the general trend is falling footfall across locations, although such a scalar measure view provides no contextual view of how places are changing. That is why the aim of this study is to identify the rhythms of social activities found in towns and cities. Hence, why discovering the meso-level territorializations of social activity within space and time are the objectives of the research design toolkit used to generate the results that follow.

In the following three chapters, the footfall data analysed is that which is decomposed by the STL function (Cleveland et al., 1990; Hyndman et al., 2019b) into annual, weekly, and daily signature components. The fuzzy cluster analysis begins by assessing the annual rhythms apparent in the data. Since Mumford et al. (2017) and Mumford et al. (2021) provide examples of annual signatures using the same Springboard data source (although based upon monthly, and not hourly values), starting with the annual signature component provided an opportunity to validate the STL algorithm signature decompositions and the fuzzy analysis methods.

5.1 Data Inputs and Fuzzy Cluster Analysis Processing

To perform the fuzzy cluster analysis, the annual signature component derived from the imputed footfall data was used, as specified below in Equation 5.1.

$$Y_v = T_v + \boxed{S_{annual}} + S_{weekly} + S_{daily} + R_{v'}$$

Equation 5.1 - STL Equation and Annual Signature Additive Component.
Where Y*v*, T*v*, S and R*v'* represent the original data, trend, seasonality (annual, weekly, and daily), and residual respectively (Source: Cleveland et al., 1990:3)

For the data input into the fuzzy cluster analysis (summarised in Table 5.1), the annual signature component was extracted from the database for each individual year, from 2007 to 2018, where each year consisted of a discrete dataset. For each individual annual dataset, the footfall sensors included were only those that had a complete set of annual component hourly values in the range 00:00 1 January to 23:00 31 December. Each individual sensor was labelled using the location identifier from the database so that each could be identified when processing the results. During the subsequent year-based fuzzy cluster analysis, the whole year of data for each footfall sensor was compared to every other sensor (8760 hourly values per sensor – 8784 in leap years).

Table 5.1. Annual Fuzzy Cluster Analysis Data Inputs

Data Input Characteristics	Details
Input Data Source	STL derived annual signatures
Period of data extraction and analysis (by year)	00:00 1 January to 23:00 31 December
Number values per data record	8760 (365*24) 8784 in leap years
Standardisation of data record?	Yes
Additional smoothing applied?	Yes – period of a week

To perform the fuzzy cluster analysis, a set of parametrisations were required for the R dtwclust package (Sardá-Espinosa, 2019) and are detailed in Appendix A: Section 12.9 Data Mining. However, an adjustment was needed for the annual signature data as initial results were dominated by outlier events. Hence, the decision was taken to further smooth the annual component data using STL over the period of a week - a technique recommended by Cleveland et al. (1990). Alternatively, a weekly mean could have been used but this was less effective at removing the outliers. Consequently, the cluster analysis was performed on smoothed hourly data for each individual year. In addition, each individual footfall sensor annual component hourly values were standardised using the R Scale Function (R Core Team, 2019) to remove differences of scale between locations and thus allowing the fuzzy analysis algorithms to focus on the shape of the annual footfall component rather than differences in magnitude of pedestrian numbers – see Chapter 4: Data Standardisation p156.

5.2 Selecting the Number of Medoids

Following the completion of the fuzzy cluster analysis for each year, the first decision that needed to be made was to determine the optimal number of medoids that best fitted the data, where a medoid is an exemplar sensor that best represents a cluster identified by the fuzzy cluster algorithms (Sardá-Espinosa, 2018). This process is detailed above in Chapter 4 on p160 and was repeated for every fuzzy cluster analysis. The fuzzy cluster outputs used to perform the number of medoids' selection are provided for each year in Appendix B. As Table 5.2 shows, the number of allocated medoids each year was not a constant nor, as the subsequent sections identify, were the same medoids chosen as exemplars across the different years. In other words, the medoid representations for each year changed due to changes in the annual signatures and as the number of operational sensors increased.

Table 5.2. Number of Medoids assigned to each year of analysis

Year	Number of Medoids	Number of Footfall Sensors Analysed
2007	3	74
2008	4	92
2009	3	140
2010	3	185
2011	5	201
2012	4	219
2013	4	253
2014	5	283
2015	4	346
2016	5	425
2017	4	459
2018	5	483

5.3 Fuzzy Cluster Analysis Process

Fuzzy cluster analysis offers a lot of detailed information about the structure of data by allocating patterns to clusters with numeric degrees of membership (Pedrycz, 2005). This then allows an assessment of the fuzzy membership allocation to determine degrees of full membership, full exclusion or uncertainty with respect to membership for each identified cluster (Pedrycz, 2005). Although methods to assess this data automatically exist (Pedrycz, 2005), none was found that could be used (based upon understanding of available packages) using R. In other examples, the fuzzy assessment techniques used by Khoo-Lattimore et al. (2019), D'Urso et al. (2018) and D’Urso and Massari (2013) required the medoids to remain unchanged over time. In the case of this study, because each year was run as an individual unsupervised cluster analysis, there was no continuity between the number of medoids between each year. A benefit of doing this removed the need to find a way of comparing annual medoids from year to year to account for periods such as Easter.

Hence, the interpretation of the results relied upon the following steps:

- A descriptive assessment and categorisation of the medoids to identify the rhythms evident for each year.

- Using the annual fuzzy membership allocations, matching the above categorisations to each footfall sensor, and assessing what this can reveal about changes in the annual signatures.

To validate the cluster results and to ensure that patterns have not been picked up randomly (Keogh and Lin, 2004), each set of findings are checked against the original footfall data.

5.4 Descriptive Analysis and Categorisation

The next section provides the descriptive assessment of the annual fuzzy cluster results from which a territorialisation categorisation is created and used for further analysis. As a starting reference point for the annual fuzzy cluster analysis, the signatures identified by Mumford et al. (2021) were used to validate the medoids (see Figure 1.1 p7) and are summarised below:

- Comparison – driven by a shopper economy with a busy Christmas period
- Holiday – driven by holiday and 'day-out' visitors
- Speciality – a mixture of attracting visitors and the local population
- Multifunctional – economy driven and serving regional (larger population size locations) as well as local populations.

The sections below are an assessment of the fuzzy cluster analysis outputs for each year.

5.4.1 Analysis Results for 2007

Figure 5.3 displays the medoids, the sensors automatically assigned by the dtwclust package (Sardá-Espinosa, 2019) to represent each cluster found in the

2007 annual component footfall data and are used to categorise the rhythms, territorialisation processes and intensities.

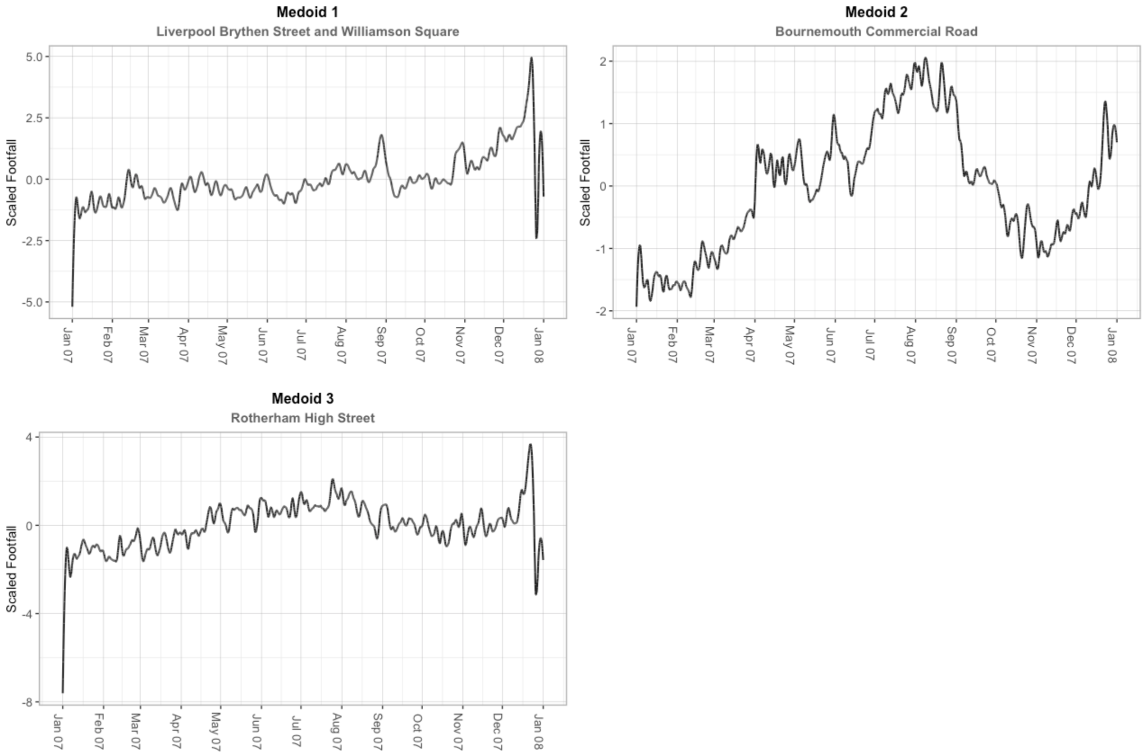


Figure 5.3. Medoids for the 2007 Annual Fuzzy Analysis

Note that as the medoids are extracted from hourly values and despite the annual series having been smoothed, there is still a lot of variability evident in the data. The descriptive analysis of each medoid follows below:

Medoid 1 broadly suggests a steady volume of footfall until the Christmas period starts to build from the end of October. This best matches the comparison signature identified by Mumford et al. (2021) but without the Christmas peak, the medoid would correspond more to the multifunctional centre signature. Even though the signature data is smoothed over a week period, there is still short-term variability, for example, the end of summer holidays peak in footfall traffic and Autumn holidays at the end of October. Additionally, there is a very sudden drop of footfall evident on Christmas Day. In terms of territorialisation, the signature approximates a constant balance between territorialisation and de-territorialisation processes (with the noted exceptions) until the Christmas period where there is an intensification of territorialisation that increases from the beginning of November to

Christmas Eve. In order to categorise Medoid 1, it is therefore labelled as a MF-Xmas analysis type and it is recognised that it is a combination of the Multifunctional and Comparison (Christmas Peak) signatures identified by Mumford et al. (2021).

Medoid 2 represents a much more seasonal pattern with a general increase of footfall for the non-Winter months. There are also specific periods of territorialisation during Easter, spring holidays and the summer holidays. There is a Christmas peak but of lesser intensity of territorialisation to that of the summer period. This corresponds to the Holiday signature identified by Mumford et al. (2021) but with the Christmas period peak, also the Speciality signature. Medoid 2 is labelled the Seasonal analysis type and is applied only where the summer peak is greater than that of the Christmas period.

Medoid 3, corresponds more with the Speciality signature identified by Mumford et al. (2021). The medoid is characterised by a seasonal territorialisation that peaks in the Summer but also has a Christmas period that although is of lesser intensity to that evident in Medoid 1, still exceeds in terms of short-term magnitude of intensity, the summer period. As this is a mix of both the Seasonal and the MF-Xmas signatures, it is labelled as the Mixed analysis type. A key criterion used to differentiate the Mixed analysis type from Seasonal in the subsequent categorisations is the greater territorialisation intensity apparent at Christmas compared to the summer period.

Table 5.3 presents the analysis of the different intensities of territorialisation of each of the medoids and includes the overall analysis type assigned to each. This process is repeated for all the years up to 2018. The results for 2007 provided initial confirmation that the medoids identified from the annual component data using the applied fuzzy cluster analysis toolkit had reproduced comparable results to those identified by Mumford et al. (2017); (2021). Subsequent analysis, as presented below, validated the research design approach.

Table 5.3. Annual Territorialisation Types for 2007

	Territorialisation Type and Intensity			
Medoid	Christmas Peak	Seasonal	Multifunctional	Analysis Type
1	High	Low	High	MF-Xmas
2	Medium	High	Low	Seasonal
3	High	Medium	Low	Mixed

5.4.2 Annual Results for 2008 – 2009

Repeating the process followed for 2007, the results for 2008 and 2009 were similar – see Figure 5.4 and Table 5.4 for the 2008 results and Figure 5.5 and Table 5.5 for the 2009 results. The additional details can be found in Appendix B: Section 13.2 Fuzzy Cluster Descriptive Analyses.

Table 5.4. Annual Territorialisation Types for 2008

	Territorialisation Type and Intensity			
Medoid	Christmas Peak	Seasonal	Multifunctional	Analysis Type
1	High	Low	Medium	MF-Xmas
2	Medium	Medium	Low	Mixed
3	High	Medium	Low	Mixed
4	Low	High	Low	Seasonal + New Year

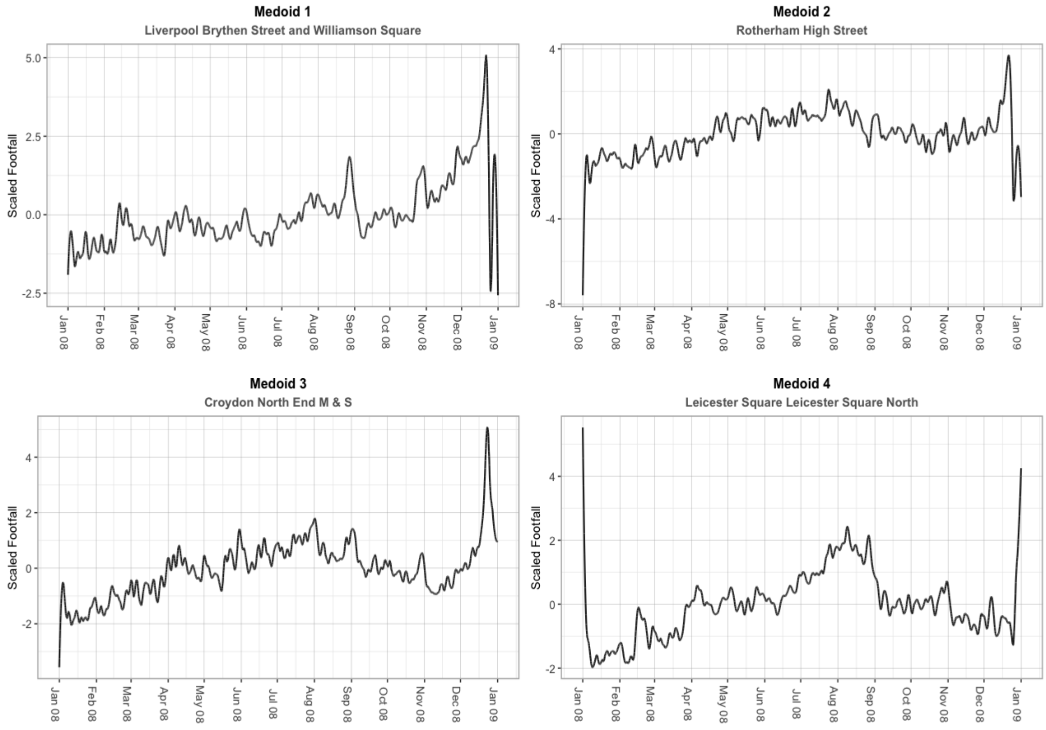


Figure 5.4. Medoids for the 2008 Annual Fuzzy Analysis

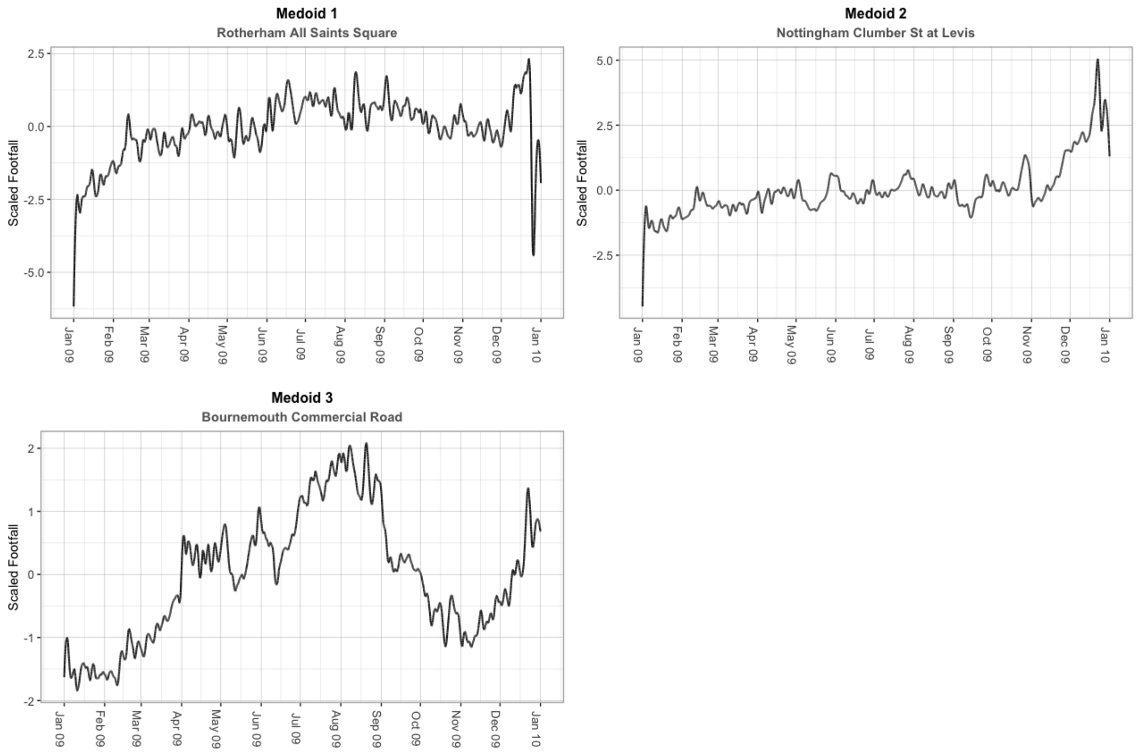


Figure 5.5. Medoids for the 2009 Annual Fuzzy Analysis

Table 5.5. Annual Territorialisation Types for 2009

	Territorialisation Type and Intensity			
Medoid	Christmas Peak	Seasonal	Multifunctional	Analysis Type
1	Medium	Medium	Low	Mixed
2	High	Low	High	Christmas
3	Medium	High	Low	Seasonal

5.4.3 Annual Results for 2010

Figure 5.6 below displays the locations and the exemplar medoids identified to represent 2010. Since the fuzzy cluster analysis process is performed for individual years, the results identify that the medoids can change from year to year, even though the shapes and rhythms identified might be like previous years.

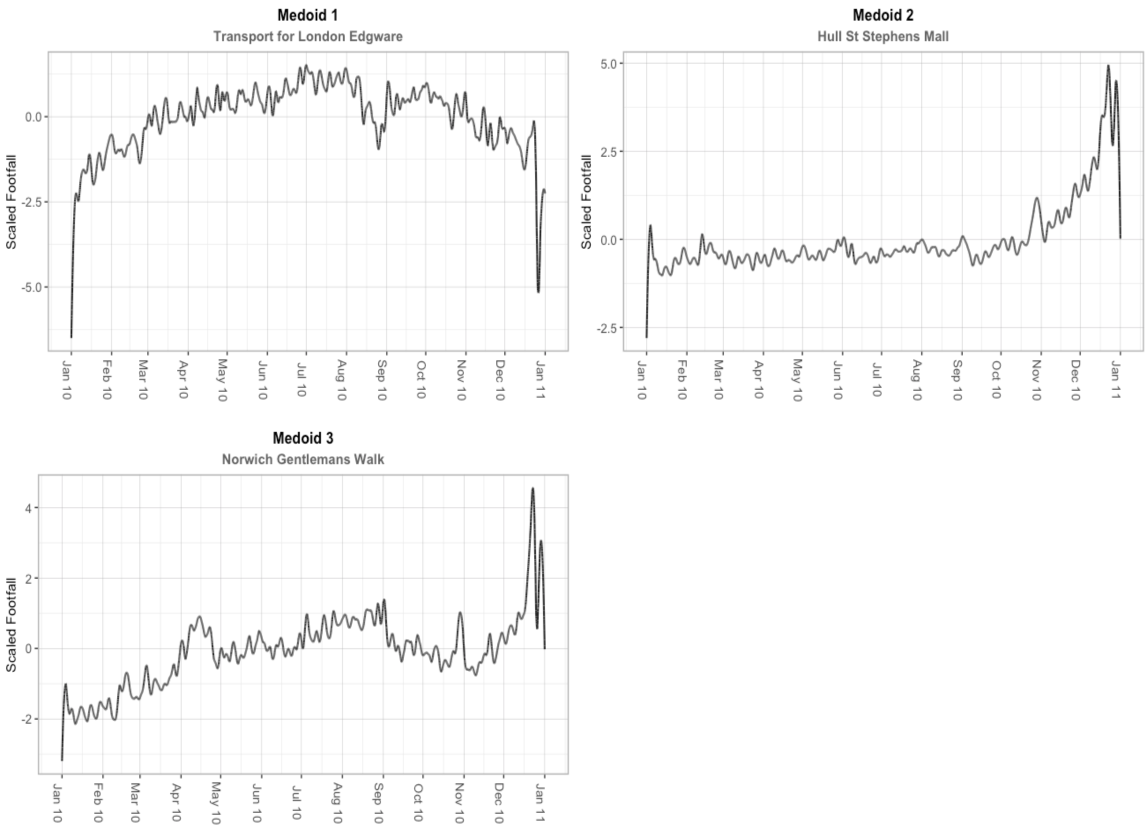


Figure 5.6. Medoids for the 2010 Annual Fuzzy Analysis

Medoid 1 presents a seasonal pattern without any Christmas period intensification and in addition, identified a period of de-territorialisation during the August period. For the analysis, this medoid was still flagged as Seasonal but the assignment of this medoid was an indicator that the cluster algorithm was starting to pick up another signature type. Table 5.6 provides the analysis summary.

Table 5.6. Annual Territorialisation Types for 2010

	Territorialisation Type and Intensity				
Medoid	Christmas Peak	Seasonal Territorialisation	Seasonal De-territorialisation	Multi-functional	Analysis Type
1	Low	High	Medium	Low	Seasonal
2	High	Low	Low	High	MF-Xmas
3	High	Moderate	Low	Low	Mixed

5.4.4 Annual Results for 2011

Figure 5.7 below displays the exemplar medoids identified to represent 2011.

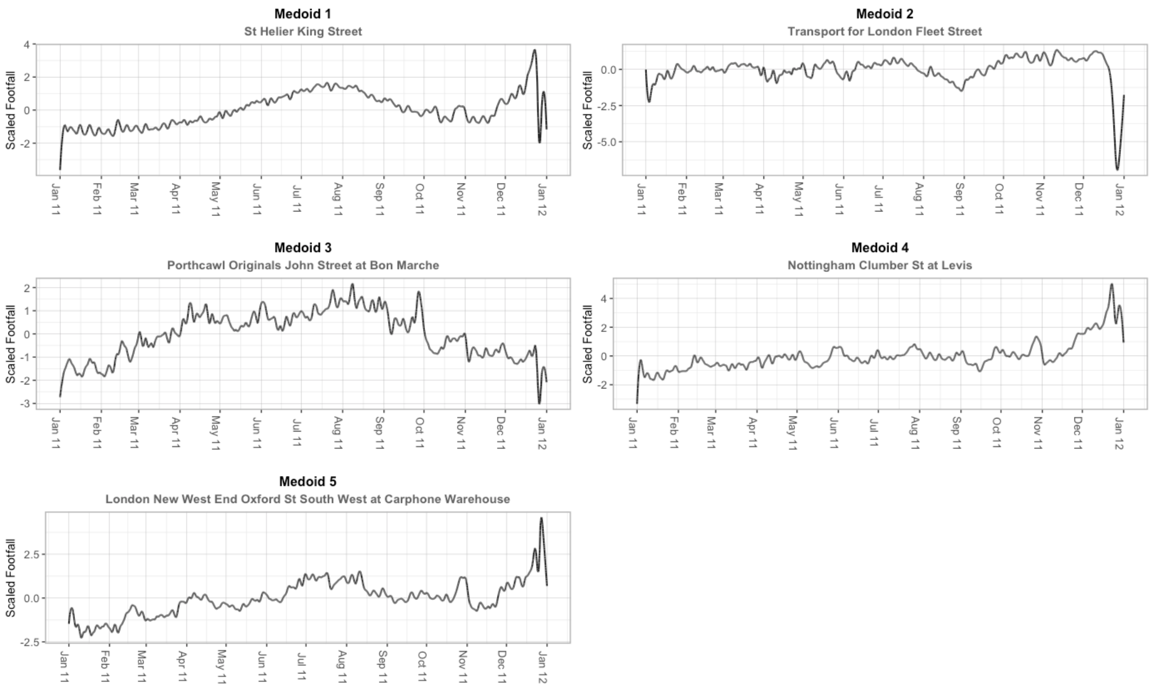


Figure 5.7. Medoids for the 2011 Annual Fuzzy Analysis

Table 5.7 above introduces a new analysis type (hinted at in the 2010 results) that medoid 2 identifies. The Summer holiday de-territorialisation period identified by this signature is also shared by locations where student populations are a dominant factor for footfall counts e.g., Durham (see Medoid 3 in Figure 5.12 p193). Hence, this is assigned an analysis type of Term-Time and is present at locations where the de-territorialisation intensity is driven by workplace holidays during the Summer (Fleet Street) and/or students at universities and schools not being present outside term times.

Table 5.7. Annual Territorialisation Types for 2011

	Territorialisation Type and Intensity				
Medoid	Christmas Peak	Seasonal Territorialisation	Seasonal De-territorialisation	Multi-functional	Analysis Type
1	High	Medium	Low	Low	Mixed
2	Low	Low	Medium	High	Term-Time
3	Low	High	Low	Low	Seasonal
4	High	Low	Low	High	MF-Xmas
5	High	Medium	Low	Medium	Mixed

5.4.5 Annual Results for 2012

Figure 5.8 below displays the exemplar medoids identified to represent 2012. Table 5.8 identifies medoids 1 and 2 as having very similar signatures except that medoid 1 does have a Summer de-territorialisation in footfall, whereas medoid 2 indicates a de-territorialisation period at the start of the year. Also, although medoid 3 has been assigned as Seasonal, the period of seasonality is not the usual period of the summer holidays but before this time, peaking at around June (a possible consequence of the London Olympics). The medoids for 2012 highlight a weakness in the analysis type categorisation used in terms of the different periods and intensities of territorialisation that are possible.

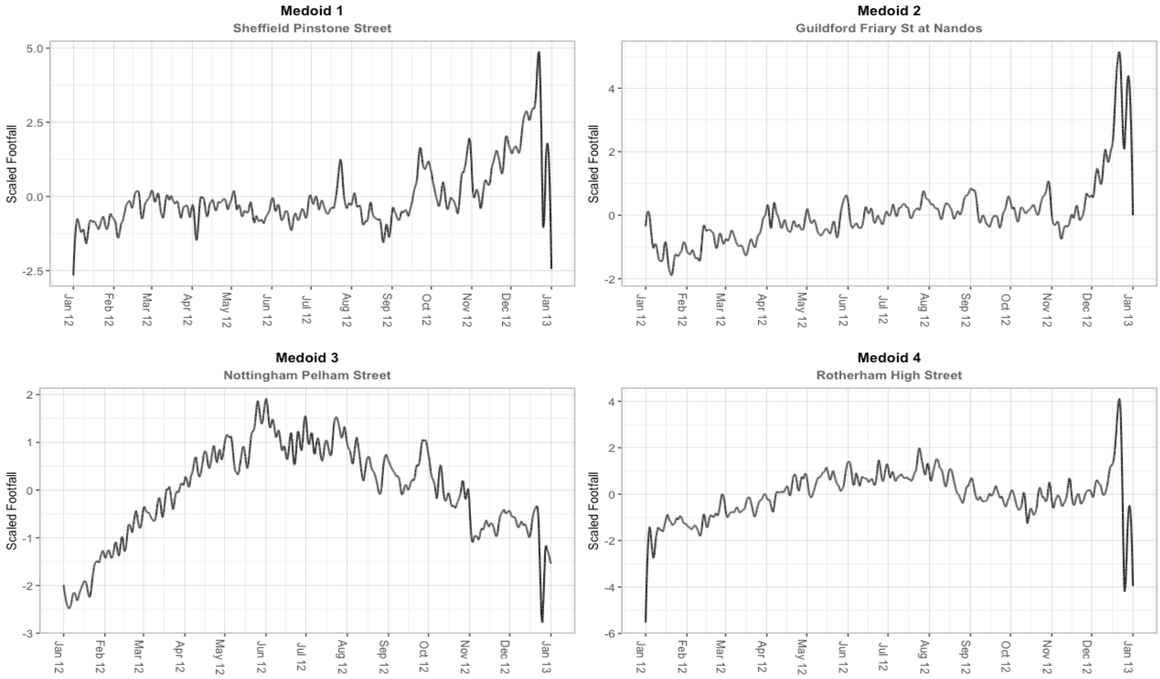


Figure 5.8 - Medoids for the 2012 Annual Fuzzy Analysis

Table 5.8. Annual Territorialisation Types for 2012

	Territorialisation Type and Intensity				
Medoid	Christmas Peak	Seasonal Territorialisation	Seasonal De-territorialisation	Multi-functional	Analysis Type
1	High	Low	Medium	Medium	MF-Xmas
2	High	Low	Low	Low	MF-Xmas
3	Low	High	Medium	Low	Seasonal
4	High	Medium	Low	Low	Mixed

5.4.6 Annual Results for 2013

Figure 5.9 below displays the exemplar medoids identified to represent 2013. Table 5.9 shows medoids 3 and 4 as being the same but in fact, the period of the Christmas territorialisation for medoid 3 is spread over a longer period than that of medoid 4. Medoid 3 also hints at a summer holiday de-territorialisation period.

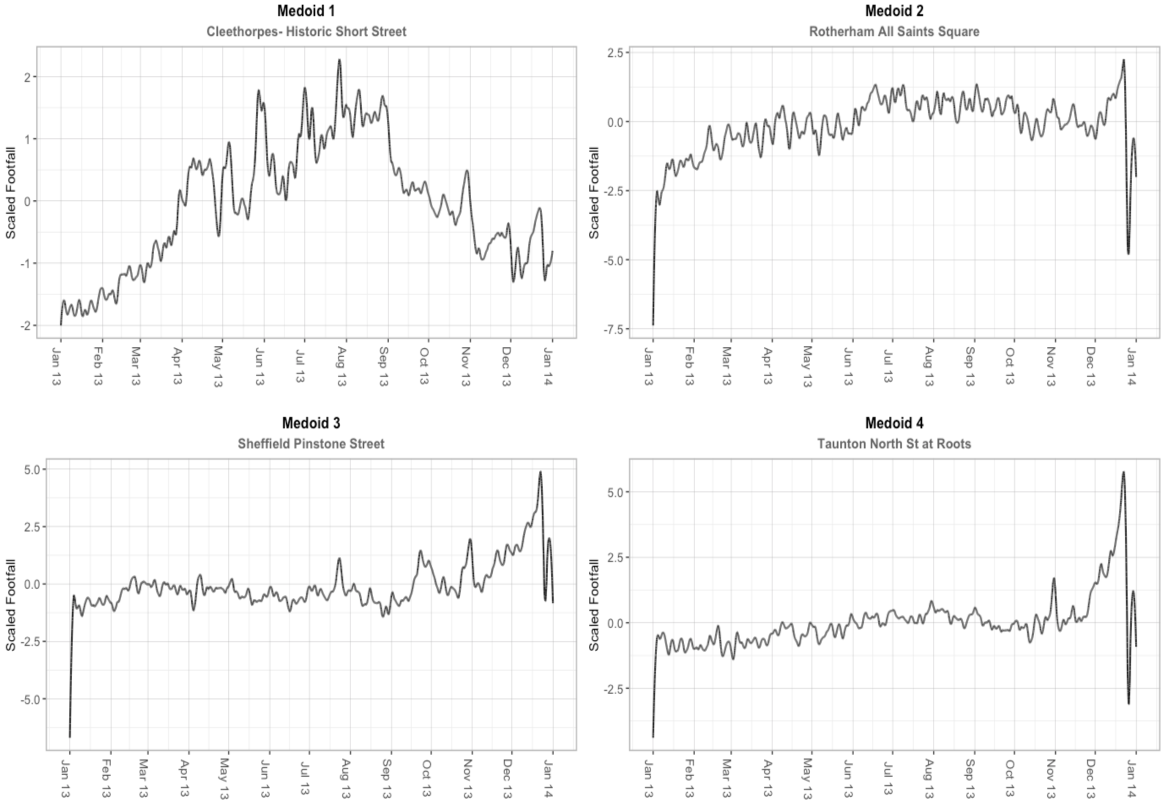


Figure 5.9. Medoids for the 2013 Annual Fuzzy Analysis

Table 5.9. Annual Territorialisation Types for 2013

	Territorialisation Type and Intensity				
Medoid	Christmas Peak	Seasonal Territorialisation	Seasonal De-territorialisation	Multi-functional	Analysis Type
1	Low	High	Low	Low	Seasonal
2	Medium	Medium	Low	Medium	Mixed
3	High	Low	Medium	High	MF-Xmas
4	High	Low	Low	High	MF-Xmas

5.4.7 Annual Results for 2014

Figure 5.10 below displays the medoids identified to represent 2014.

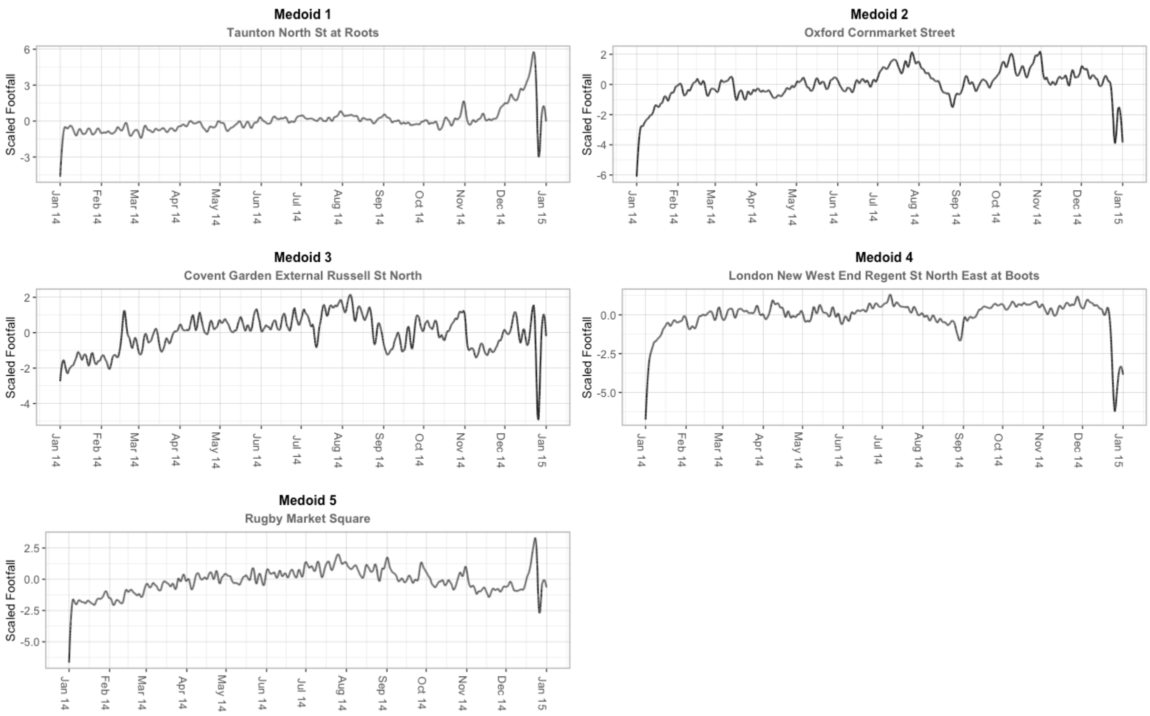


Figure 5.10. Medoids for the 2014 Annual Fuzzy Analysis.

In Table 5.10, medoids 2 and 4 resemble the multifunctional signatures identified by Mumford et al. (2021), being relatively constant throughout the year. However, as both have a Summer de-territorialisation period in footfall, they are identified as Term-Time signatures.

Table 5.10. Annual Territorialisation Types for 2014

	Territorialisation Type and Intensity				
Medoid	Christmas Peak	Seasonal Territorialisation	Seasonal De-territorialisation	Multi-functional	Analysis Type
1	High	Low	Low	High	MF-Xmas
2	Low	Medium	Medium	Medium	Term-Time
3	Low	High	Low	Low	Seasonal
4	Low	Low	Medium	Medium	Term-Time
5	Medium	Medium	Low	Low	Mixed

5.4.8 Annual Results for 2015

Figure 5.11 below displays the medoids identified to represent 2015.

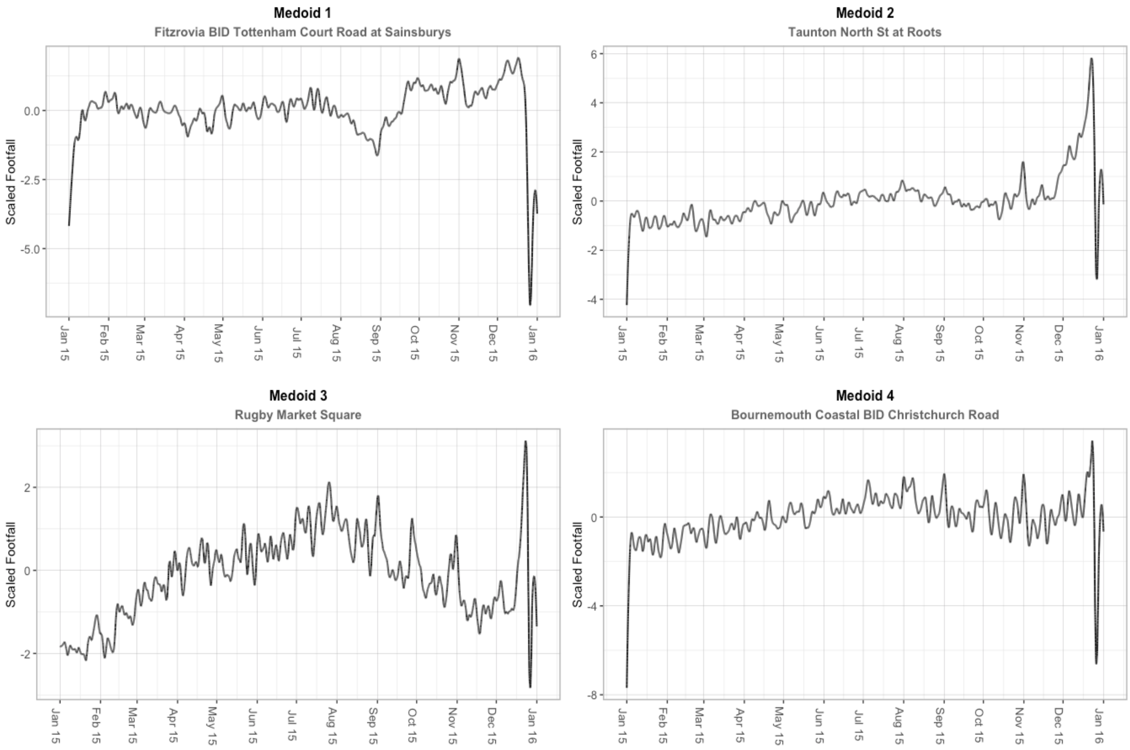


Figure 5.11. Medoids for the 2015 Annual Fuzzy Analysis

Medoid 4 in Figure 5.11 is for a sensor based in Bournemouth and assigned an analysis type of Mixed. In the 2007 results (see Figure 5.3 p181), a different sensor in Bournemouth was assigned as a medoid and categorised as Seasonal. What this picks out is the plurality of footfall signatures found in any town or city and how signatures can change over time. Table 5.11 summarises the types identified for 2015. Note also that the Christmas period for Medoid 3 is very short but intense as otherwise, this Medoid would have been identified as Seasonal. The length of the Christmas period (determined by when the period begins), as well as the territorialisation intensity, therefore differs between places.

Table 5.11. Annual Territorialisation Types for 2015

	Territorialisation Type and Intensity				
Medoid	Christmas Peak	Seasonal Territorialisation	Seasonal De-territorialisation	Multi-functional	Analysis Type
1	Medium	Low	Medium	High	Term-Time
2	High	Low	Low	Medium	MF-Xmas
3	Medium	High	Low	Low	Mixed
4	Medium	Medium	Low	Low	Mixed

5.4.9 Annual Results for 2016

Table 5.12 displays the medoids identified to represent 2016. In Figure 5.12, Medoid 3, which uses data from a footfall sensor located in Durham, is a very clear example of a footfall signature influenced by term times. Medoid 2 is identified as a MF-Xmas type since the Christmas peak is more significant than it initially appears, due to the very significant New Year fall in footfall. Medoid 2 demonstrated that care was needed in checking the scale of the vertical axes when interpreting the results.

Table 5.12. Annual Territorialisation Types for 2016

	Territorialisation Type and Intensity				
Medoid	Christmas Peak	Seasonal Territorialisation	Seasonal De-territorialisation	Multi-functional	Analysis Type
1	High	Low	Low	Medium	MF-Xmas
2	Moderate	Low	Medium	Medium	MF-Xmas
3	Low	Low	High	Medium	Term-Time
4	Medium	High	Low	Low	Seasonal
5	High	Medium	Low	Low	Mixed

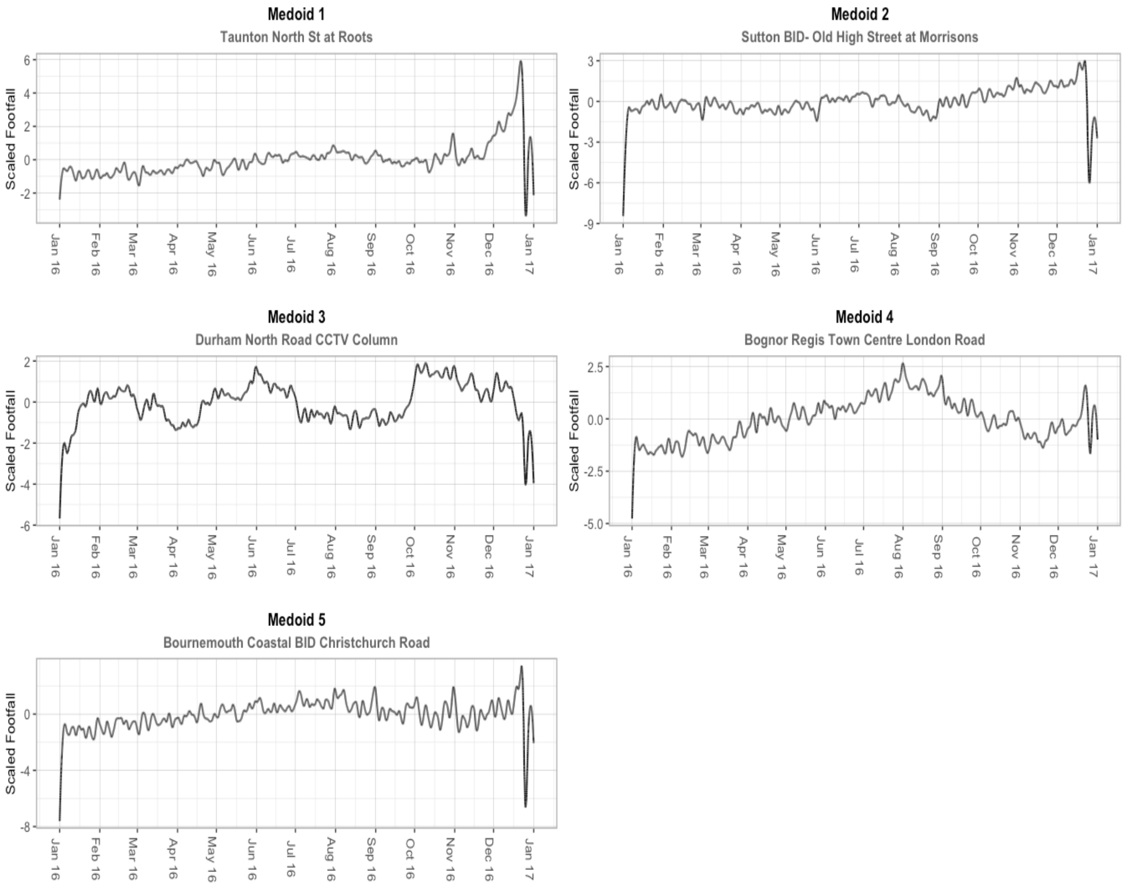


Figure 5.12. Medoids for the 2016 Annual Fuzzy Analysis

5.4.10 Annual Results for 2017 and 2018

As neither 2017 nor 2018 presented any new analysis types, the descriptive analysis for both years can be found in Appendix B: Section 13.2 Fuzzy Cluster Descriptive Analyses. In the following section, the analysis types assigned to each sensor will be analysed further.

5.4.11 Summary of Annual Analysis Types

Based upon the initial descriptive analysis, the annual medoid analysis types identified are summarised in Table 5.13.

Table 5.13. Annual Analysis Types

Annual Medoid Analysis Type	Description
Multi-Functional and Christmas (MF-Xmas)	A combination of the Balanced multi-functional Rhythm and Christmas Peak.
Seasonal	A combination of seasonal and holiday rhythms, where the seasonal plus holiday signature totals are greater than the Christmas period.
Mixed	A combination of seasonal, holiday and Christmas rhythms, where Christmas is the dominant peak period.
Term-Time	A combination of Seasonal and holiday Rhythms where the holiday Rhythm de-territorialises a location during non-term time.

5.5 Fuzzy Membership Results

Whereas the previous sections employed a descriptive analysis based upon the exemplar medoids assigned to each year, this section takes the descriptive analysis types (Table 5.13) and assigns them to each footfall sensor using the yearly based fuzzy membership allocations. Table 5.14 illustrates a sample of the fuzzy analysis outputs for the year 2007. The table includes examples of the fuzzy allocations of the medoids to individual footfall sensors (represented by the location identifier) - note the exemplar medoids for 2007 can be viewed in Figure 5.3, p181. For location identifier 48 in Table 5.14 (shaded a darker grey), the fuzzy allocation is 1.0 for Medoid 1, identifying this footfall sensor as an exemplar medoid (Liverpool).

The initial outputs from the R dtwclust package (Sardá-Espinosa, 2019) provided the medoid membership values and the location identifier for each sensor. The results were then processed to identify the best and next-best fitting medoids for each location. Then, for each sensor, the annual analysis type was assigned based upon the following rules:

- Where the best fitting medoid fuzzy membership value was greater than 0.9 (90%), the analysis type was assigned as a single type - the assumption being made that at 0.9, the contribution from other medoids would be minimal.

- Locations where the sum of the best and next-best fitting fuzzy membership scores totalled between 0.7 and 0.9 (the contribution column in Table 5.14), were treated as a combination of the best and next-best assigned annual types. For example, a location could have a predominantly MF-Xmas analysis type but also have a contribution from the Mixed analysis type. The label assigned was therefore ‘MF-Xmas + Mixed’.

- Where the combined contribution of the best and next-best fuzzy allocated values was less than 0.7, these locations were marked as undefinable.

Table 5.14. Sample of 2007 fuzzy medoid membership allocations for each footfall sensor and assigned annual analysis types

Location Identifier	Urban Type	Medoid 1 Allocation	Medoid 2 Allocation	Medoid 3 Allocation	Best Fitting Medoid	Next Best Fitting Medoid	Contribution	Annual Analysis Type
2	Sub-Regional Centre	0.895	0.025	0.079	1	3	0.974	MF-Xmas
3	Sub-Regional Centre	0.804	0.038	0.156	1	3	0.961	MF-Xmas & Mix
23	Major City	0.726	0.051	0.221	1	3	0.948	MF-Xmas & Mix
24	Major City	0.912	0.022	0.0655	1	-	0.912	MF-Xmas
48	Major City	1.000	0	0	1	-	1.000	MF-Xmas
1	Town	0.005	0.870	0.124	2	3	0.994	Seasonal & Mix
12	Regional Centre	0.050	0.559	0.390	2	3	0.949	Seasonal & Mix
61	Sub-Regional Centre	0.014	0.930	0.054	2	-	0.930	Seasonal
10	Sub-Regional Centre	0.220	0.152	0.627	3	1	0.847	Mix & MF-Xmas
56	Major Town	0.109	0.184	0.705	3	2	0.890	Mix & Seasonal
57	Major Town	0.032	0.475	0.492	3	2	0.967	Mix & Seasonal
58	Major Town	0.040	0.203	0.756	3	2	0.959	Mix & Seasonal

Having assigned best and next-best annual analysis types to the individual footfall sensors fuzzy analysis outputs for each year, the yearly results were then aggregated for the period 2007 to 2018. The initial view of these results is limited to the best fitting analysis types only (as shown in Table 5.15) indicates how membership of the best fitting annual analysis type changes by year (based upon the percentage occurrence for each year). Percentages by year are used to remove the impact of the increasing number of footfall sensors over time. These percentages are also plotted in Figure 5.13.

Table 5.15. Best Fit Medoid Annual Analysis Type Assignments

Year	Undefined	Mixed	Seasonal	Term Time	MF-Xmas	Totals
2007	4.1%	27.0%	24.3%	0.0%	44.6%	100.0%
2008	4.3%	40.2%	13.0%	0.0%	42.4%	100.0%
2009	5.1%	20.4%	23.4%	0.0%	51.1%	100.0%
2010	1.1%	32.4%	33.0%	0.0%	33.5%	100.0%
2011	9.1%	24.9%	19.8%	12.2%	34.0%	100.0%
2012	14.4%	19.1%	22.8%	0.0%	43.7%	100.0%
2013	10.0%	24.1%	24.9%	0.0%	41.0%	100.0%
2014	15.1%	30.8%	7.5%	11.8%	34.8%	100.0%
2015	3.2%	52.8%	0.0%	12.4%	31.6%	100.0%
2016	5.1%	34.0%	18.3%	2.7%	40.0%	100.0%
2017	7.6%	58.8%	0.0%	10.9%	22.7%	100.0%
2018	9.5%	46.8%	0.0%	8.3%	35.4%	100.0%

The results suggest that the distinctiveness of the MF-Xmas and Seasonal analysis types reduces over time whereas that of the type Mixed (Christmas and Seasonal period signatures) increased. This reduction though could be due to the increasing contribution to the fuzzy cluster analyses of non-major city locations as displayed in Figure 4.5 p130.

Despite the above caveat, Figure 5.13 nevertheless shows some interesting changes despite the change in urban type and sensor sampling size. The annual analysis type identified as term-type only becomes apparent in 2011. However, the term-type analysis type appears to be a hybrid of locations where non-term times appear to result in de-territorialisation. For example, locations such as Durham (student population), or locations such as Fleet Street (holiday exodus) in London where the main characteristic is a reduction in summer footfall. This suggests that different processes of territorialisation are acting upon these locations.

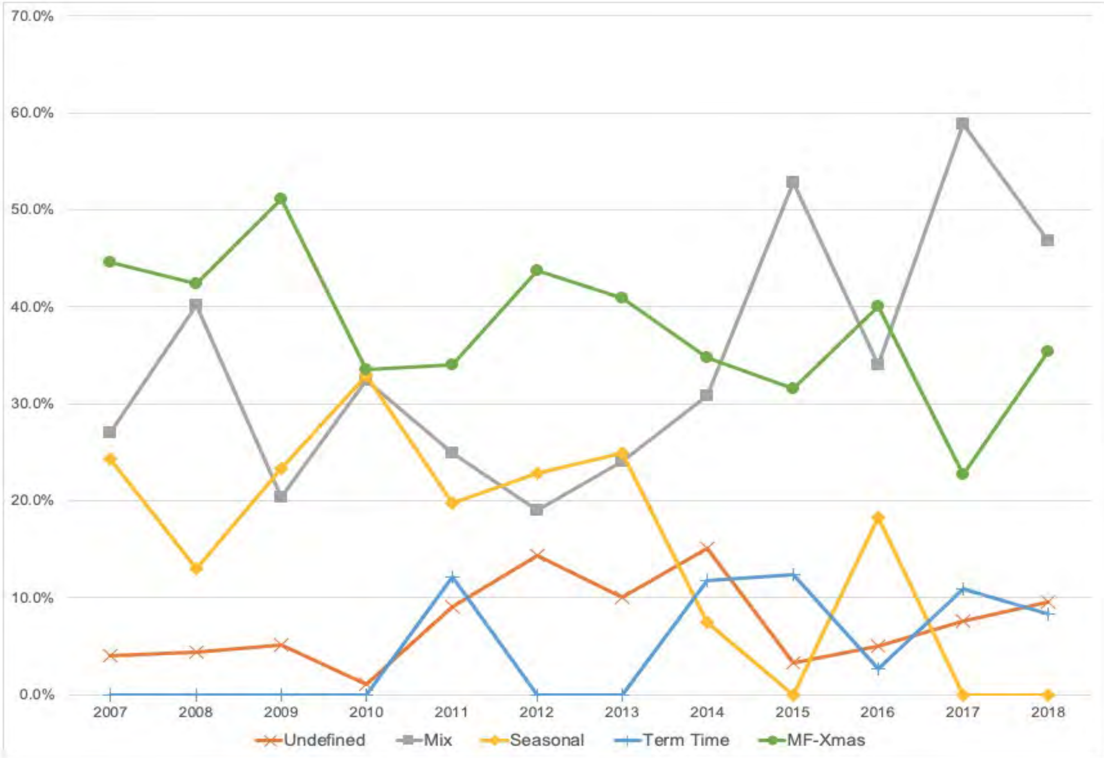


Figure 5.13. Plot of the results listed in Table 5.15.

Progressing beyond the initial view of the best fitting medoid analysis types, Table 5.16 shows the combination of best fitting and next best fitting annual analysis types and how they change over time. Note, where a year included two medoids that were assigned the same type e.g., 2015 where medoids 3 and 4 are both assigned as type Mixed, these results are aggregated as Mixed.

Table 5.16. The combination of best fit and next best fit annual signature types 2007 to 2018

Year	Undefined	Mixed	Mixed & Seasonal	Mixed & Term Time	Mixed & MF-Xmas	Seasonal	Seasonal & Mixed	Seasonal & Term Time	Seasonal & MF-Xmas	Term Time	Term Time & Mixed	Term Time & Seasonal	TermTime & MF-Xmas	MF-Xmas	MF-Xmas & Mixed	MF-Xmas & Seasonal	MF-Xmas & Term Time	Total
2007	4.1%	1.4%	21.6%	0.0%	4.1%	6.8%	17.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	20.3%	24.3%	0.0%	0.0%	100.0%
2008	4.3%	32.6%	4.3%	0.0%	3.3%	3.3%	8.7%	0.0%	1.1%	0.0%	0.0%	0.0%	0.0%	14.1%	28.3%	0.0%	0.0%	100.0%
2009	5.1%	0.7%	10.2%	0.0%	9.5%	6.6%	16.1%	0.0%	0.7%	0.0%	0.0%	0.0%	0.0%	24.8%	26.3%	0.0%	0.0%	100.0%
2010	1.1%	5.5%	15.4%	0.0%	11.5%	4.4%	24.2%	0.0%	4.4%	0.0%	0.0%	0.0%	0.0%	13.2%	15.4%	4.9%	0.0%	100.0%
2011	9.1%	17.8%	4.1%	0.0%	3.0%	1.5%	16.8%	1.5%	0.0%	2.5%	1.5%	2.5%	5.6%	6.6%	21.8%	0.0%	5.6%	100.0%
2012	14.4%	0.5%	12.6%	0.0%	6.0%	0.9%	21.9%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	32.6%	11.2%	0.0%	0.0%	100.0%
2013	10.0%	0.4%	14.5%	0.0%	9.2%	5.6%	19.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	31.7%	8.8%	0.4%	0.0%	100.0%
2014	15.1%	0.4%	27.2%	0.0%	3.2%	0.4%	6.8%	0.0%	0.4%	10.4%	0.7%	0.0%	0.7%	7.9%	12.2%	1.4%	13.3%	100.0%
2015	3.2%	43.7%	0.0%	1.5%	7.7%	0.0%	0.0%	0.0%	0.0%	1.8%	5.6%	0.0%	5.0%	5.0%	21.2%	0.0%	5.3%	100.0%
2016	5.1%	0.2%	22.7%	0.0%	11.1%	2.7%	15.7%	0.0%	0.0%	0.7%	0.0%	0.0%	1.9%	17.8%	17.1%	0.0%	5.1%	100.0%
2017	7.6%	22.3%	0.0%	0.2%	36.3%	0.0%	0.0%	0.0%	0.0%	1.1%	0.4%	0.0%	9.4%	0.2%	16.7%	0.0%	5.8%	100.0%
2018	9.5%	36.6%	0.0%	0.8%	9.3%	0.0%	0.0%	0.0%	0.0%	0.2%	3.3%	0.0%	4.8%	17.0%	13.3%	0.0%	5.2%	100.0%
Total	7.8%	16.3%	9.7%	0.3%	11.9%	1.8%	9.6%	0.1%	0.4%	1.6%	1.4%	0.2%	3.3%	14.3%	16.5%	0.5%	4.4%	100.0%

The Seasonal analysis type and combined Seasonal types all indicate a decrease in fuzzy contribution. Interestingly, the most assigned Seasonal type is the Seasonal & Mixed type - so even though the summer peak dominates, the Christmas peak period also has a contribution. As the assignment of the Seasonal and Mixed types reduces after 2013, there is a corresponding increase in the assignment of the combined Mixed analysis type. This is suggestive of the summer period becoming less territorialised and/or, the Christmas period becoming more territorialised, or, at least, because of a summer period reduction, Christmas becomes more prominent even if the actual Christmas footfall numbers do not change from one year to the next. There is also a switching between the Mixed and Mixed & Seasonal types; when the Seasonal signature type is not represented, the Mixed type dominates, again, suggestive of a reduction in the Seasonal component of the annual signatures. This implies that places where there is a Summer (holiday) season and Christmas peak, that both periods of territorialisation intensity can alternate in their relative importance to each other over time. The dominance of the Mixed & MF-Xmas annual type in 2017 where MF-Xmas rather than Seasonal is the most significant secondary type, perhaps reinforces this idea.

Table 5.16 also suggests that the idea that places can be represented by individual signature types is questionable. Despite the simplifications of the categorisation scheme used for the descriptive analysis, Table 5.16 shows by using fuzzy cluster analysis, places can be viewed as blends and combinations of signatures. The changes between the years also suggest that these combinations change from year to year, in particular, the relative dominance of the summer vs Christmas periods.

To validate that switching does occur between peak footfall periods at Christmas versus Summer, the footfall data was aggregated into weekly summed footfall totals (imputed values) and the week within each year where the maximum weekly sum took place, was flagged. This information is provided in Appendix C: Table 13.3 p431 and visualised in Figure 5.14 which not only draws attention to the fact there are more footfall sensors as time progresses, but also shows a very distinct concentration at Christmas time. From 2012 onwards, other contour bands become apparent that cover the periods of Easter, Spring holidays, summer holidays, Autumn holidays and at week 43, Halloween. Note the peaks in Summer are spread over several weeks unlike Christmas, but nevertheless the peaks are evident. Figure 5.14 supports the cluster analyses that distinguish between Christmas and the Summer periods but provide no clue as to how interchangeable they might be. The result also suggests that analysing the residual values should also provide very interesting results and possibly account for the peaks outside of the Summer and Christmas periods.

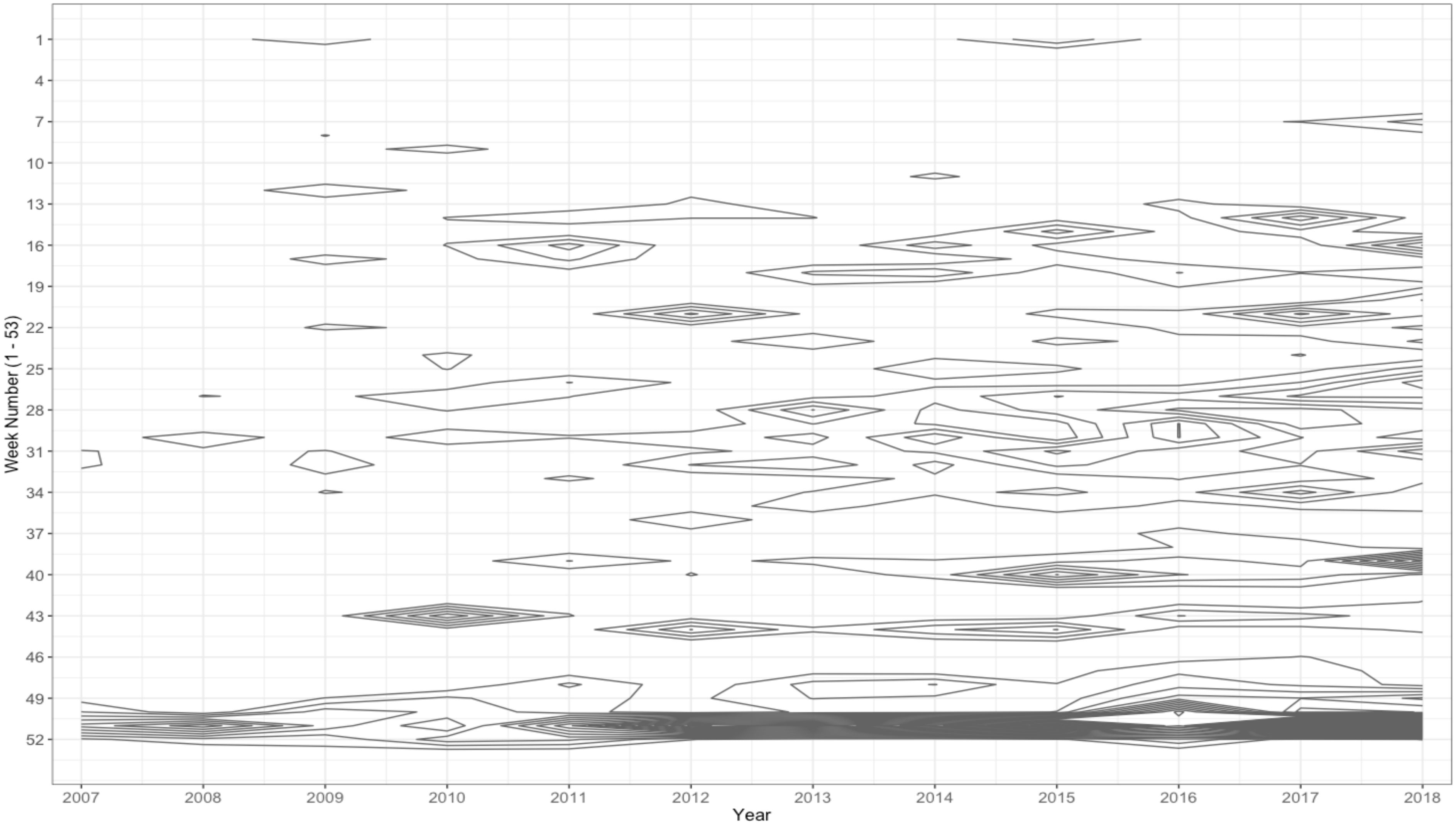


Figure 5.14. Contour plot of peak footfall weeks by year

To analyse the interchangeability between the Summer and Christmas periods, the approach taken was to compare the actual footfall over the periods of the summer school holidays (approximately weeks 29 to 36) to that of Christmas (weeks 48 to 53). Table 5.17 provides a sample of the data used to calculate the resulting comparison ratio, the intention of choosing the length of both periods being to prevent a single week skewing the results too much.

Since the number of weeks for the two periods were not equal, the initial ratio was corrected to account for this. However, the Christmas period for some years included week 53 so the correction factor also needed to account for this. In Table 5.17, the Correction Factor used distinguishes between those years with 5- or 6-weeks data used for the Christmas period and takes the value of 1.6 (5 weeks) or 1.33 (6 weeks). The corrected ratio of the summer total vs Christmas total could then be calculated for each year where ratio values equal or below 1.0, identified sensor locations where the Christmas footfall volumes was greater than that of summer period.

Table 5.17. Example data used to calculate the summer vs Christmas peak ratio

Year	Peak Footfall Week	Christmas Period Summed Footfall	Summer Holidays Summed Footfall	Ratio (Summer / Xmas)	Ratio Corrected	Corr Factor
2006	49	482438.69	493070.00	1.02	0.64	1.60
2007	51	471471.00	525156.00	1.11	0.70	1.60
2008	51	453473.00	512447.00	1.13	0.71	1.60
2009	50	553809.00	489226.00	0.88	0.66	1.33
2010	49	528248.00	537781.00	1.02	0.64	1.60
2011	49	411782.00	398540.31	0.97	0.60	1.60
2012	51	458967.00	453779.00	0.99	0.62	1.60
2013	51	454436.51	435537.00	0.96	0.60	1.60
2014	51	434886.34	530351.00	1.22	0.76	1.60
2015	51	452764.00	486000.00	1.07	0.81	1.33
2016	50	373954.58	474798.89	1.27	0.79	1.60
2017	51	219181.15	273768.58	1.25	0.78	1.60

To track changes over time, the ratio results were processed for individual sensor locations from 2007 to 2018, but only for those sensors that became operational from 2007 to the end of 2009. Table 5.18 presents results for the sensor subset and summarises how the Christmas peak versus Summer peak ratios change. Table 5.18 shows that the annual characteristic of footfall at the assessed locations is dynamic, with 72 instances where the Christmas vs summer peak periods are interchangeable - these are not fixed annual signature types but change from year to year. Apart from sensor locations designated as Towns (due to a very small sample size), the other urban classification types indicate a tendency to change rather than persist as one type. In other words, the fuzzy cluster outputs are correct to suggest that places are a blend of signatures and that these change over time.

Table 5.18. Table showing the consistency of summer vs Christmas Peak Footfall

Urban Classification	Mixture - no consistency	Consistent Summer Peak	Consistent Christmas Peak	Total
Major City	37	5	15	57
Regional Centre	9	2	8	19
Sub-Regional Centre	18	7	6	31
Major Town	7	3	1	11
Town	1	2	2	5
Total	72	19	32	123

5.6 Summary

The initial objective of determining whether similar annual footfall rhythms (signatures) could be identified by the fuzzy cluster analysis, to those identified by Mumford et al. (2021) and Monheim (1998) was achieved. For the initial three medoids identified for 2007 in Figure 5.3, Monheim (1998) provides evidence of a signature that resembles the first medoid, with a relatively constant footfall pattern throughout the year plus a peak in volume in the Christmas period. This same signature is also found by Mumford et al. (2021) using the same data source but using monthly averaged footfall volumes and k-means clustering. In fact, medoid 2 for 2007 matches both the seasonal and speciality signature identified by Mumford et al. (2021), and medoid 3 matches the speciality signature. That similar signatures are identified in the data was viewed as validation of the fuzzy cluster and data preparation techniques.

The annual medoid analysis types identified are summarised in Table 5.13, p194. By looking at the relative allocations of the chosen medoids to locations where both seasonal and Christmas territorialisation occurs, the results for the annual signatures suggest that these places can be quite dynamic with switching between years where the Christmas period or summer holiday period is where peak footfall for the year occurs. At the same time, the fuzzy assignments can also help identify those locations where the signature allocation is stable and consistent, such as the 15 locations in Table 5.18 that are assigned as locations dominated by the Christmas period. This suggests then that at least for the annual signatures, using fuzzy clusters is advantageous.

The approach taken resulted in a fuzzy cluster analysis being performed for each year. Thus, for each year, different medoids were assigned to represent the data. For this reason, the descriptive analysis approach was adopted but the optimal approach would have been to generate the clusters from the 2007 footfall data and then monitor how these clusters evolved year on year. This was attempted using the R packages, but the results were confusing. It was not possible to distinguish whether changes were a result of actual change from year to year or simply a change in the representation of the sample population as the number of sensors increased. Additionally, no proven method to compare periods such as Easter year on year was identified. Hence a simpler, less deterministic approach was followed but one that allowed the annual clusters to be discovered each year so that as new rhythms emerged, these became apparent. This approach helped identify the Term-time pattern, not identified by Mumford et al. (2021) (a consequence of using hourly data smoothed to a weekly resolution) and was distinguished by a period of de-territorialisation during term-time holidays, particularly the Summer UK holidays.

6 Results - Combined Daily Rhythms

Having analysed the combined annual signatures, the next STL component investigated was the combined sensors' daily component signatures. This is identified below in Equation 6.1 and had the largest root mean square (mean and variability) contribution of all the seasonal components extracted using the STL function (see Figure 4.12 p149). Note that the daily signatures extracted using the STL algorithm provide a daily signature 'meaned' over a 7-day running period. Therefore, the daily signatures discussed below do not represent the differences between individual days of the week. The adjustments needed to account for individual days of the week are discussed in the Weekly Results Analysis in Chapter 9.

$$Y_v = T_v + S_{annual} + S_{weekly} + \boxed{S_{daily}} + R_{v'}$$

Equation 6.1 - STL Equation and Daily Signature Additive Component

As with the annual signature component, the focus of the analysis was to provide answers to the first research question:

> *"As a performance measure, what insights can footfall offer to identify how collectively, places change over time?"*

The next section details the data inputs and how the fuzzy cluster analysis was performed.

6.1 Data Inputs and Fuzzy Cluster Analysis Processing

For the data input into the fuzzy cluster analysis (summarised in Table 6.1), the daily signature component was extracted from the database for each footfall sensor and every 24-hour period within the chosen year of analysis. To enable analysis by individual weeks of the year, the yearly period started at the beginning of week 1 through to the end of week 52 or, if applicable, week 53. Hence, week 1 and week 52/53 could also include daily signature values from the previous or following years. Each daily record was labelled using the location identifier and the date (year, month, week number and day) from the database to enable identification when processing the results. During the subsequent year-based daily fuzzy cluster analysis, the whole extracted period of individual daily records for each footfall sensor was compared to every other sensor and day.

Table 6.1. Daily Fuzzy Cluster Analysis Data Inputs

Data Input Characteristics	Details
Input Data Source	STL derived daily signatures
Period of data extraction and analysis (by year)	Individual days, from Week 1 to Week 52 (53 where applicable)
Number values per data record	24
Standardisation of data record?	Yes
Additional smoothing applied?	No
Sampling required?	Yes

The parameterisations required for the daily signature clustering analysis using the R dtwclust package (Sardá-Espinosa, 2019) are provided in Appendix A: Section Data Mining12.9 Data Mining. Unlike the annual signatures, no extra smoothing was applied. Each individual footfall sensor daily component hourly values were standardised using the R Scale Function (R Core Team, 2019) to remove differences of scale between locations and thus allowing the fuzzy analysis algorithms to focus on the shape of the daily footfall component rather than differences in magnitude of pedestrian numbers – see Chapter 4 p156.

As a result of memory constraints (the fuzzy clustering algorithms required more computer memory than was physically available), the total number of daily signatures available for all the sensors stored in the database for each year had to be reduced to a sample size of 21,000 randomly selected instances. This was done using the R function Sample (R Core Team, 2019), configured to prevent the same data record being selected more than once. Table 6.2 provides details of the total numbers of sensor daily records stored in the database vs the sample size used for each year of the fuzzy cluster analysis.

Table 6.2. Available daily footfall signatures vs sample size used

Year	Available Daily Signatures (Number Sensors * Days in year)	Sample Size
2006	23139	21000
2007	31132	21000
2008	41334	21000
2009	63540	21000
2010	71280	21000
2011	78567	21000
2012	88350	21000
2013	97263	21000
2014	114683	21000
2015	145487	21000
2016	164753	21000
2017	183201	21000
2018	200995	21000

As Table 6.2 shows, all years needed to be sampled. Using R package pwr (Champely, 2020) which is based upon the work of Cohen (1988), power sample tests using a Two-sample t-test power calculation suggested a minimum individual group size of 393.4057 was required. From the fuzzy cluster results, all individual clusters had more than this number. As a guide, this at least reassured that the sample size could produce statistically valid results:

```
> pwr.t.test(d = 0.2, power = 0.8, sig.level = 0.05)

     Two-sample t test power calculation

              n = 393.4057

              d = 0.2

      sig.level = 0.05

          power = 0.8

    alternative = two.sided

NOTE: n is number in *each* group
```

The test used is provided above with the power, significance level and effect size provided. The most problematic value to set was the effect size (Kabacoff, 2015:249), so a value suggested by Cohen (1988) was chosen that favoured the calculation of a larger sample size.

6.2 Selecting the Number of Medoids

After performing the cluster analysis for each year, the first step was to check the cluster validation indices, to identify the best fitting number of medoids (see Table 6.3). The process followed is provided in Chapter 4 p160 and for all the CVI, Radviz and Boxplot output used, see Appendix C - 14.1 Fuzzy Cluster Outputs

Table 6.3. The number of daily medoids selected for each year

Year	Number of Medoids	Number of Sensors
2006	4	64
2007	4	74
2008	7	92
2009	6	140
2010	8	185
2011	6	201
2012	6	219
2013	4	253
2014	6	283
2015	6	346
2016	8	425
2017	5	459
2018	7	483

6.3 Assessing the Fuzzy Results and Medoids

The process of analysis began using the same year-by-year descriptive procedures used for the annual rhythm results. The steps taken include:

- A descriptive assessment of the medoids identified for each year
- An analysis of how territorialisation intensity changes over time
- An assessment of fuzzy membership changes over time

6.3.1 Daily Results for 2006

Figure 6.1 displays the four medoids assigned for the 2006 daily signatures. For the daily results, the horizontal access shows the period from 23:30 (the previous day) to 22:30. This is because the results, for example those for midnight, cover the period 23:00 to 00:00. Hence the data points are labelled using the mid-point periods for all the subsequent graphs of daily results.

Whereas for the annual results where a full year of data was not available for any of the sensors using the 2006 data, there were sufficient daily signatures for results to be generated. Medoid 3 has a peak period of territorialisation late morning, medoid 1 has a peak at lunchtime, medoid 2 has an elongated peak from lunchtime to ‘home-time’.

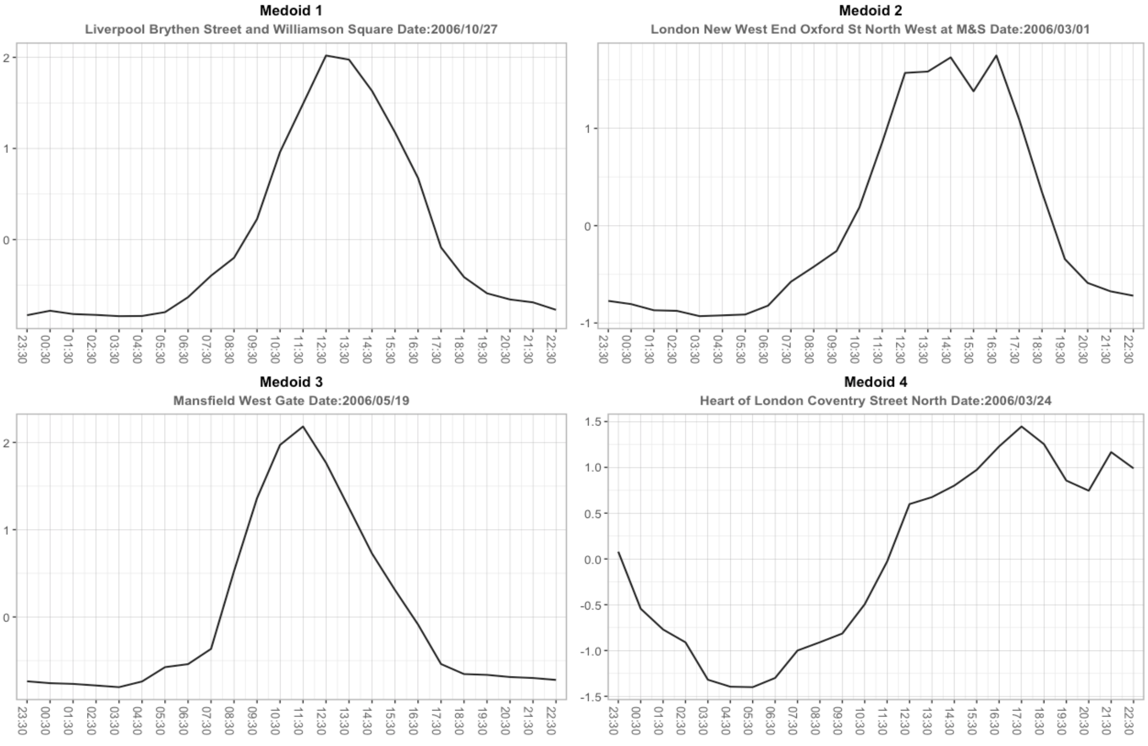


Figure 6.1. Medoids for 2006 Daily Fuzzy Analysis

Whilst medoid 4 has a similar lunchtime peak to medoid 2, footfall then continues to rise until the end of the 18:00 period. Unlike all the other medoids, there is not a rapid fall in footfall but a steady decrease until the early hours of the morning. Medoid 4 therefore suggests it is a location where lunchtime activity is important, but it is a key location for evening and night-time footfall.

Returning to medoid 3, the signature evidences an early morning increase in territorialisation (perhaps explained by workers and commuters) from 05:00 to 08:00. After 08:00, there is a rapid rise to the peak between 11:00 and 12:00 followed by a steadier decline up to about 18:00. Medoid 1, like medoid 3, has an early morning increase in footfall but in this case, it appears to be greater in amount, rising to a peak traffic volume between 12:00 to 14:00. There then follows a less abrupt de-territorialisation and slightly higher volumes into the evening, but still significantly less than during the day. Medoid 2 follows the same pattern as medoid 1 but sustains the peak territorialisation until early evening after which volumes fall rapidly away. Medoid 4, as already described, has a mini lunchtime peak, but footfall keeps rising afterwards and there is significant evening and night-time territorialisation, unlike all the other 3 medoids.

To categorise the medoids based upon their shapes, the following descriptions were assigned:

- Medoid 1 - morning commute, 2-hour lunchtime peak (12:00 - 14:00)
- Medoid 2 - morning commute, lunchtime extends to late afternoon peak plus early evening
- Medoid 3 - morning commute, late morning peak
- Medoid 4 - morning commute, lunchtime, late afternoon peak, evening, and night-time

To visualise how the individual daily signatures, relate to each of the chosen medoids, a Radviz diagram is used to plot the individual daily signature fuzzy allocations in relation to the exemplar medoids. The Radviz plot in Figure 6.2 suggests that Medoid 4 (labelled cluster_4) is the least related to the other three medoids and that medoid 1 has an association with both medoids 2 and 3. This is confirmed in Table 6.4 which displays the aggregated percentage of fuzzy assignments for the best fitting medoid versus the next-best fitting medoid for each sensor. Medoid 1 is evenly distributed between medoids 2 and 3 whilst Medoid 2 has the most certain assignment of membership with almost half of membership assignment being greater than 90% for medoid 2. Note, the next-best fitting medoids where the best fitting medoid accounts for 90% or more of the assigned contribution, are listed in the column <10% and no next-best fitting medoid is accounted for. Table 6.4 shows that almost 70% of sensors have medoids 1 or 2 assigned as their best fitting assigned daily signature.

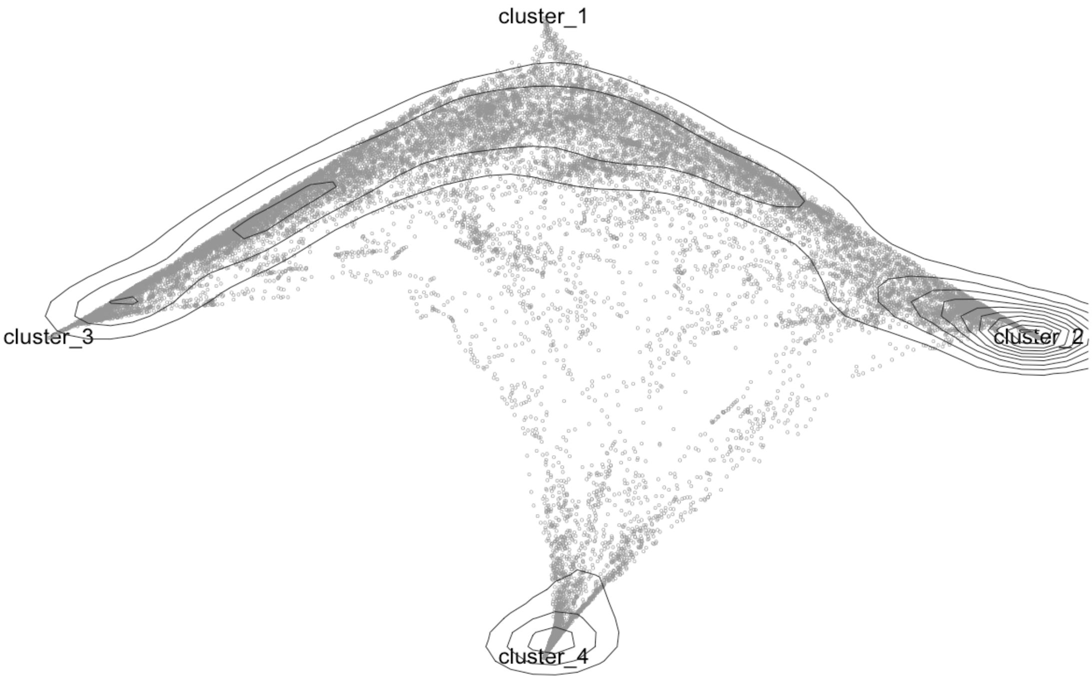


Figure 6.2. Radviz plot for 2006 Daily Fuzzy Analysis

Table 6.4. Best and next best fitting medoid allocations for all 2006 daily records

	Next Best Fitting Medoid					
Best Fitting Medoid	1	2	3	4	<10%	Total
1	0.00%	17.41%	17.48%	0.05%	0.36%	35.30%
2	16.88%	0.00%	0.00%	0.82%	15.93%	33.63%
3	17.32%	0.00%	0.00%	0.07%	2.15%	19.53%
4	0.08%	5.31%	0.29%	0.00%	5.85%	11.54%
Total	34.28%	22.72%	17.77%	0.94%	24.30%	100.00%

Table 6.5 provides a view of how the best fitting medoid assignments relate to urban classification types (see Appendix A: Section 12.3 Data Sources for place classifications). Table 6.5 identifies that medoid 3, the later morning peak daily signature, is the only signature assigned to towns - although note the sample size of towns is 1. Despite the sampling size, there still is a visible change from town to

major city with medoids 1 and 3 being more significant for the smaller places and medoids 2 and 4 being more significant for the major cities.

Table 6.5. Urban classification and medoid assignment for 2006 daily medoids

Best Fitting Medoid	Major City	Regional Centre	Sub-Regional Centre	Major Town	Town	Total
1	27.89%	68.35%	51.55%	36.92%	0.00%	35.30%
2	51.21%	17.98%	3.83%	0.00%	0.00%	33.63%
3	2.69%	13.67%	43.26%	63.08%	100.00%	19.53%
4	18.21%	0.00%	1.35%	0.00%	0.00%	11.54%
Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

6.3.2 Daily Results for 2007 – 2013

Below is a summary of the daily results for the period 2007 to 2013. For the full descriptive analysis for each year see Appendix C: Section 13.2 Fuzzy Cluster Descriptive Analyses. As Appendix C shows, the patterns uncovered repeated themselves over the period of investigation.

The most noticeable feature apparent from 2006 onwards of the daily signatures was that as place size (complexity) increases, so did the tendency for there to be afternoon, evening, and night-time intensities of territorialisation. By 2009, a distinct pattern of towns and major towns being dominated by a midday or late morning daily medoid signatures was evident. Major cities had a larger range of signatures and included signatures where afternoon, evening and night-time footfall existed. Regional and Sub-Regional centres mostly had lunchtime focused signatures but also appeared to have more afternoon, evening, and night-time footfall. By 2010, a daily signature became more apparent picking out morning and evening commuter periods plus a lunchtime peak – this was not only limited to major cities but was most prominent in such locations.

6.3.3 Daily Results for 2014

Figure 6.3 displays the exemplar location medoids derived from the 2014 daily signatures.

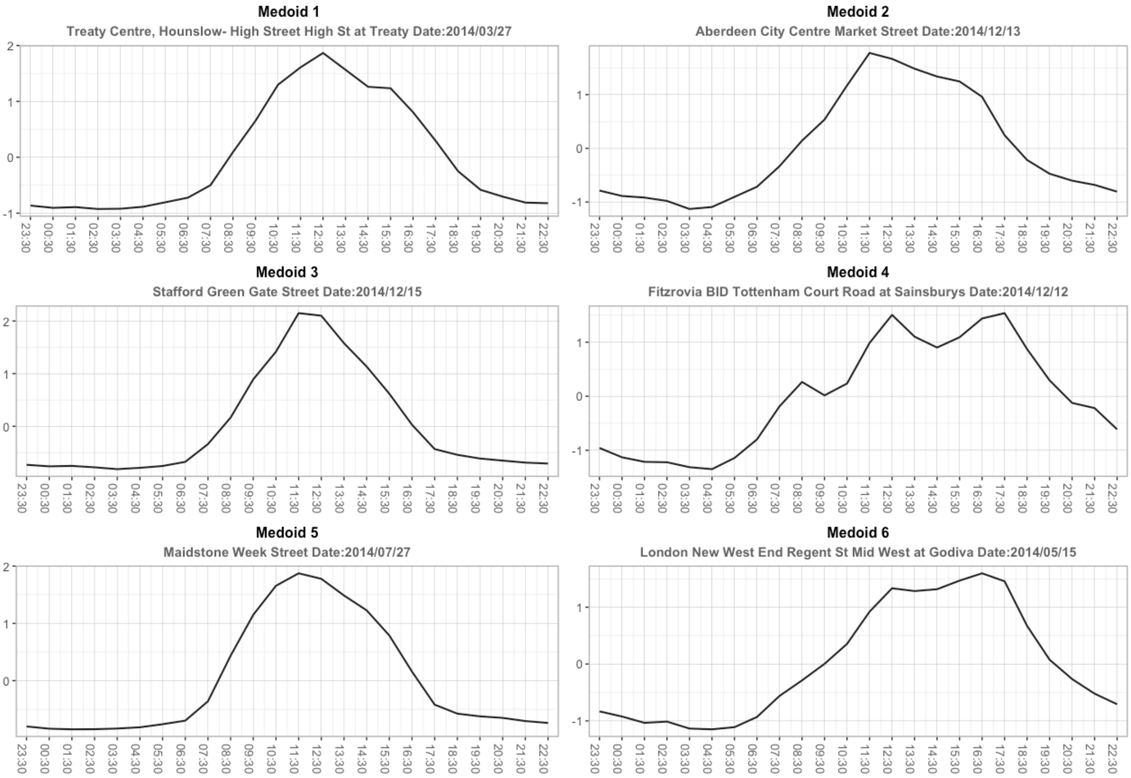


Figure 6.3. Medoids for 2014 Daily Fuzzy Analysis

Figure 6.3 shows the six medoids allocated for 2014 daily signatures. Following the same process of descriptive analysis for the previous years, the medoids have been categorised below:

- Medoid 1 - lunchtime peak extending into the afternoon and early evening
- Medoid 2 - late-morning peak and extended afternoon and evening
- Medoid 3 - late-morning peak and lunchtime
- Medoid 4 - morning, lunchtime and late afternoon peak, evening plus minor night-time
- Medoid 5 - late-morning peak and lunchtime with slightly extended afternoon
- Medoid 6 - lunchtime and late afternoon peak, evening plus minor night-time

Table 6.6 continues to show the continuing trend of towns and major towns having footfall focused on lunchtime, or the hour before, with perhaps some afternoon traffic, whereas major cities have much more footfall traffic continuing into the afternoon, evening, and night-time. The range of the midday peak periods in medoids 1,3,5 is also greater than those of the more distributed footfall signatures associated with major cities. Medoids 1,3 and 5 also suggest that for smaller locations such as towns, the morning growth in footfall begins later than for the cities. This implies that the territorialisation of space for a city is spread over a longer period whereas it is more concentrated in smaller locations.

The Major City vs Town/Major Town distinction is much clearer than between Regional and Sub-Regional centres. Regional centres suggest that they have a lunchtime focus, yet footfall is extended out to the afternoon and to a lesser degree the evening. The two signatures, 4 and 6 with some degree of night-time footfall are the least associated signatures with these place types.

Table 6.6. Urban classification and medoid assignment for 2014 daily medoids

Best Fitting Medoid	Major City	Regional Centre	Sub-Regional Centre	Major Town	Town	Total
1	14.61%	23.18%	13.52%	12.36%	19.11%	15.89%
2	23.69%	25.30%	20.41%	11.16%	7.46%	20.76%
3	9.43%	15.84%	23.32%	32.66%	21.20%	17.75%
4	19.50%	14.02%	9.31%	1.77%	0.00%	12.42%
5	6.89%	17.90%	20.23%	41.68%	52.16%	19.13%
6	25.88%	3.77%	13.21%	0.38%	0.07%	14.05%
Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

6.3.4 Daily Results for 2015-2017

The results for 2015 to 2017 present no new significant findings apart from the fact that the medoid signatures and allocations remain very much in agreement with the previous years (see Appendix C: Section 14.2 Fuzzy Cluster Descriptive Analyses).

6.3.5 Daily Results for 2018

Figure 6.4 displays the medoids identified from the 2018 daily signatures. Medoids 3, 6 and 7 are dominated by the lunchtime period of intensification with subtle changes between them. Medoid 6 (the dominant medoid for towns and major towns) has a peak intensification between 11am and noon. Medoids 3 and 6 have a lunchtime intensity between noon and 1pm with medoid 7 also indicating a slower de-territorialisation period in the afternoon than medoids 3 and 6. In fact Medoid 7 (present for all the urban classifications) and the subsequent medoids all include different degrees of intensifications of territorializations in the afternoon, evenings, and night-time.

Following the same process of descriptive analysis for the previous years, the medoids have been categorised below:

- Medoid 1 - early lunchtime and lunchtime peak plus extended afternoon
- Medoid 2 - morning, lunchtime, and late afternoon peak plus night-time
- Medoid 3 – lunchtime peak with slight extension into afternoon
- Medoid 4 - lunchtime peak with extension into afternoon and evening
- Medoid 5 - lunchtime and late afternoon peak plus minor night-time
- Medoid 6 – early lunchtime peak with extension into afternoon
- Medoid 7 - lunchtime peak with extension into afternoon

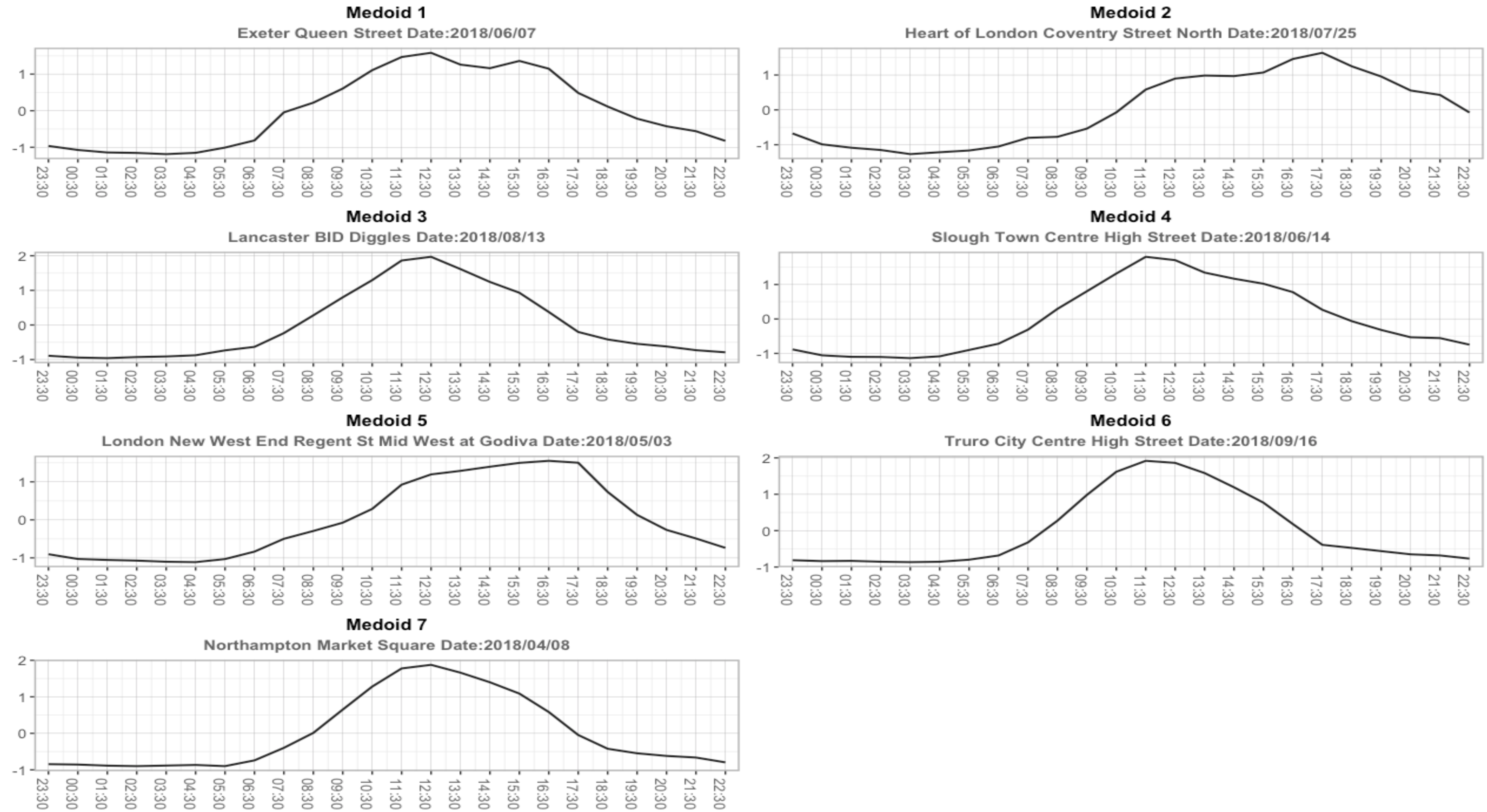


Figure 6.4. Medoids for 2018 Daily Fuzzy Analysis

Table 6.7. Urban classification and medoid assignment for 2018 daily medoids

Best Fitting Medoid	Major City	Regional Centre	Sub-Regional Centre	Major Town	Town	Total
1	6.36%	4.47%	2.85%	0.26%	0.94%	3.24%
2	3.99%	2.11%	0.58%	0.02%	0.96%	1.48%
3	5.92%	11.09%	9.52%	6.90%	8.59%	8.70%
4	11.09%	16.32%	11.68%	9.71%	6.50%	11.56%
5	34.61%	7.70%	10.86%	0.63%	0.65%	12.07%
6	11.03%	25.47%	30.21%	50.67%	48.98%	30.72%
7	27.00%	32.83%	34.31%	31.81%	33.37%	32.23%
Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

Table 6.7 supports the finding that the lunchtime signature exists across all urban classification types but as size and complexity of place increases, so does the intensity of territorialisation into the afternoon, evening, and night-time periods.

Table 6.8 below identifies the relationship between the best and next best fitting assigned medoids. A similar relationship exists between medoids 1 (Major Cities and Regional Centres), 4 (Major Cities, Regional and Sub-Regional Centres) and 5 (Major Cities predominantly). Medoid 2 (Major Cities and Regional centres) is the least likely to be assigned and is most closely associated with medoid 5. Medoids 3,6 and 7 all indicate a relationship between each other. The medoids form three distinct groupings. Medoids 3,6 and 7 represent locations where the lunchtime peak in footfall is the key pattern. Medoids 1 and 4 modify the lunchtime peak signatures and include an afternoon peak period. Signatures 2 and 5 are those where the afternoon and evening peaks are most developed.

Table 6.8. Best and next best fitting medoid allocations for 2018

	Second Best Fitting Medoid							
Best Fitting Medoid	1	2	3	4	5	6	7	>90%	Total
1	0.00%	0.01%	0.28%	8.90%	5.09%	0.00%	0.51%	0.00%	14.80%
2	0.12%	0.00%	0.00%	0.01%	2.76%	0.00%	0.00%	0.48%	3.38%
3	0.15%	0.00%	0.00%	1.69%	0.00%	5.48%	5.91%	0.00%	13.23%
4	7.27%	0.00%	2.93%	0.00%	0.06%	0.71%	2.20%	0.00%	13.19%
5	8.04%	2.12%	0.00%	0.18%	0.00%	0.00%	0.56%	0.12%	11.02%
6	0.00%	0.00%	14.01%	0.53%	0.00%	0.00%	8.79%	0.04%	23.36%
7	0.70%	0.00%	11.01%	1.85%	0.38%	7.06%	0.00%	0.00%	21.01%
Total	16.28%	2.13%	28.23%	13.17%	8.30%	13.25%	17.97%	0.66%	100.00%

6.3.6 Summary of Daily Rhythm Types

To summarise the results so far, the daily signatures identified from the descriptive analysis show a close relationship between the urban classification type and assigned medoid signatures. For Town and Major Town locations in the urban hierarchy, the late morning and lunchtime period is identified as the most important period of territorialisation. As places increase in size and complexity (as places of work, retail, entertainment, and other services), so does the tendency for the periods of territorialisation to extend into the afternoons and evenings. The daily rhythm types are summarised in Table 6.9.

Table 6.9. Daily Rhythm Types

Daily Rhythm Type	Description
Morning Commute	The initial rise and sometimes visible peak in morning footfall.
Early morning visitors	Following the initial commute period, there occurs a period of early visitor activity, sometimes reaching a peak for the day in some towns
Lunchtime Visitors	The lunchtime period is a key daily rhythm and often the peak period of daily footfall.
Afternoon visitors	Depending upon place size and complexity, afternoon visitors can extend the footfall count beyond the lunchtime maximum
Evening Commute	Period of people leaving work and for some places an inflection point for footfall to fall rapidly.
Evening visitors	For some places, can be greater than lunchtime peaks but only for the Major City locations.
Night-time visitors	Can extend into the early hours of the morning for specific City locations.

6.4 Changes to Daily Territorialisation Intensities

The above descriptive analyses identified that for different urban location types, the daily signatures show that as place size and diversity increases, so the tendency for footfall to extend into the afternoon, evening and night-time also increases. This suggests that for the different urban classification types, there should be evidence that the periods of hourly territorialisation differ between the classification types. From the descriptive analyses, there is also the suggestion that the daily signatures persist from year to year, so analysing the changes over the years is also of interest.

In the following sections, using the imputed footfall data, a series of plots displays the annual mean and variance of hourly changes in footfall counts (change in territorialisation intensity). The daily hourly differences for every available sensor are aggregated over each day to provide annual mean and variance hourly values. The results are also segmented using the urban classification type assigned to each place. The hourly change in territorialisation is defined in Equation 6.2 below:

$$\Delta Territorialisation = Count_{hour(n)} - Count_{hour(n-1)}$$

Equation 6.2. Change in Territorialisation of Hourly Footfall Counts

Thus, for any period where there is a positive difference, this represents a period of territorialisation, in other words, increasing footfall. Conversely, where the difference is negative, this identifies a period of de-territorialisation. The greater the hourly difference in footfall count corresponds to a greater degree of intensity of either territorialisation or de-territorialisation. By using the imputed footfall data, differences between days of the week also are identifiable.

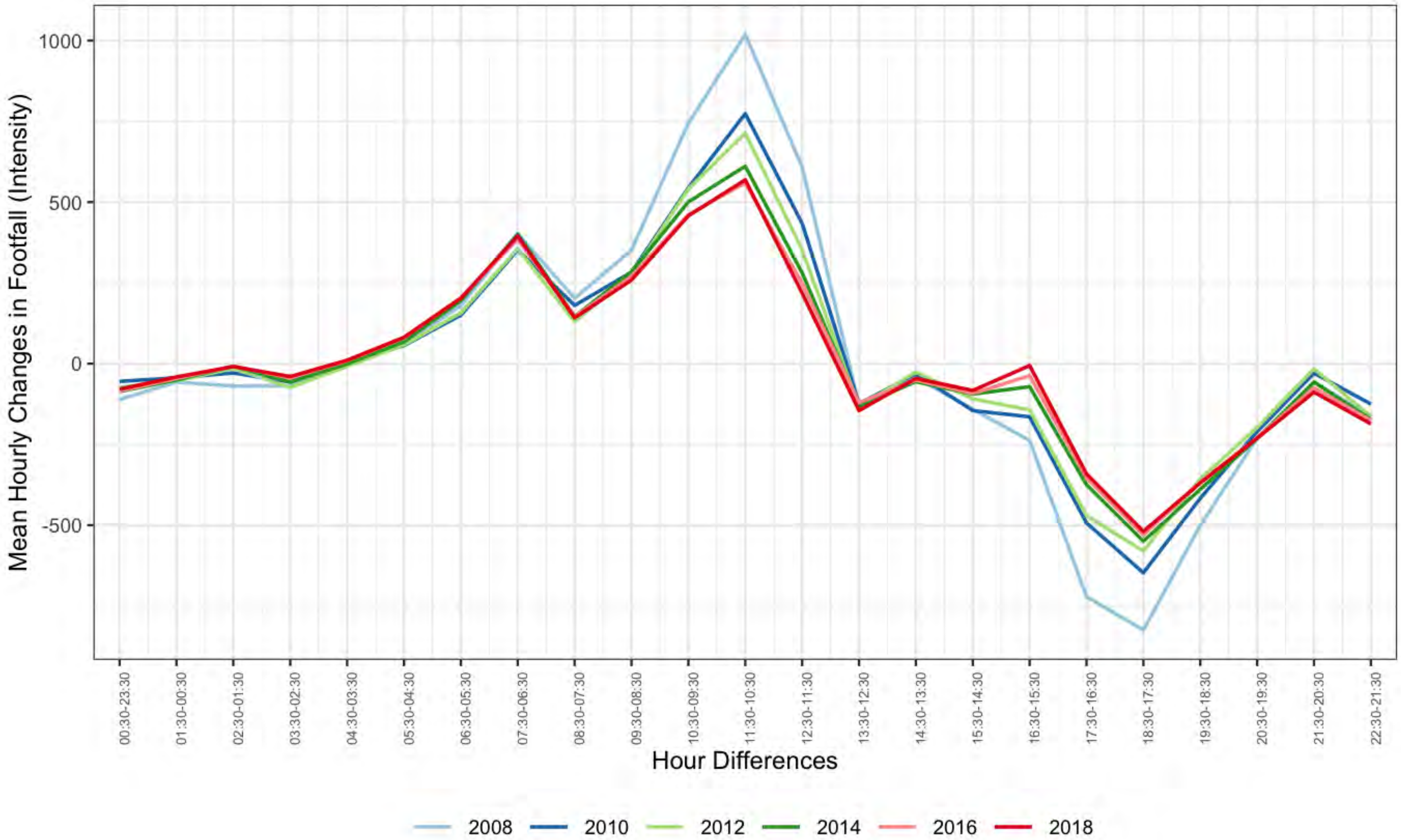


Figure 6.5. Annual hourly mean territorialisation differences 2008 to 2018 for Major City locations

6.4.1 Major City Territorialisation Changes

Figure 6.5 plots the hourly differences meaned over each year for the period 2008 to 2018 for places identified as Major Cities using the Planning Classification Scheme (see Appendix A p384). The hour difference labels identify the mid-point of each hour of footfall, hence the hourly difference for the period 00:30-23:30 subtracts footfall summed over the period 23:00 to 00:00 from that summed over 00:00 to 01:00. In terms of periods of peak territorialisation (intensity of footfall change), the 07:00 to 08:00 period identifies the increase in footfall that marks the morning commute period. An interesting observation from Figure 6.5 is how consistent this morning peak remains over the whole of the study period.

The process of territorialisation continues with the next peak period being 11:00 - 12:00 and then reducing intensity until 13:00-14:00. The peak period remains constant over the years but does reduce in intensity over the years assessed, indicative of reducing footfall during the morning and lunchtime periods.

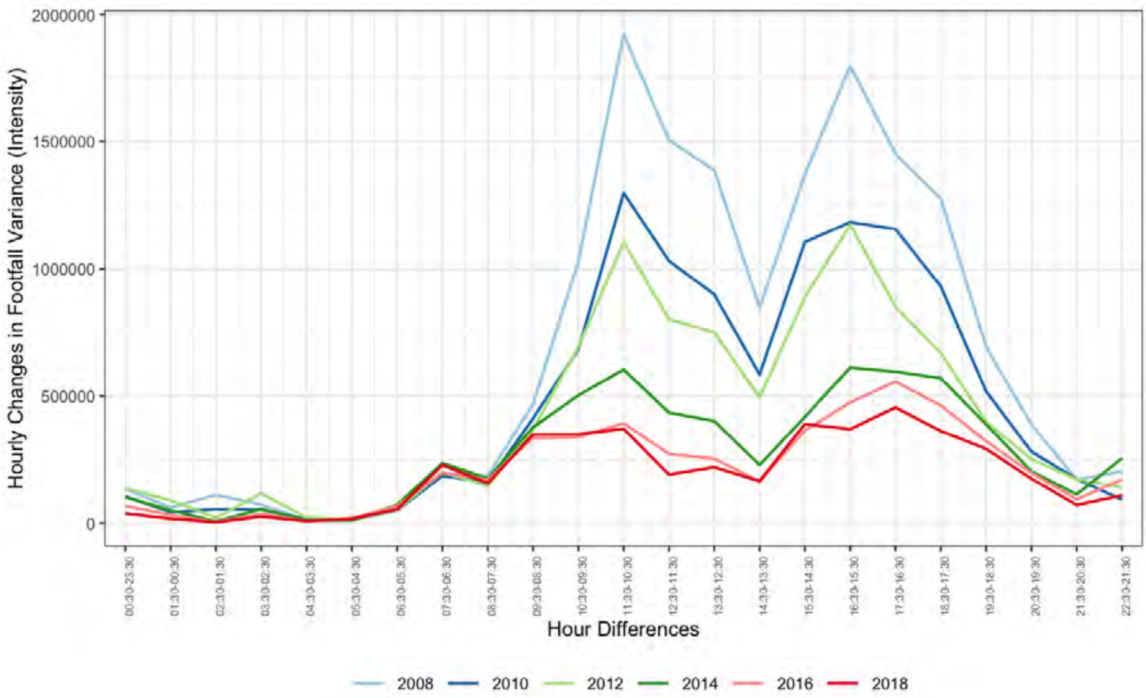


Figure 6.6. Annual Hourly Variance of the Differences for Major City Locations

At 16:00-17:00, de-territorialisation intensity increases rapidly, marking the start of the evening commute and reaches maximum intensity between 18:00-19:00. After this period, de-territorialisation continues but with reducing intensity. Looking at key inflection points of territorialisation/de-territorialisation intensity, the pattern over the years appears not to change, though the magnitude of the intensities of (de)territorialisation do reduce over the study period. This suggests that the daily signatures identified for the major cities are relatively stable. As noted, the initial morning commute period shows the least differences over time. This is supported by Figure 6.6, a plot of the variances between the hourly footfall counts, which shows very little difference in the variances over time up to 08:00-09:00.

Only after the period of the morning commute do the variances show any marked differences over the years and even then, the differences follow the same pattern for each year. Most variation occurs at the periods of peak territorialisation before lunchtime and the start of the evening commute period at 16:00-17:00. This reflects the finding that for some major city locations, the intensity of territorialisation increases during the afternoon into the evening rather than being a period of de-territorialisation. It is also apparent that over the years displayed, the variance for the major city locations reduces, a result of the reducing footfall counts as shown in Figure 5.2.

6.4.2 Town and Major Town Territorialisation Changes

For places classified as Towns (Figure 6.7) and Major Towns (Figure 6.8), there are immediate differences compared to the Major City locations that can be identified. Firstly, there is no distinct morning commuter peak period. However, the peak territorialisation period is in the morning before lunchtime, occurring between the periods covering 08:00-10:00. Although territorialisation continues after this period, the intensity continues to reduce until 12:00-13:00 (depending on year). This accounts for the late morning peaks evident in the footfall daily medoid signatures (for example, see Medoid 4, Figure 6.3). Secondly, the period of de-territorialisation begins far sooner than the Major Cities, from 12:00-13:00 instead of 16:00-17:00. Hence maximum de-territorialisation occurs at 16:00-17:00 and by 18:00-19:00, the intensity has reduced towards zero. This matches the daily signature findings where the town locations are dominated by the late morning and lunchtime peak period rhythms.

Like the Major City difference plots, apart from the years 2009 to 2011 (where the sample size is small), the Town and Major Town signatures follow very consistent patterns. Even the earlier years show the same peaks of territorialisation and de-territorialisation, only differing in the magnitude of these intensities. Also, the period of de-territorialisation is more abrupt as the lunchtime period appears to be extended by an hour. Like the Major City plots, the early morning period indicates more uniformity than later hours over the years plotted.

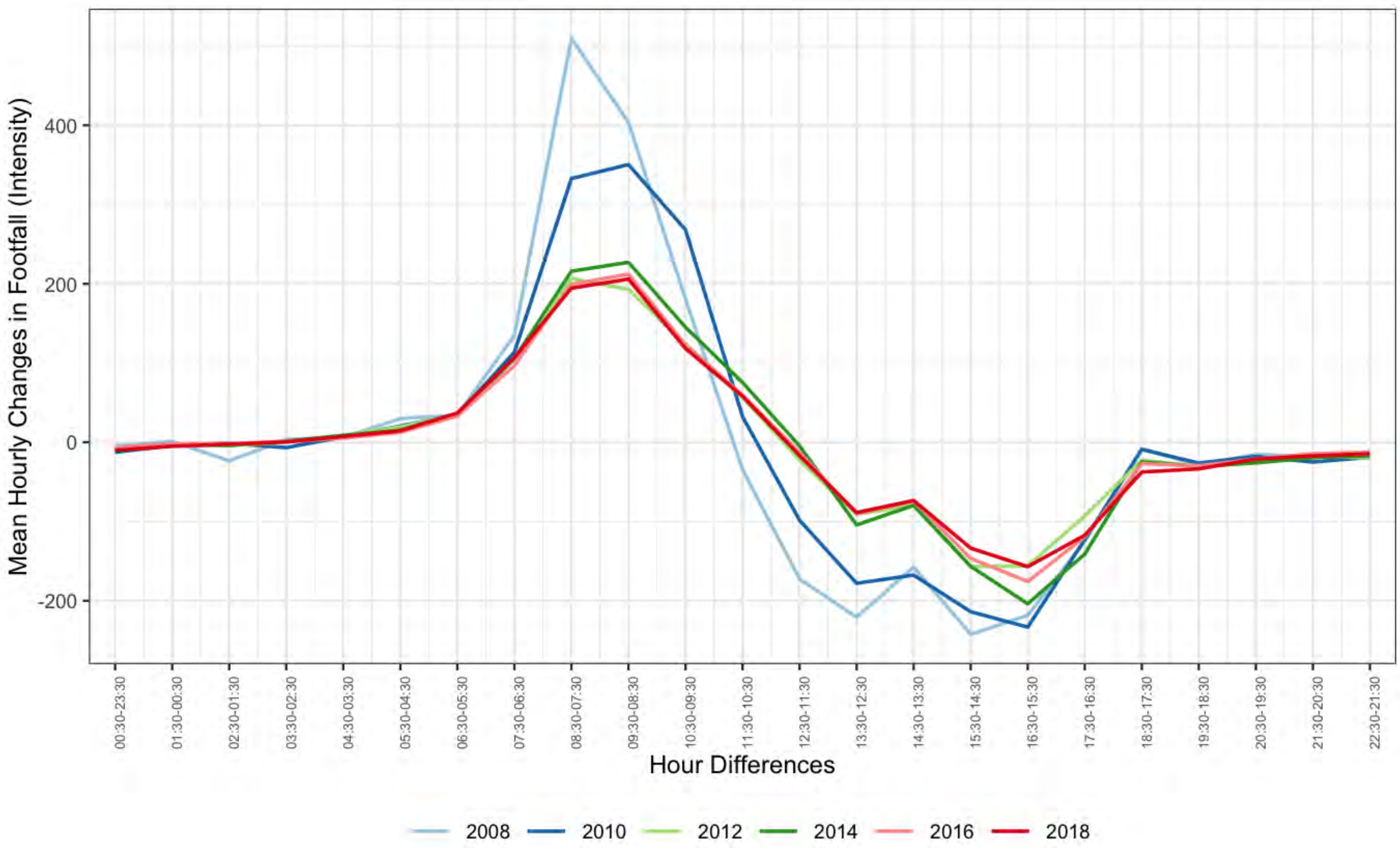


Figure 6.7. Annual hourly mean territorialisation differences 2008 to 2018 for Town locations

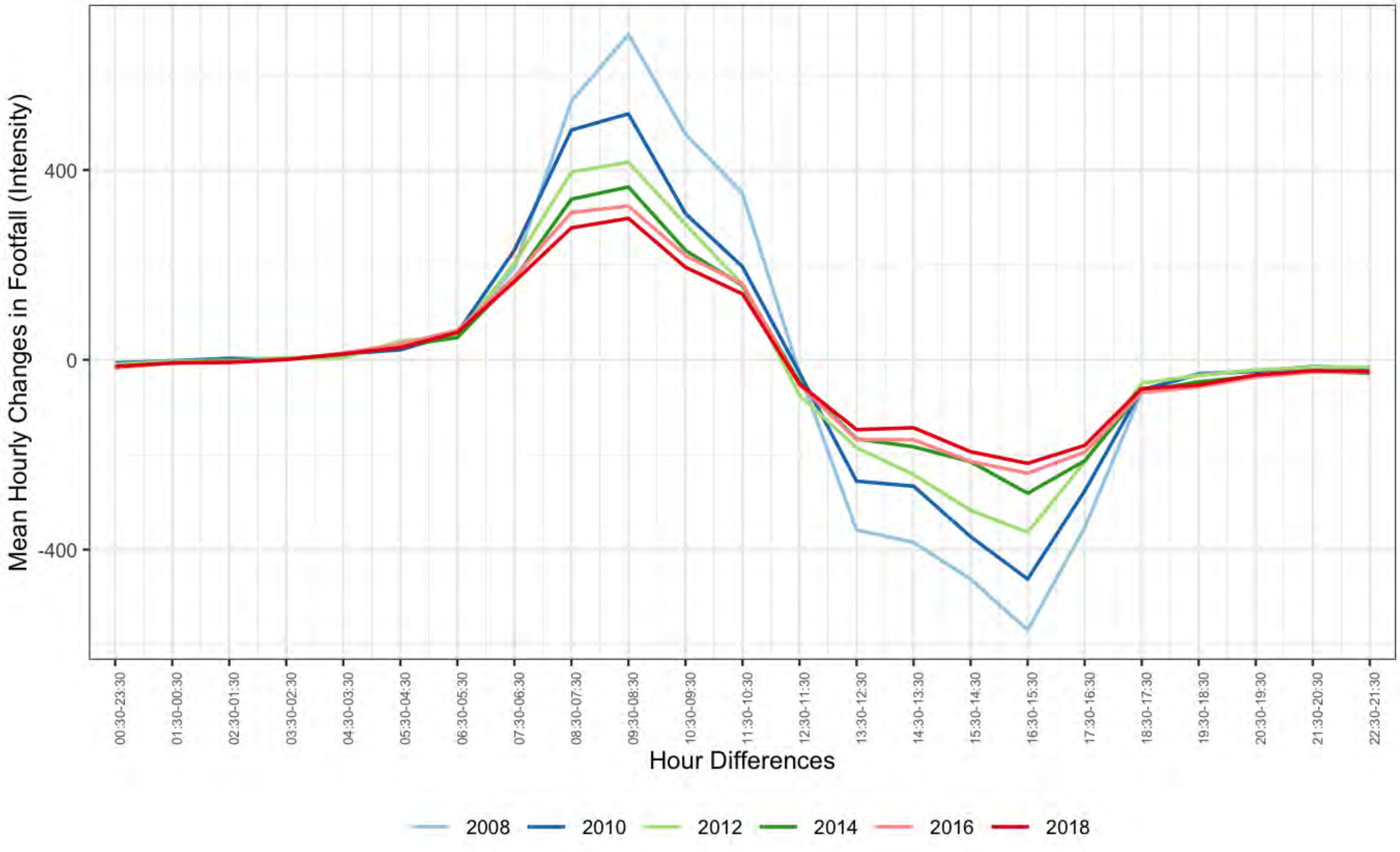


Figure 6.8. Annual hourly mean territorialisation differences 2009 to 2018 for Major Town locations

6.4.3 Regional and Sub-Regional Territorialisation Changes

Both the Sub-Regional (Figure 6.9) and Regional (Figure 6.10) Centre difference plots highlight the morning commuting period, but only after 2014, identifying that this mini-peak only becomes apparent once other non-commuting territorialisation activities decrease in intensity. The sub-regional locations show a reducing growth in footfall over the years from 07:00-08:00 to 11:00-12:00. By 2018, the distinction between the hourly differences for these hours has much reduced and therefore highlights this as a period where footfall has been lost. The same can be observed for the regional centres where the rate of territorialisation still increases over the same period, although this reduces over the years.

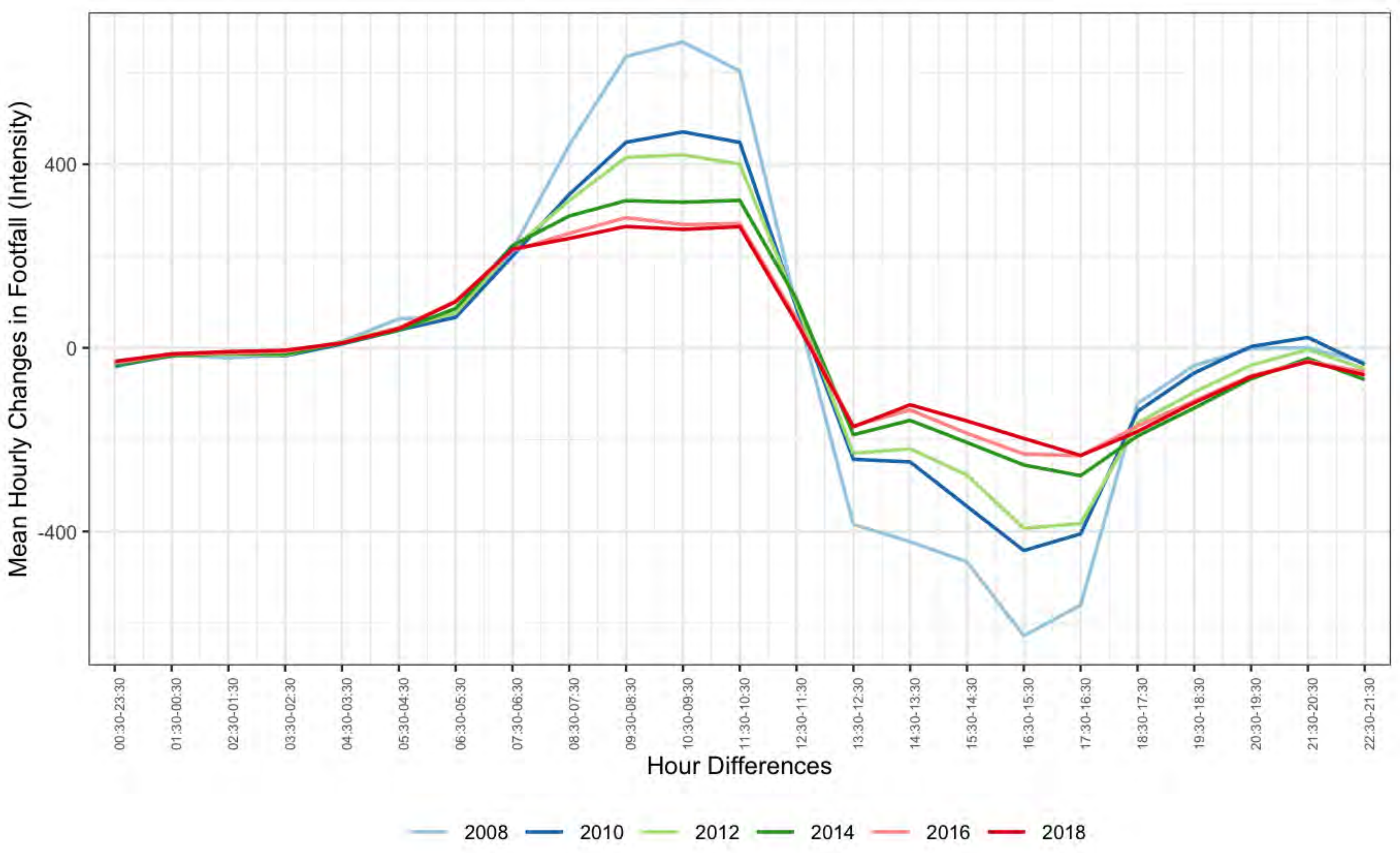


Figure 6.9. Annual hourly mean territorialisation differences 2009 to 2018 for Sub-Regional Centres

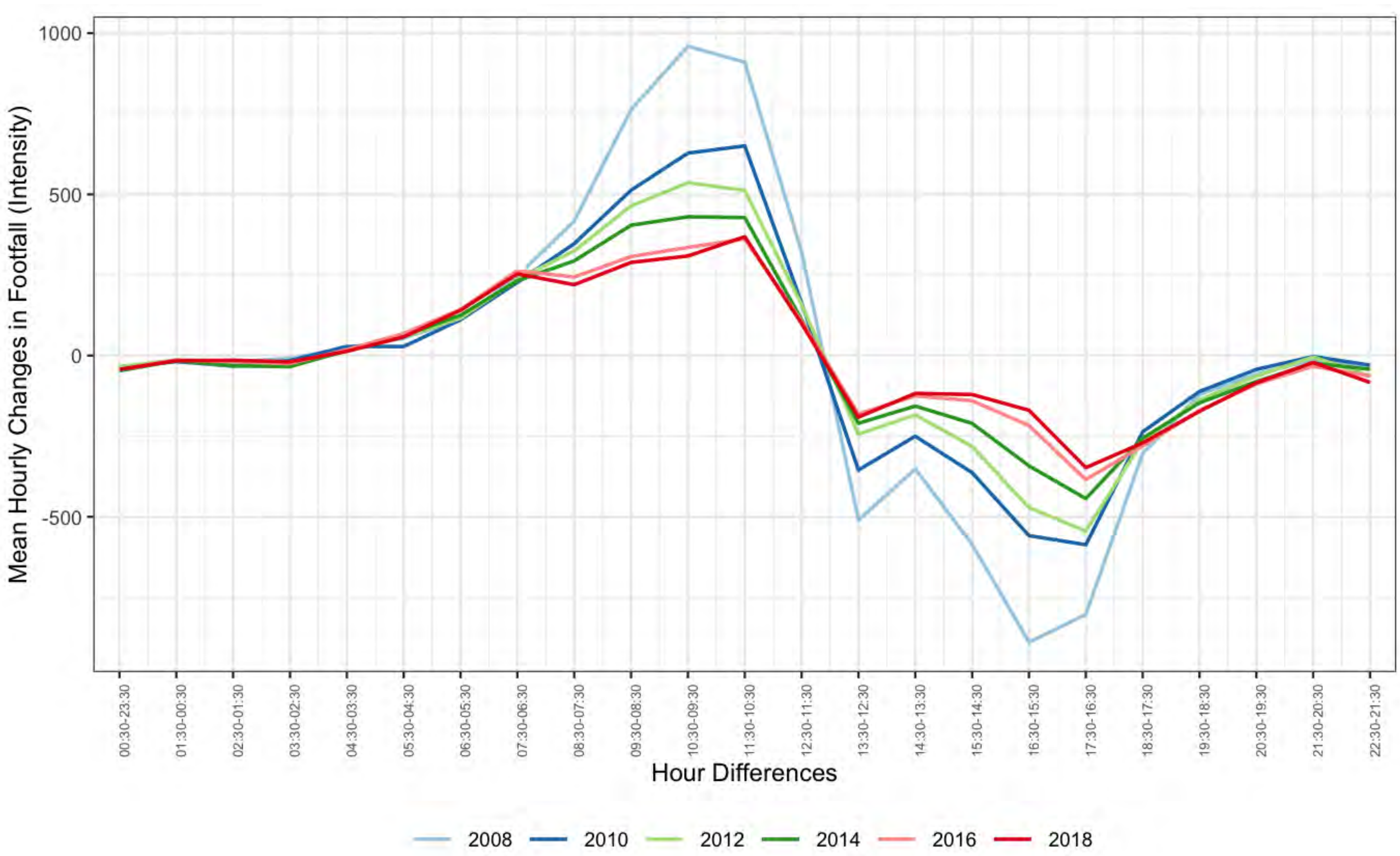


Figure 6.10. Annual hourly mean territorialisation differences 2009 to 2018 for Regional Centres

6.4.4 Summarising Changes to Daily Territorialisation Intensities

Apart from the regional and sub-regional centres, the daily footfall patterns of territorialisation appear relatively constant over the years. What changes are the magnitudes of the peaks in intensity, and the reduction of these over the years reflects falling footfall counts. Table 6.10 below summarises the periods of peak intensity (the maximum and minimum values) for the different urban classification types and picks out whether the period of morning commute was distinguishable.

Table 6.10. Peak Intensity Hours of Territorialisation/De-territorialisation

Urban Classification Type	Morning Commute Peak	Time of Peak Territorialisation	Time of Peak De-territorialisation
Major City	Yes	11:00 – 12:00	18:00 – 19:00
Regional Centre	Yes (2014 +)	10:00 – 11:00 (2008) 11:00 – 12:00	16:00 – 17:00 (2008) 17:00 - 18:00
Sub-Regional Centre	Yes (2014 +)	10:00 – 11:00 09:00 – 12:00 (2014 +)	16:00 – 17:00 17:00 – 18:00 (2014 +)
Major Town	-	09:00 – 10:00	16:00 – 17:00
Town	-	09:00 – 10:00	16:00 – 17:00

Table 6.10 highlights that Towns and Major Towns have insufficient growth in footfall during the morning commute period for this to be identified as a distinct territorialisation period. For the period of peak territorialisation, the larger the urban type, the later this period occurs in the day supporting the medoid signatures assigned to Towns and Major Towns where peak footfall occurs late morning, before 12:00 whereas for the Major Cities, peak footfall can occur any time after 12:00 up to 17:00 (later in a few select cases). Conversely, the period of peak de-territorialisation occurs earliest for the Towns and Major Towns, again though, supporting the daily medoid patterns where footfall is heavily skewed to the morning period for Towns.

Table 6.11 and Table 6.12 provide a more detailed view of the key territorialisation periods based on individual days of the week. This is possible since the analysis uses the imputed footfall data and not the STL derived daily signature component, which as a 7-day running mean profile, essentially removes the day of the week variability. Apart from Towns and Major Towns, the urban types show differences from weekdays to weekends where the commuter period disappears at weekends and is replaced by a late morning period of territorialisation. In addition, the weekend period of peak de-territorialisation occurs an hour earlier than during the week. For Towns and Major Towns, Saturday peak territorialisation occurs an hour later in the morning and Sunday opening hours appear to drive the periods of territorialisation. For Sub-Regional and Regional centres, indicate a morning commute pattern for all the years and follow a similar weekday pattern to the Major Cities apart from the peak period of de-territorialisation being an hour earlier. The fact that the Sub-Regional and Regional centres all display a morning peak period does suggest that over the years, the degree of territorialisation taking place that is not commuter based has reduced, whereas the commuter footfall remains relatively constant. Hence, why the commuter peak did not appear in the results of Table 6.10 until from 2014.

Table 6.11. Times of Territorialisation Intensity Changes for Major Cities, Towns and Major Towns

	Inflection Point of Territorialisation	**Mon**	**Tue**	**Wed**	**Thu**	**Fri**	**Sat**	**Sun**
Major City	Morning Peak	07:00 - 08:00	07:00 - 08:00	07:00 - 08:00	07:00 - 08:00	07:00 - 08:00	Undefined	Undefined
	Peak Territorialisation	11:00 - 12:00	11:00 - 12:00	11:00 - 12:00	11:00 - 12:00	11:00 - 12:00	10:00 - 11:00	10:00 - 11:00
	Peak De-territorialisation	18:00 - 19:00	18:00 - 19:00	18:00 - 19:00	18:00 - 19:00	18:00 - 19:00	17:00 - 18:00	2008 - 17:00 - 18:00 2010+ - 18:00 - 19:00
Major Town	Peak Territorialisation	08:00 - 10:00	08:00 - 10:00	09:00 - 10:00	09:00 - 10:00 (2008) 08:00 - 09:00	09:00 - 10:00 (2008) 08:00 - 09:00	09:00 - 10:00	10:00 - 11:00 (2008) 09:00 - 10:00
	Peak De-territorialisation	16:00 - 17:00	16:00 - 17:00	13:00 - 14:00 16:00 - 17:00	13:00 - 14:00 16:00 - 17:00	16:00 - 17:00	16:00 - 17:00	15:00 - 16:00
Town	Peak Territorialisation	08:00 - 09:00	08:00 - 10:00	08:00 - 10:00	08:00 - 10:00	08:00 - 10:00	08:00 - 09:00 (2008) 09:00 - 10:00	09:00 - 10:00
	Peak De-territorialisation	13:00 - 14:00 16:00 - 17:00	13:00 - 14:00 16:00 - 17:00	13:00 - 14:00 2012+ 16:00 - 17:00	16:00 - 17:00	13:00 - 14:00 (2008) 16:00 - 17:00	16:00 - 17:00	15:00 - 16:00

Table 6.12. Times of Territorialisation Intensity Changes for Regional and Sub-Regional Centres

	Inflection Point of Territorialisation	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Sub-Regional	Morning Peak	07:00 - 08:00	07:00 - 08:00	07:00 - 08:00	07:00 - 08:00	07:00 - 08:00	Undefined	Undefined
	Peak Territorialisation	11:00 - 12:00	11:00 - 12:00	11:00 - 12:00	11:00 - 12:00	09:00 - 10:00 11:00 - 12:00	10:00 - 11:00 2014 + 09:00 - 10:00	10:00 - 11:00
	Peak De-territorialisation	13:00 - 14:00 17:00 - 18:00	13:00 - 14:00 17:00 - 18:00	13:00 - 14:00 17:00 - 18:00	13:00 - 14:00 17:00 - 18:00	16:00 - 18:00	16:00 - 17:00	15:00 - 16:00
Regional	Morning Peak	07:00 - 08:00	07:00 - 08:00	07:00 - 08:00	07:00 - 08:00	07:00 - 08:00	Undefined	Undefined
	Peak Territorialisation	11:00 - 12:00	11:00 - 12:00	11:00 - 12:00	11:00 - 12:00	11:00 - 12:00	10:00 - 11:00	10:00 - 11:00
	Peak De-territorialisation	13:00 - 14:00 17:00 - 18:00	13:00 - 14:00 17:00 - 18:00	13:00 - 14:00 17:00 - 18:00	13:00 - 14:00 17:00 - 18:00	13:00 - 14:00 17:00 - 18:00	16:00 - 17:00	15:00 - 17:00

6.5 Annual Distribution of Medoid Assignments

Having identified that the daily signatures are relatively persistent over a year-to-year period, the next section explores how much change there is within a year. The following analysis explores how the fuzzy medoid allocations change over the period of a year (Angstenberger, 2001; 2017; D'Urso et al., 2018). The analysis assesses weekly summed counts of percentage-based allocations of the best fitting medoids; that is, how each best fitting medoid was assigned as a percentage of the weekly total of best-fitting medoids. For the analysis, 2018 was chosen as this year had the greatest variety of footfall sensor location types. The results are segmented by Urban Classification type to aid the identification of patterns over time. The medoids identified for the 2018 fuzzy analysis are presented in Figure 6.4 on page 217.

6.5.1 Annual Distribution of Medoids for Towns

Figure 6.11 below presents the results for the distribution of the best fitting medoids over the period of 2018. As was evident in Table 6.7 on page 218, medoids 6 (lunchtime peak) and 7 (lunchtime peak with small extension into the afternoon) are the dominant signatures. Medoid 6 suggests no real trend or pattern whereas medoid 7 hints at more significance during the holiday periods when it might be expected that more people would be attracted into a town centre and therefore linger more in the town after lunch – hence the increase in the cluster allocation for the medoid with an intensification in the degree of afternoon footfall traffic.

6.5.2 Annual Distribution of Medoids for Major Towns

Figure 6.12 for Major Towns indicates much less of a trend or pattern. The one noticeable change is the greater influence of Medoid 4, suggesting the increased likelihood that Major Town locations de-territorialise slower in the afternoons than Town locations.

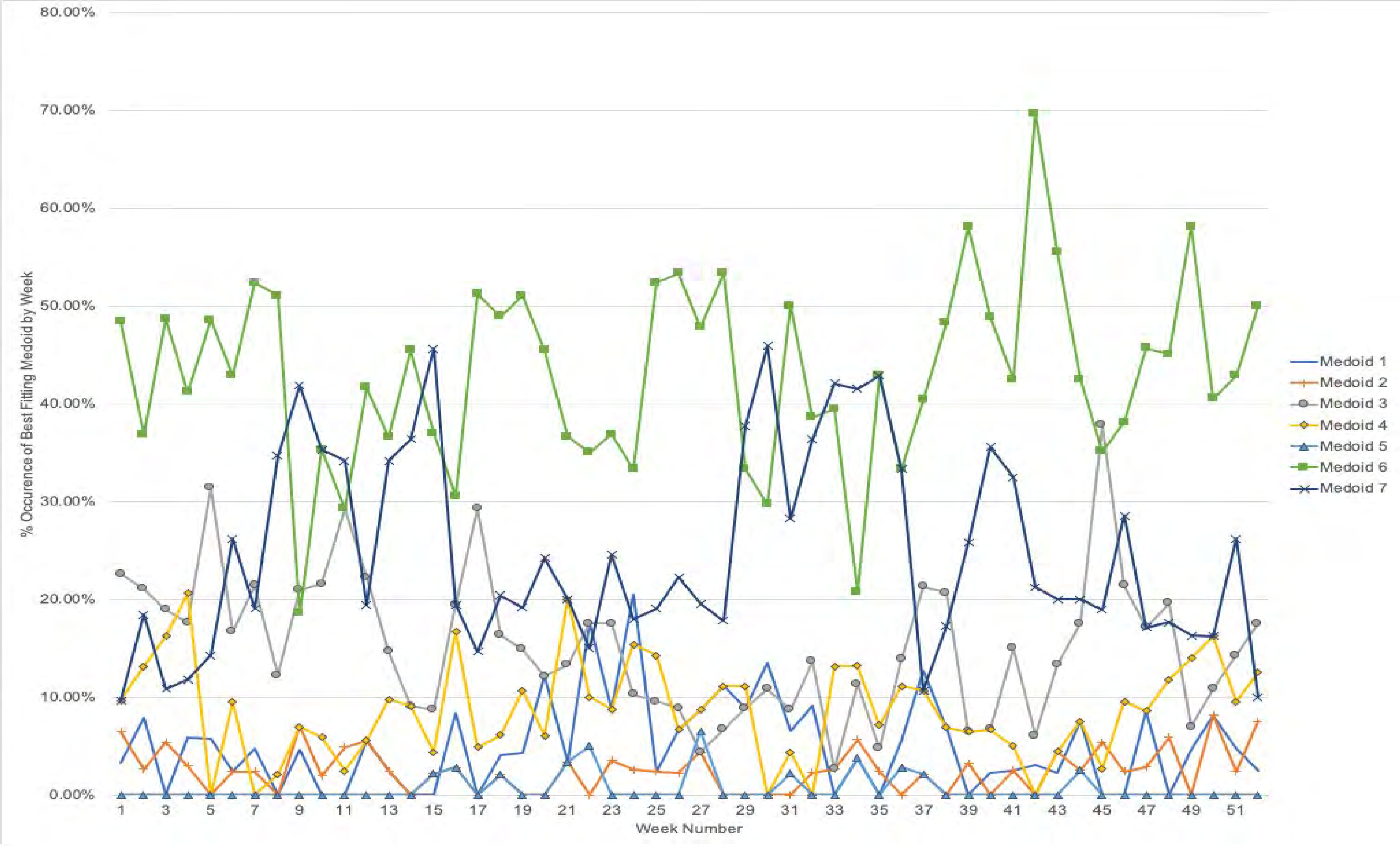


Figure 6.11. Weekly Distribution of the Best Fitting Medoids in 2018 for Towns

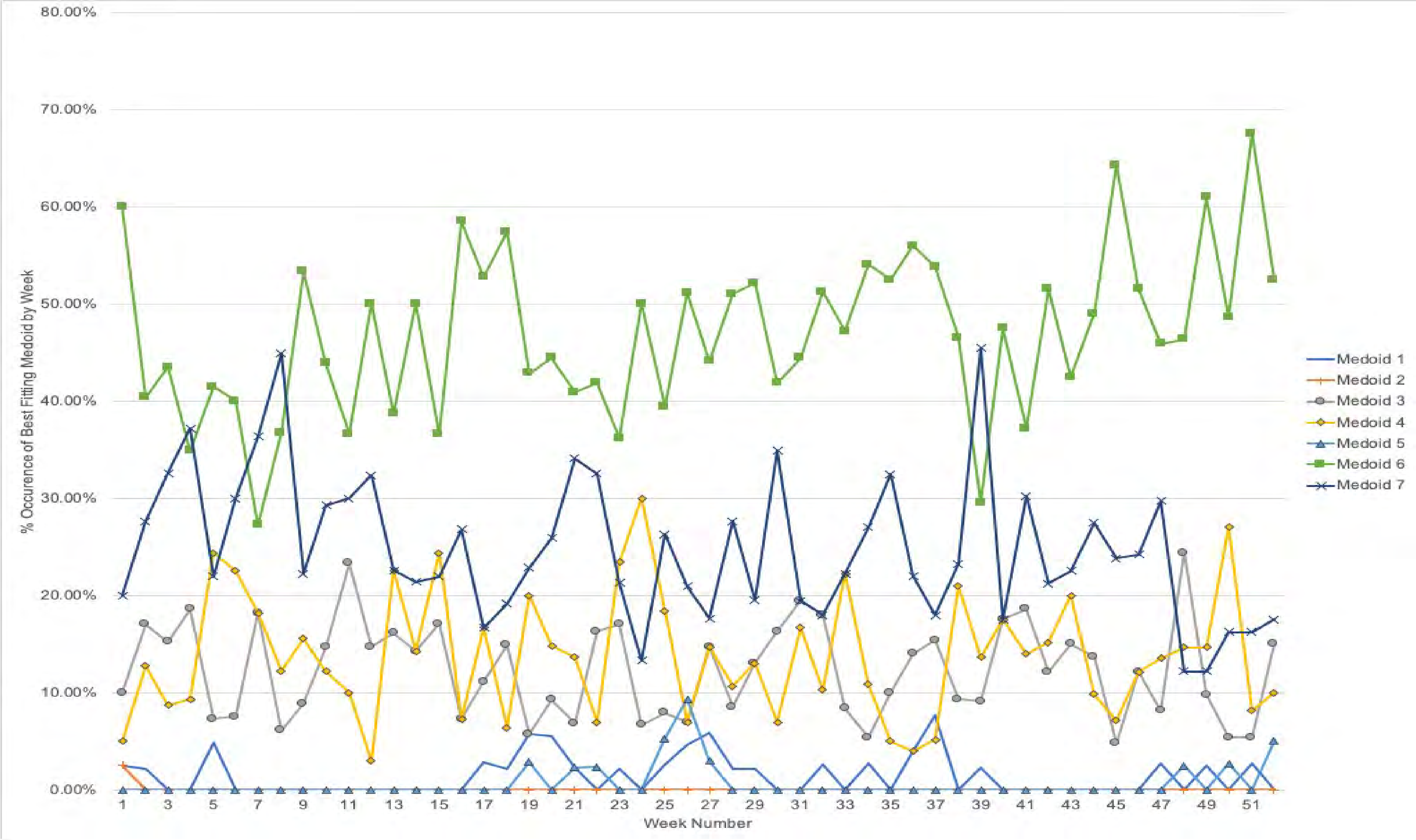


Figure 6.12. Distribution of the Best Fitting Medoids in 2018 for Major Towns

6.5.3 Annual Distribution of Medoids for Sub-Regional Centres

Figure 6.13 showing the distribution of results for sub-regional centres displays a reduction in the influences of medoids 6 and 7 and increased contributions from the medoids with more afternoon and evening focused signatures. Also, medoid 6 suggests a seasonal pattern with increased influence coming up to Christmas and the Winter periods – where visitors are less likely to stay late. Conversely, the medoids that extend footfall into the afternoon and evening periods suggest increased influence in the non-Winter and Christmas periods - for example, Medoid 5.

6.5.4 Annual Distribution of Medoids for Regional Centres

Figure 6.14 showing the results for Regional Centres continues to show the declining influences of the lunchtime focused medoids. However, medoid 6 continues to show a seasonal pattern with more influence in Winter and at Christmas – again, a sign of visitors not staying out beyond daylight hours. Medoids 1 and 4 are now more significant and, medoids 2 and 5 have a higher contribution. Medoid 5 suggests a summer holiday period peak influence, the other medoids appear to be much more randomly distributed.

6.5.5 Annual Distribution of Medoids for Major Cities

Figure 6.15 displays the results for Major Cities. Medoids 1 and 5 are clearly dominant showing that Major Cities are much more likely to have locations where territorialisation of locations extends well beyond the period of lunchtime. Both medoids also suggest a seasonal cycle with both being more significant during the summer months. Still evident is the seasonal allocation of medoid 6, suggesting that in the Winter months, a de-territorialisation of locations in the later afternoons and evenings takes place – evidence of the seasonal rhythm found in the annual signatures.

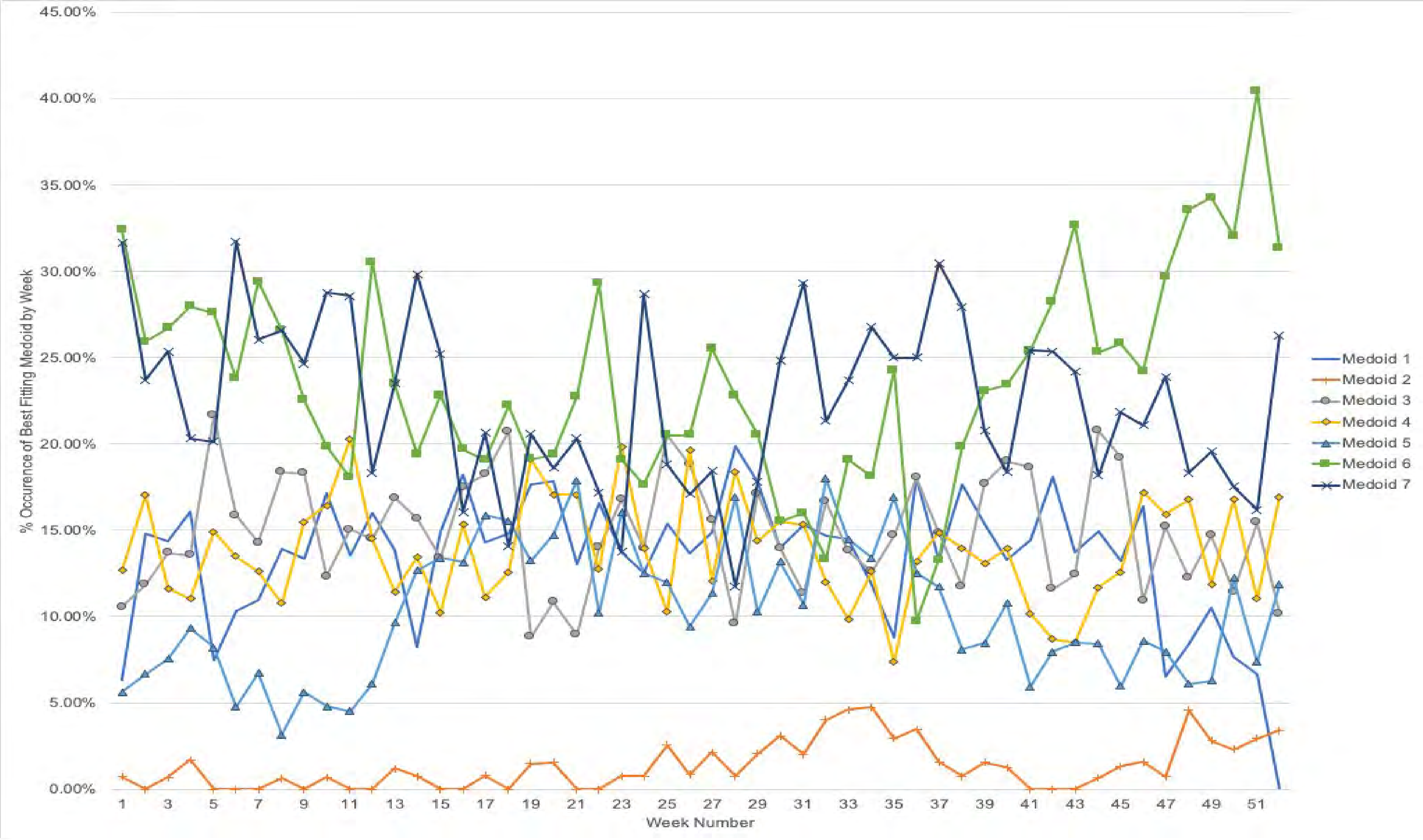


Figure 6.13. Distribution of the Best Fitting Medoids in 2018 for Sub-Regional Centres

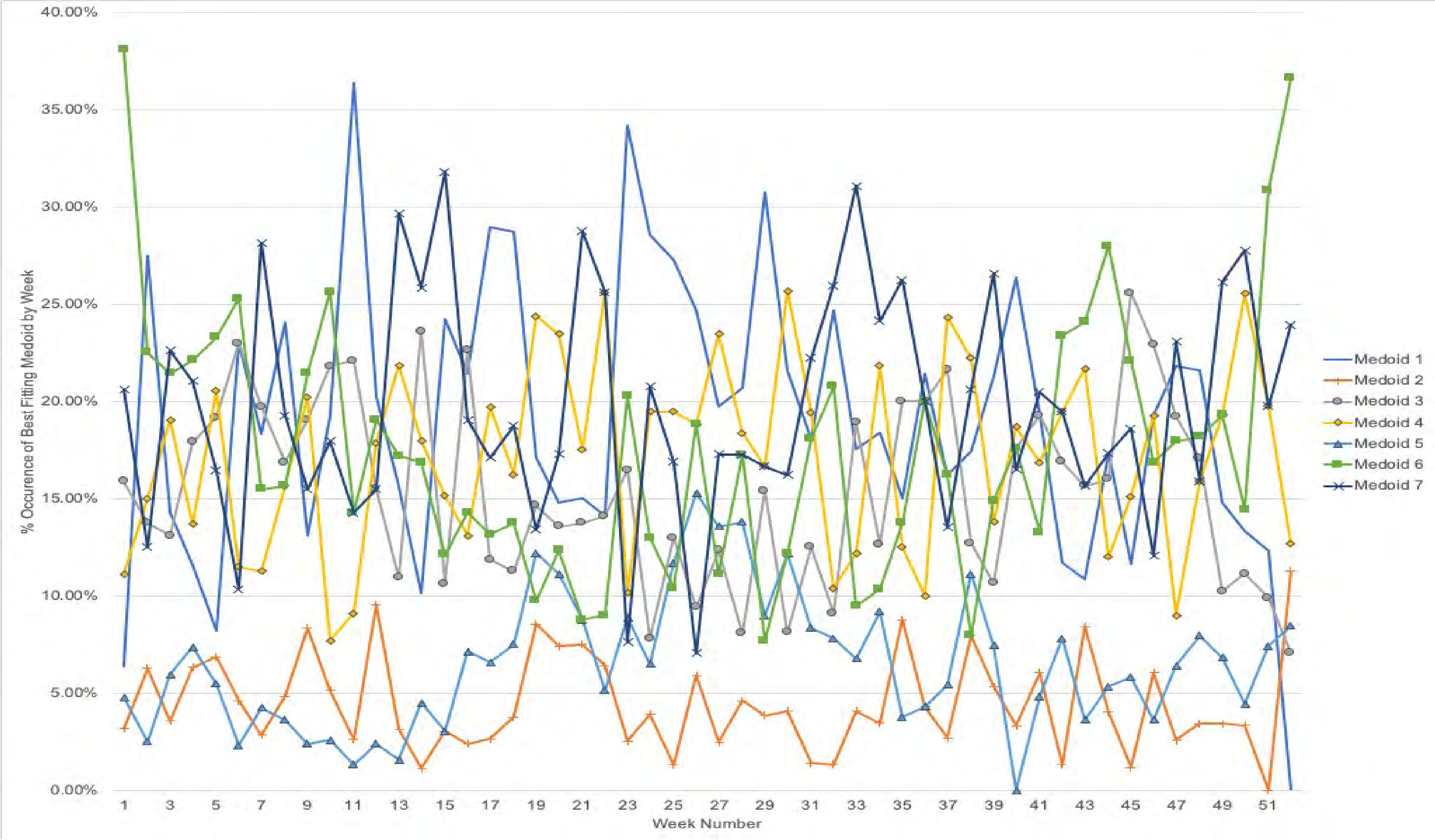


Figure 6.14. Distribution of the Best Fitting Medoids in 2018 for Regional Centres

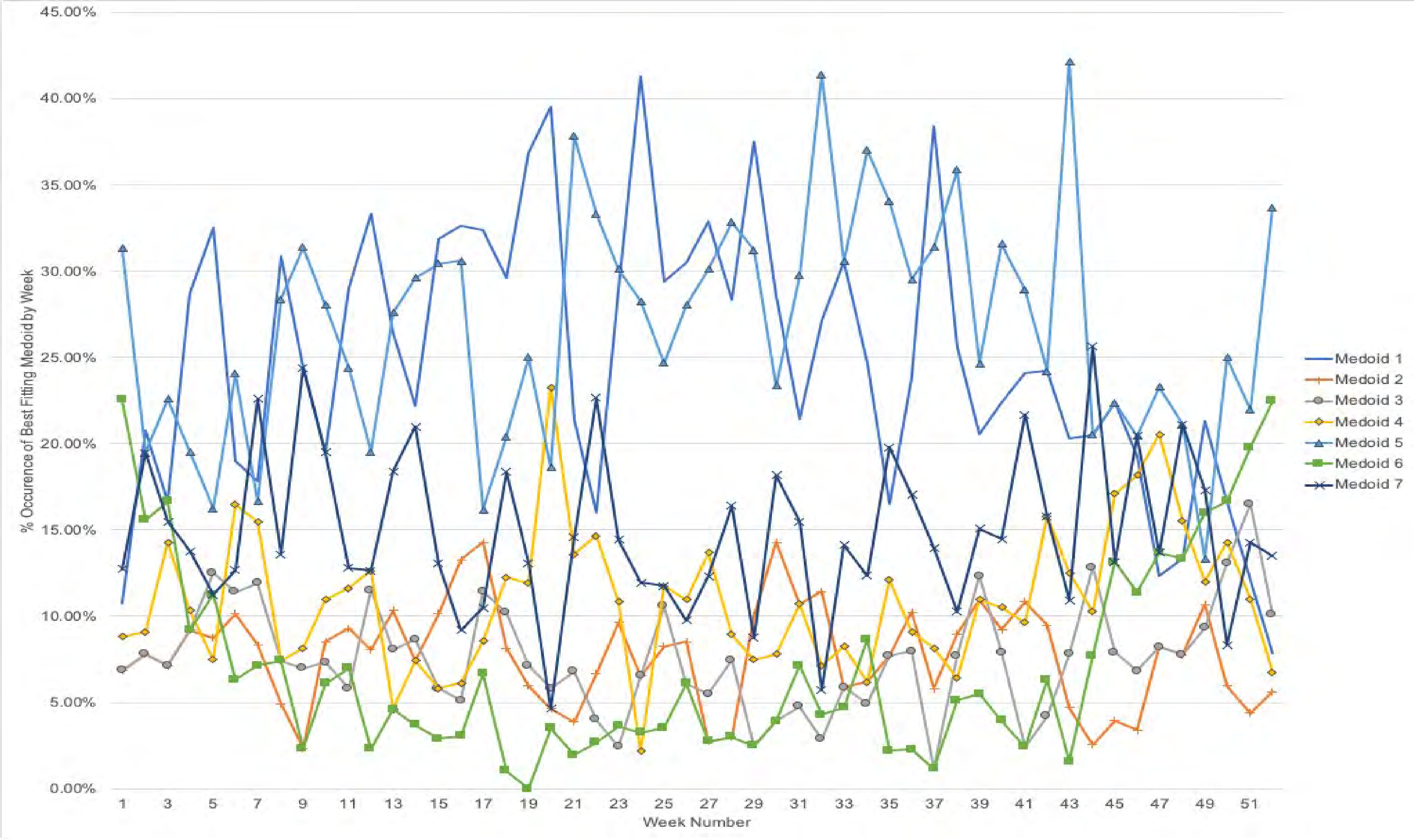


Figure 6.15. Distribution of the Best Fitting Medoids in 2018 for Major Cities

6.6 Summary

To answer the question regarding how places differ, the daily signatures show a close relationship between the urban classification type and assigned medoid signatures. For Town and Major Town locations in the urban hierarchy, the late morning and lunchtime period is identified as the most important period of territorialisation. As places increase in size and complexity, so too does the tendency for the periods of territorialisation to extend into the afternoons and evenings. The daily rhythm types are summarised in Table 6.9, p220.

Whilst the medoids identified through the fuzzy cluster analysis identified the different types of daily rhythms, the intensity plots picked the periods of peak change in territorialisation and de-territorialisation. Confirming the daily medoid signatures, these plots followed a similar pattern, of Towns and Major Towns being dominated by territorialisation peaks before lunchtime whereas the larger places extended this period into lunchtimes and the afternoons. Changes in footfall volumes also enabled footfall signatures to emerge such as the early morning commute period for Regional and Sub-Regional places. This suggests that where social activities are more variable and complex, only the dominant patterns can be identified and that other daily rhythms are obscured.

Looking at how the daily clusters change over the period of a year, a seasonal pattern in the allocation of the medoid signatures suggests that in the summer months and holiday periods, the daily signatures indicate an increased intensification of territorialisation taking place later in the day. By analysing individual days for every footfall sensor, the daily signature analysis highlights an advantage of using the fuzzy cluster approach. As the chosen medoids represent specific periods in time, the fuzzy medoid assignments can then be plotted as a time-series to provide a view of how the fuzzy allocations change over time. In the case of the daily signatures, this provides evidence of the identified seasonal patterns.

7 Results - Combined Weekly Rhythms

The weekly signature component defined below in Equation 7.1 was the last of the combined results to be analysed. The weekly signature component extracted using the STL algorithm (see Equation 7.1), provided the adjustments needed to understand the differences between the days of the week.

$$Y_v = T_v + S_{annual} + \boxed{S_{weekly}} + S_{daily} + R_{v'}$$

Equation 7.1. STL Equation and Weekly Signature Additive Component

As with the daily signature component, the focus of the analysis was to provide answers to the first research question:

> *"As a performance measure, what insights can footfall offer to identify how collectively, places change over time?"*

7.1 Data Inputs and Fuzzy Cluster Analysis Processing

For the data input into the fuzzy cluster analysis (summarised in Table 7.1), the weekly signature component was extracted from the database for every footfall sensor and each weekly period (00:00 Monday to 23:00 Sunday) of a chosen year in the range week 1 to week 52 or where applicable, week 53.

Table 7.1. Weekly Fuzzy Cluster Analysis Data Inputs

Data Input Characteristics	Details
Input Data Source	STL derived weekly signatures
Period of data extraction and analysis (by year)	Week of data (00:00 Monday to 23:00 Sunday) Week 1 to Week 52 (53 where applicable)
Number values per data record	168 (7 * 24)
Standardisation of data record?	Yes
Additional smoothing applied?	No
Sampling required?	Yes (where necessary)

Hence, week 1 and week 52/53 could also include weekly signature values from the previous or following years. Each weekly record was labelled using the location identifier and the date (year, week number) from the database to enable identification when processing the results. During the subsequent year based weekly fuzzy cluster analysis, the whole extracted period of individual weekly records for each footfall sensor was compared to every other sensor and week.

The parameterisations required for the weekly signature clustering analysis using the R dtwclust package (Sardá-Espinosa, 2019) are provided in Appendix A: Section 12.9 Data Mining and Chapter 4: Section 4.6.4 Data Mining. Each individual set of footfall sensor weekly component hourly values were standardised using the R Scale Function (R Core Team, 2019) to remove differences of scale between locations and thus allowing the fuzzy analysis algorithms to focus on the shape of the weekly footfall component rather than on differences in magnitude of pedestrian numbers – see Chapter 4 p156. No smoothing of the data was performed.

Table 7.2. Available number of weekly signatures and sampling sizes used

Year	Available Weekly Signatures (Number of Weeks * Number Sensors)	Sample Size
2006	3298	No Sampling Required
2007	4439	
2008	5879	
2009	9053	
2010	10175	
2011	11215	
2012	12603	
2013	13878	
2014	16352	
2015	20749	
2016	23516	21000
2017	26139	21000
2018	28704	21000

As a consequence of memory constraints (the fuzzy clustering algorithms required more computer memory than was physically available), the total of available weekly signatures from 2016 onwards had to be limited to a sample of 21,000 randomly selected instances, using the R function Sample (R Core Team, 2019). Table 7.2 below provides details of the extracted total population of sensor weekly records vs the sample size for each year.

7.2 Selecting the Number of Medoids

After performing the cluster analysis for each year, the first step was to check the cluster validation indices, to identify the best fitting number of medoids (see Table 7.3). The process followed is provided in Chapter 4 p160 and for all the CVI, Radviz and Boxplot output used, see Appendix D – Combined Sensor Weekly Results.

Table 7.3. The number of weekly medoids selected for each year

Year	No. of Medoids	No. of Sensors
2006	4	64
2007	2	74
2008	3	92
2009	4	140
2010	4	185
2011	4	201
2012	4	219
2013	5	253
2014	5	283
2015	2	346
2016	4	425
2017	6	459
2018	4	483

7.3 Assessing the Fuzzy Results and Medoids

The process of analysis that follows includes:

- A descriptive assessment of the medoids identified for each year and an assessment of fuzzy membership for each year
- An assessment of how the medoids change over the period of a year
- A summary of the results.

7.3.1 Weekly Results for 2006

As with the daily results, although there is not a whole year of data for 2006, there was enough for the weekly fuzzy analysis. Figure 7.1 below shows the dtwclust automatically assigned medoids for 2006 based on the best fitting cluster being k = 4.

Immediately apparent for all the medoid plots is the extra footfall contribution assigned to Saturday lunchtimes and early afternoons whereas on Sundays, there are varied degrees of de-territorialisation. More subtly, medoids 1,3 and 4 show periods of de-territorialisation for the afternoons for Mondays to Thursdays where the degree of de-territorialisation decreases as the week advances, and by Friday, this has become a period of territorialisation. However, for Medoid 2, rather than being periods of de-territorialisation, the late morning and lunchtime periods indicate a degree of territorialisation for the same weekdays, reaching a peak on Friday lunchtime.

Medoids 3 and 4 display a significant additional contribution for Saturday lunchtime/early afternoon footfall. However, Medoid 3 has a larger reduction in lunchtime footfall on Sundays, whereas this happens later in the day for Medoid 4. More subtly, Medoid 4 indicates larger reductions in afternoon footfall than Medoid 3 at the start of the week. Medoid 2 displays a very significant reduction in Sunday footfall and although there are peaks for additional footfall on Saturday afternoons, and to a lesser degree for Fridays, these do not have the magnitude displayed by Medoids 3 and 4. Medoid 1 also has a marked Friday and Saturday peak in footfall traffic, where the additional contributions are for the late afternoon and evening periods.

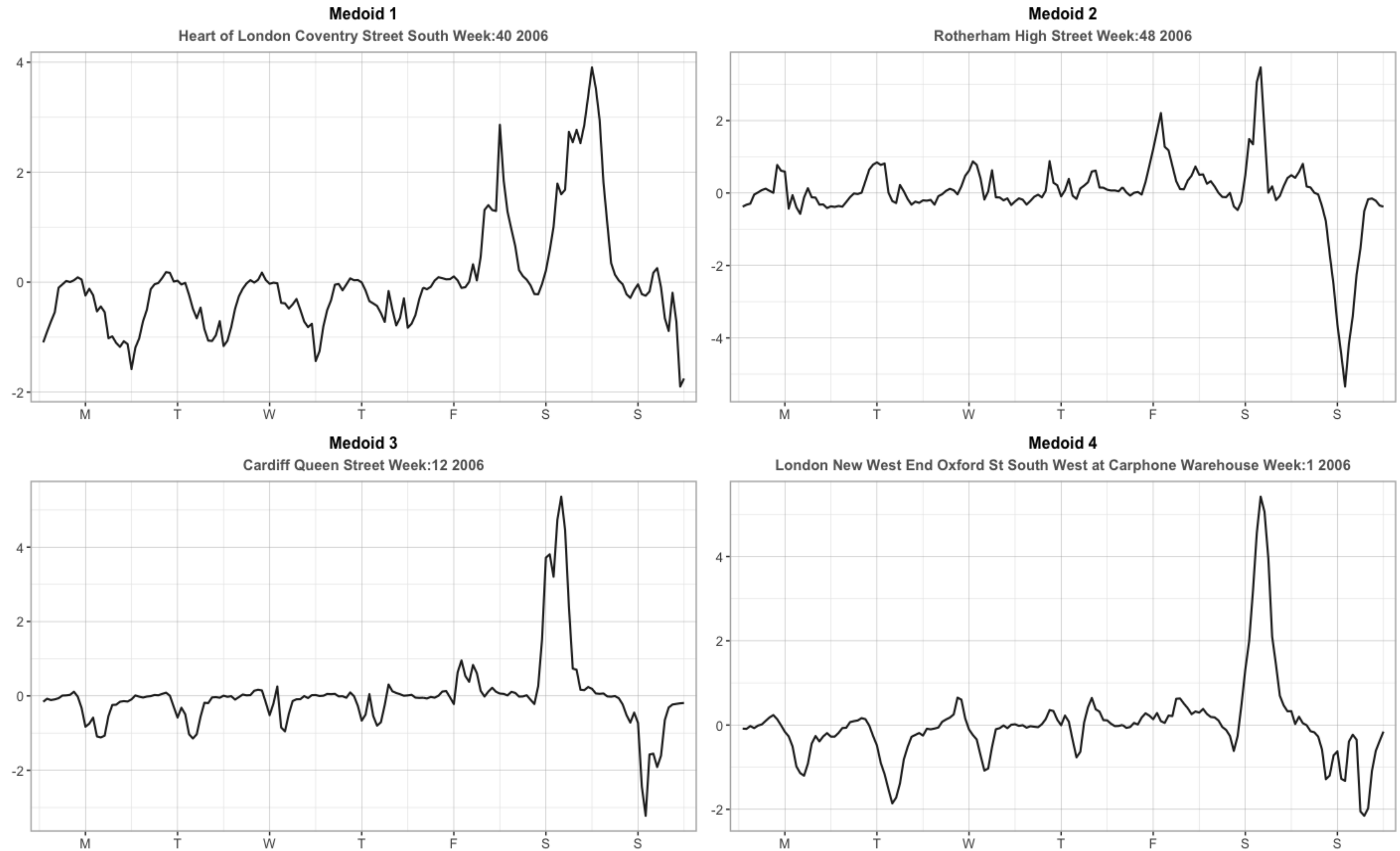


Figure 7.1 Weekly medoids for 2006

Table 7.4 details the relationships between the best and next best fitting medoids for the weekly clusters in 2006. Where the best fitting medoid accounts for 90% or more of the assigned fuzzy contribution, the next best fitting Medoid is accounted for in the column <10%.

Table 7.4. Best vs Next Best Fitting Medoids for 2006 Weekly Clusters

	Next Best Fitting Medoid					
Best Fitting Medoid	1	2	3	4	>90%	Total
1	0.00%	2.73%	0.00%	2.03%	7.34%	12.10%
2	1.18%	0.00%	15.22%	5.25%	5.88%	27.53%
3	0.03%	7.06%	0.00%	11.67%	0.21%	18.98%
4	0.85%	1.94%	37.90%	0.00%	0.70%	41.39%
Total	2.06%	11.73%	53.12%	18.95%	14.13%	100.00%

Table 7.4 identifies Medoid 4 as the most frequently assigned best fitting medoid followed by Medoid 2 suggesting a difference between places is the degree of the Saturday peak of territorialisation versus the Sunday peak in de-territorialisation. However, for the next-best fitting medoid, Medoid 3 is most frequently assigned to Medoids 2 and 4, suggesting that the Sunday de-territorialisation peak of Medoid 2 can be reduced, and that the Saturday peak of territorialisation Medoid 4 can also be reduced in intensity. Medoid 1, although less significant as a cluster, nevertheless can be seen to be a distinct cluster pattern and appears to match very well the daily pattern where there is significant footfall in the late afternoons, evenings, and night-time.

Although the footfall sensors for 2006 represent a sample that has more representation from Major Cities than is the case in later periods, the interpretation of the weekly medoids can be seen to be more difficult than either the annual or daily results. Despite the obvious Saturday and Sunday corrections, there are also minor corrections to the afternoon and lunchtime periods, and these vary according to the day of the week.

7.3.2 Weekly Results for 2007

Only two medoids are assigned for the 2007 results as displayed in Figure 7.2 below.

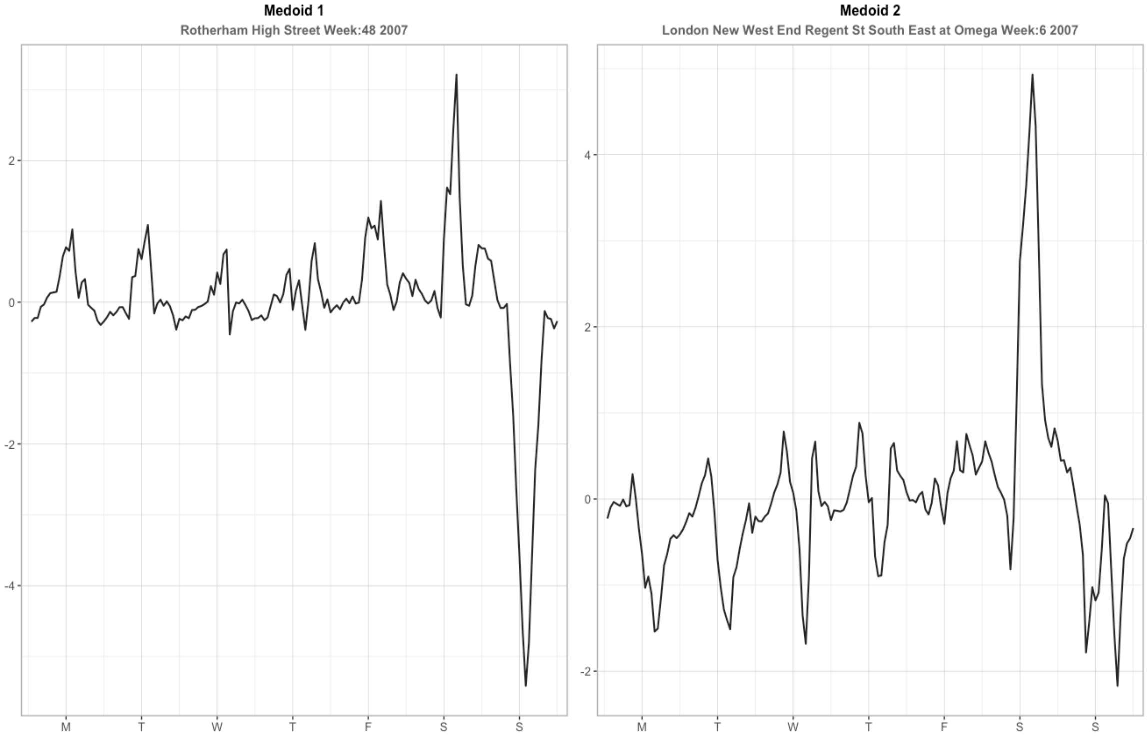


Figure 7.2. Weekly Medoids for 2007

Both medoids display the same signature types as Medoids 2 and 4 for the 2006 weekly fuzzy analysis. Table 7.5 shows that a large percentage (44.69%) of the best fitting medoids are assigned a fuzzy score of 90% or more.

Table 7.5. Best vs Next Best Fitting Medoids for 2007 Weekly Clusters

	Next Best Fitting Medoids			
Best Fitting Medoids	1	2	>90%	Total
1	0.00%	27.33%	16.06%	43.39%
2	27.98%	0.00%	28.63%	56.61%
Grand Total	27.98%	27.33%	44.69%	100.00%

7.3.3 Weekly Results for 2008

Figure 7.3 below continues the theme of picking out a positive correction for Saturdays and a negative correction for Sundays and to a lesser degree, weekday adjustments.

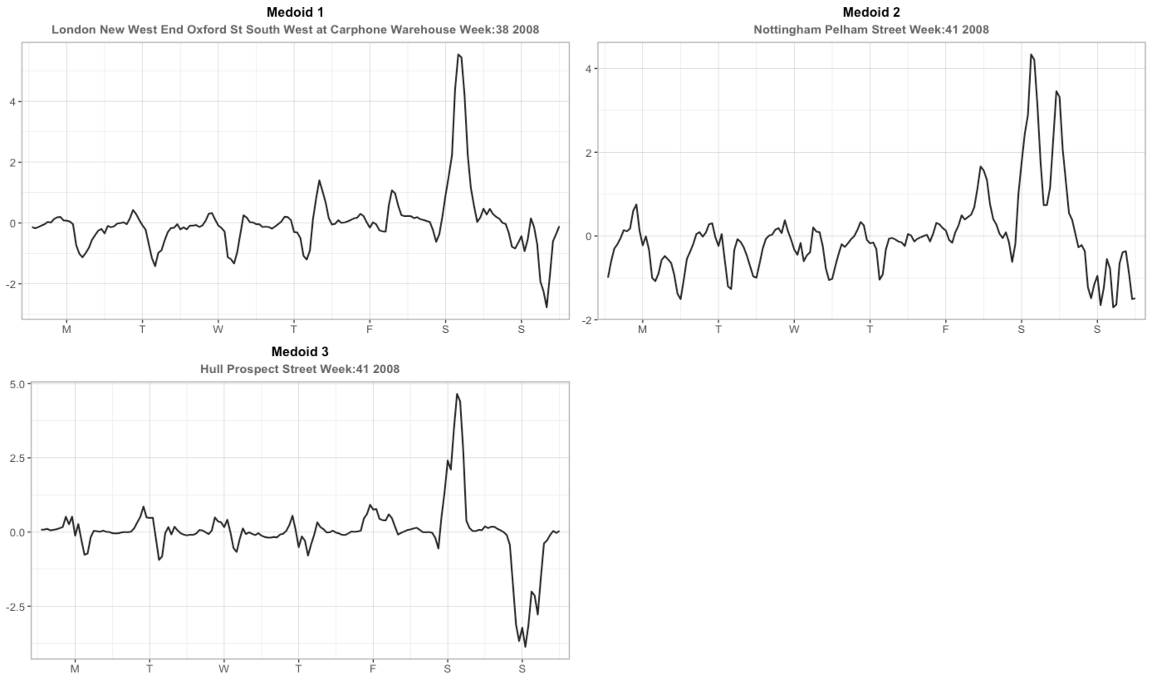


Figure 7.3. Weekly Medoids for 2008

Medoid 3 has picked out a large fall in footfall on a Sunday, a characteristic also seen with Medoid 2 for the 2006 data, but without the associated reduction in the Saturday peak. Medoid 2 also includes a Saturday peak but includes, not only a lunchtime / early afternoon peak, but also another peak in the evening. As seen in Table 7.6, it is the least occurring best fitting Medoid.

Table 7.6. Best vs Next Best Fitting Medoids for 2008 Weekly Clusters

	Next Best Fitting Medoid				
Best Fitting Medoid	1	2	3	>90%	Total
1	0.00%	10.55%	17.52%	4.49%	32.56%
2	10.95%	0.00%	5.10%	1.55%	17.61%
3	22.35%	14.56%	0.00%	12.93%	49.84%
Total	33.30%	25.11%	22.62%	18.97%	100.00%

7.3.4 Weekly Results for 2009

For 2009, k=4 provided the best fitting cluster results, with the associated medoids displayed below in Figure 7.4. The Saturday peak adjustment appears in Medoids 1 and 3 again but a larger Sunday drop in footfall correction is associated with Medoid 1 versus the larger Saturday peak and smaller Sunday decrease of Medoid 3.

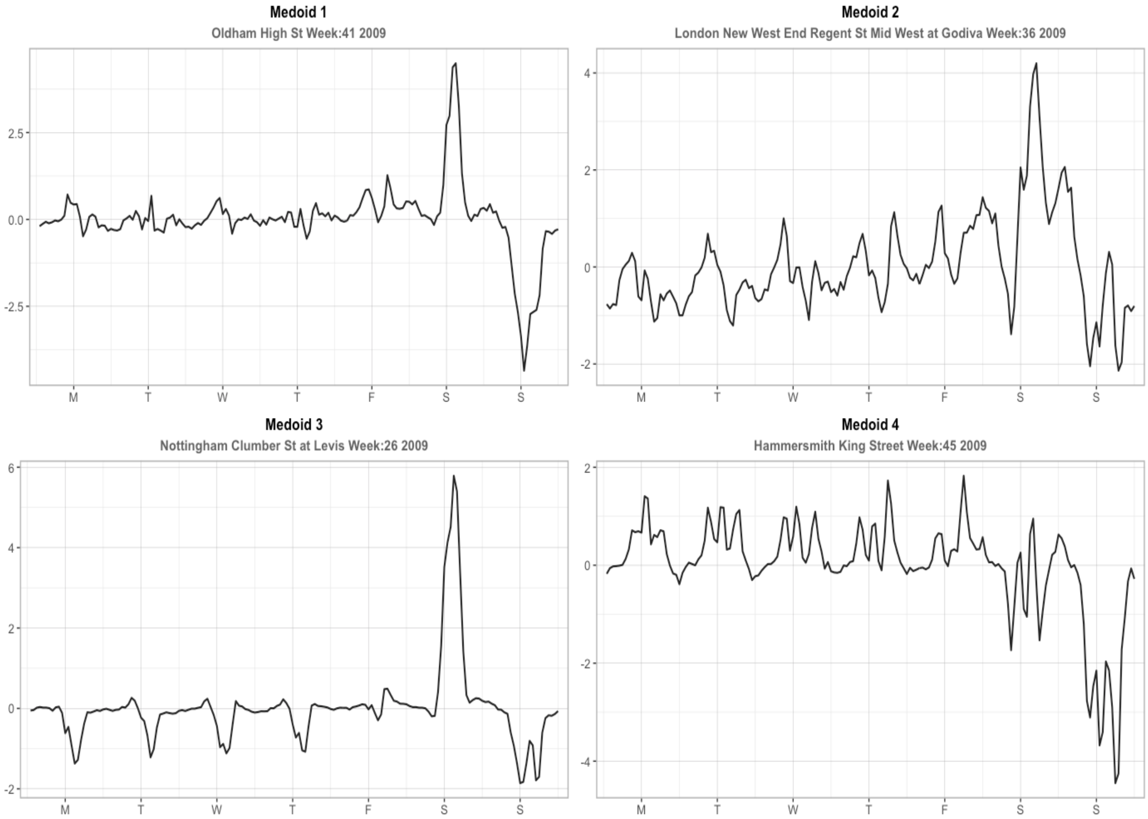


Figure 7.4. Weekly Medoids for 2009

Medoid 2 presents quite a 'noisy' signature, with footfall increasing during the working week and, on Thursday and Friday, increases in evening footfall as well as at lunchtime. Saturday shows increases for both these periods but in much greater volume. Although Sunday is corrected to have the lowest footfall for the week, the negative correction is not large. Medoid 4 displays a Sunday correction but no Saturday peak. This suggests Medoid 4 identifies a location where the working week results in the footfall maximums whereas the weekends have fewer visitors. In fact, the working week footfall corrections show increases in footfall for morning and evening rush hour periods and lunchtime.

7.3.5 Weekly Results for 2010 - 2017

For the years 2010 to 2017, rather than detail every year, the medoids selected for each year are available in Appendix D: Section 14.1 Fuzzy Cluster Outputs. For these years, similar patterns in the weekly patterns are repeated over time, although the number of assigned clusters is not constant.

7.3.6 Weekly Results for 2018

Despite Table 7.3 showing that the number of sensors increases significantly over time, from 64 to 483, the number of clusters found to best fit the fuzzy analysis for the weekly results did not vary significantly. So, for 2018, the number of clusters is 4, just as was identified in the 2006 data. Figure 7.5 displays the medoid signatures that best represent each cluster.

In Figure 7.5, Medoids 1 to 3 clearly show that for Saturdays, there is a marked increase in footfall compared to the rest of the week. The range of values needs to be interpreted with care however, as the vertical scale represents the standardised values derived from all the footfall data. So, even though for Medoid 1, the Saturday peak is greater than 4, that does not mean the footfall amount is four times greater. However, the standardised values still present interesting differences between the different medoids.

Below is a detailed description of each Medoid, based upon ‘learning’ how to interpret the weekly cluster outputs from the previous years.

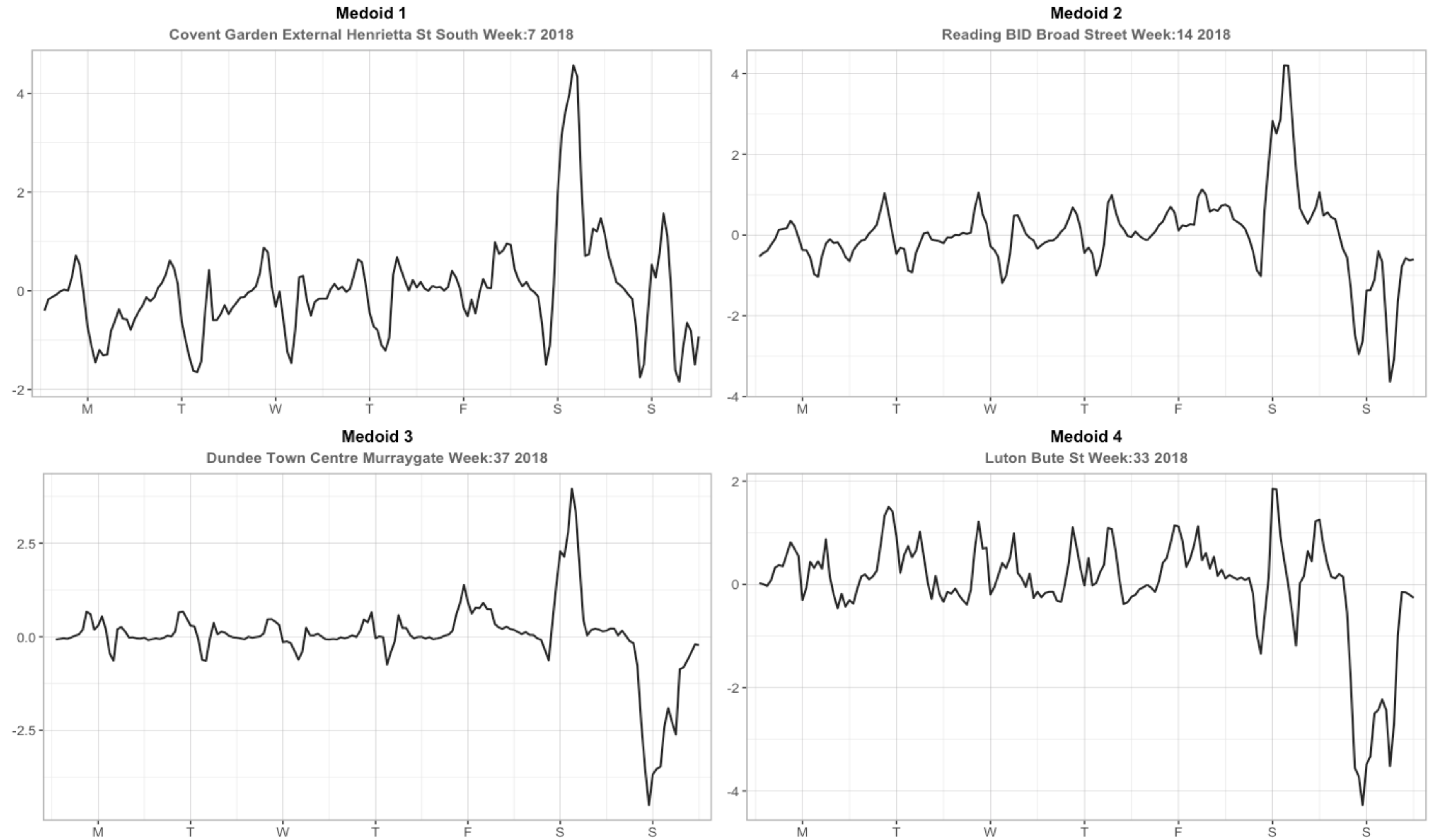


Figure 7.5 - Weekly Medoids for 2018

Medoid 1 has a large increase of Saturday footfall but also a lesser increase for Sunday that exceeds any additional corrections for any of the weekdays. The range of values for the working week indicates the largest range of negative corrections to the daily footfall volumes, especially early afternoons for Monday, Tuesday, Wednesday, and Thursday. Fridays indicate a much smaller reduction in early afternoon footfall and an increase in the evening and night-time volumes. Saturdays begin with a large negative correction suggesting a phase shift of around an hour in the start of the day. This is then followed by the Saturday lunchtime and afternoon peak increase with a lesser peak for evening and night-time footfall. As already mentioned, Sundays have a negative correction for the evening and night-time.

Medoid 2 has a very similar pattern to Medoid 1, except for Sunday and the range of corrections during the week. For Sundays, there is an initial large negative correction, with a slight increase around lunchtime and the early afternoon followed by another decrease in footfall. Sunday is clearly the day with the lowest footfall volumes.

Medoid 3 follows on from Medoid 2 with a much more marked negative correction to Sunday footfall. It is also evident that the increase in Saturday footfall is less for this medoid than is identified in Medoids 1 and 2.

Medoid 4 presents a different pattern to the other medoids. Although there is a very slight increase in footfall for Saturdays and a phase shift on Saturday mornings, the medoid clearly indicates a location where the working week footfall is as significant as that of Saturday. Sunday, like that of Medoid 3, has a very significant fall in footfall volumes.

Table 7.7 shows that Medoid 2 is the most frequently identified best fitting medoid although all the medoids are assigned to locations in an even distribution. The next best fitting medoid though shows a tendency to assign Medoids 2 or 3, suggesting that the Sunday correction to footfall is a better match than identified in Medoid 1.

Table 7.7. Best vs Next Best Fitting Medoids for 2018 Weekly Clusters

	Next Best Fitting Medoid					
Best Fitting Medoid	1	2	3	4	>90%	Total
1	0.00%	22.20%	0.00%	0.04%	1.13%	23.37%
2	14.93%	0.00%	12.36%	2.78%	0.03%	30.10%
3	0.01%	10.44%	0.00%	11.59%	0.24%	22.28%
4	0.11%	3.97%	20.03%	0.00%	0.14%	24.24%
Total	15.06%	36.60%	32.39%	14.40%	1.54%	100.00%

7.3.7 Summary of Weekly Rhythm Types

Table 7.8 lists the weekly rhythm types identified from the descriptive analysis. The most obvious adjustments to territorialisation that the weekly signatures make to the daily signatures are at the weekends, especially Saturdays. However, there are more subtle adjustments also apparent during weekdays.

Table 7.8. Weekly Rhythm Types

Weekly Rhythm Type	Description
Saturday Territorialisation	The increase in footfall associated with Saturdays. However, this is not constant and adjusts throughout the year. For some locations (work locations), there is no increase.
Sunday De-territorialisation	The reduction in footfall associated with Sundays. This though is not constant and can adjust throughout the year. The scale of de-territorialisation is dependent upon urban classification type, with maximum de-territorialisation being experienced by Towns.
Weekday Territorialisation	The adjustments for weekdays can be positive and negative. The adjustments reflect changes in the Daily Rhythms and vary from day to day for the working week. The changes are much less evident than those of the weekend (apart from locations where Saturday has no peak territorialisation).

7.4 Annual Distribution of Medoid Assignments

The previous section considered the weekly medoid assignments for each year with no consideration as to how these change over the period of the year. As with the daily clustering results, 2018 provides the most representative results for all place types, and so were the results investigated. Referring to the medoids identified in Figure 7.5, Figure 7.6 displays for each week, the seasonal variation of the percentage occurrence of assigned best fitting medoids for the 2018 fuzzy cluster results. Figure 7.6 identifies that the assignment of the medoids is not constant over the period of 2018.

Medoid 4 is more prominent in the summer holiday period, suggesting that there are locations where the differences in footfall volumes between weekdays and Saturdays becomes less differentiated – that weekdays increase their territorialisation intensity. The specific increase in Medoid 1 in the autumn period is more difficult to interpret. Medoid 1 not only has an increased territorialisation on Saturdays, but also includes de-territorialisation periods in the afternoon that are at a maximum for Monday and reduce in intensity to being periods of territorialisation for the same period by Friday evening. This suggests that Medoid 1 could be a medoid particularly related to the more functionally complex place locations as found at Major City and Regional Centre locations where the daily signature has already been seen to extend into the afternoons, evening, and night-times. This could imply that the urban classification types can identify different medoid relationships as discussed in the following sections.

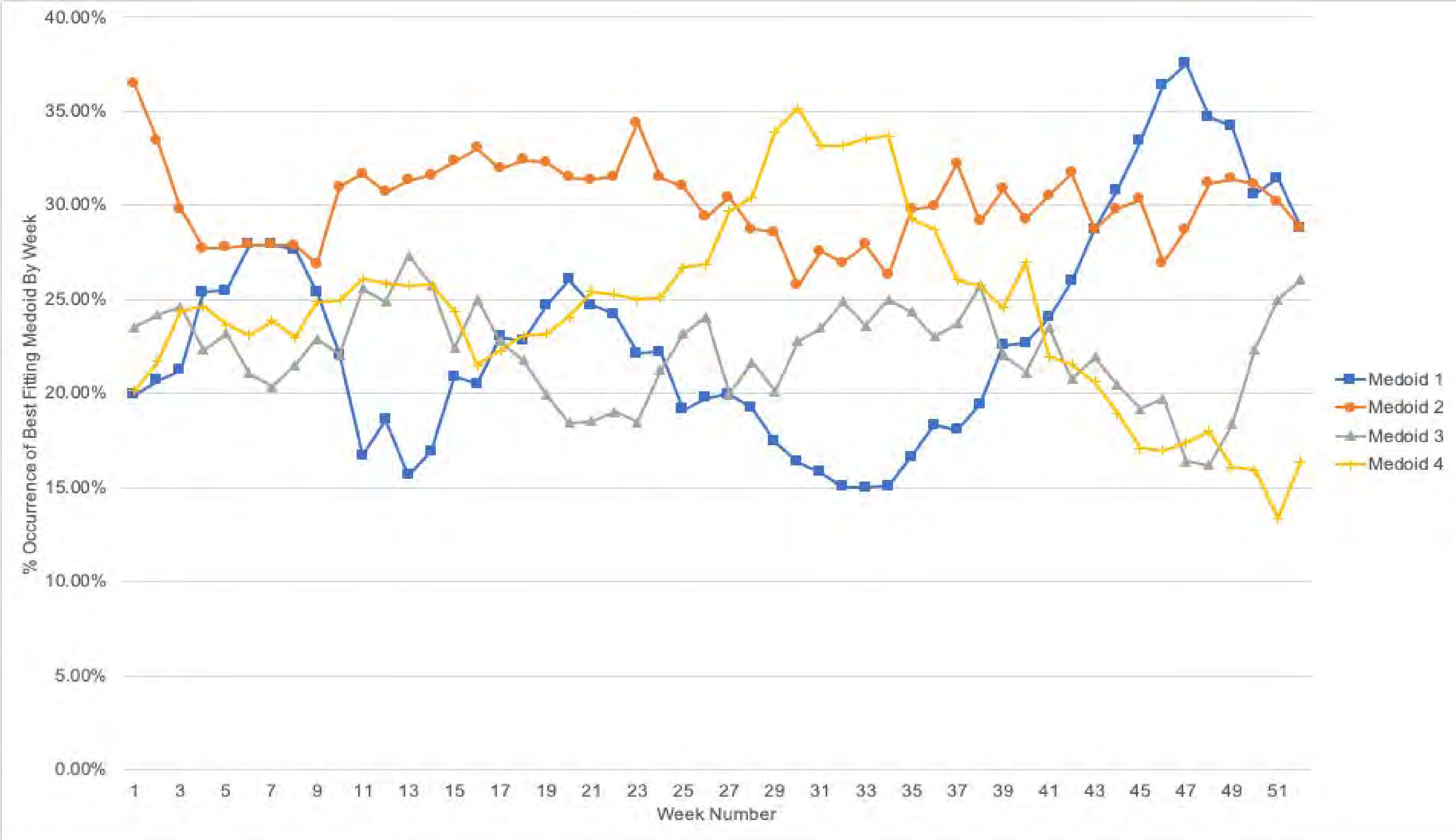


Figure 7.6. Seasonal variation of 2018 fuzzy cluster allocations

7.4.1 Annual Distribution of Medoids for Major Cities

From Figure 7.7, it is evident that Medoid 3 only has a minor contribution. Medoid 2 follows the trend from Figure 7.6 with a relatively constant assignment over the annual period whereas Medoids 1 and 4 suggest a more seasonal pattern. Medoid 1 appears to be more dominant outside the holiday periods suggesting that the weekday and Saturday de-territorialisation and territorialisation adjustments already noted for this Medoid are more significant for these periods. Conversely, Medoid 4 suggests an increased territorialisation for weekdays and a degree of de-territorialisation for Saturdays in comparison so that the weekdays and Saturdays are less differentiated during the summer holiday period.

To conclude, for Major City locations, the following observations are made:

- During the Summer holidays, the medoids suggest that the differences between weekdays and Saturdays are reduced compared to other times of the year.

- Outside of holiday periods, the corrections to weekday afternoon, evening and night-time footfall suggest a reducing de-territorialisation from Monday to Thursday.

- Outside the Summer period, the day of maximum territorialisation is Saturday.

- Sundays are the day with the greatest de-territorialisation, but this correction is less intense for Major Cities than other location types.

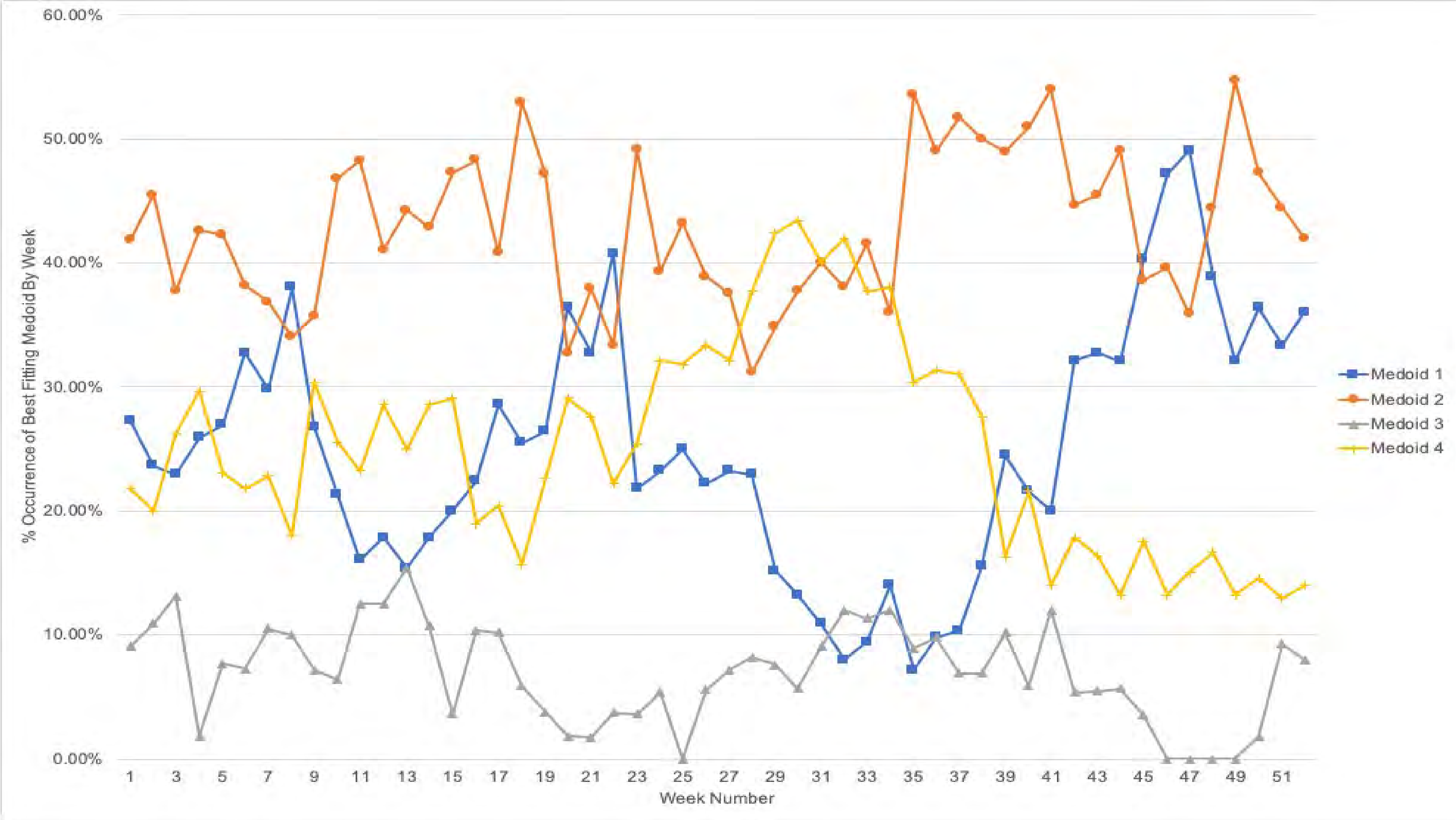


Figure 7.7. Seasonal variation of 2018 fuzzy clusters - Major Cities

7.4.2 Annual Distribution of Medoids for Towns

In contrast to the Major City plot in Figure 7.7, Figure 7.8 shows that for Towns, Medoid 3 is by far the most significant signature. This suggests that towns are much more likely to have a Saturday peak but also a very large reduction in footfall on Sundays. Additionally, although the weekday corrections are of a lesser magnitude to that of Medoid 1, there is still a pattern of Monday to Thursday territorialisation late morning/lunchtime followed by a de-territorialisation correction. By Friday though, the lunchtime, afternoon and evening periods show a positive correction to the daily footfall signature - end of the week and Friday night UK culture resulting in territorialisation of the sensor locations for the Towns.

The main observations are:

- The largest de-territorialisation takes place on Sundays, and so is the day of minimum footfall.

- There is much less of a seasonal pattern than displayed by the city locations.

- However, there is still a suggestion that a degree of weekday vs Saturday footfall volumes become less differentiated over the summer period.

- Medoid 3 is the dominant signature for Towns.

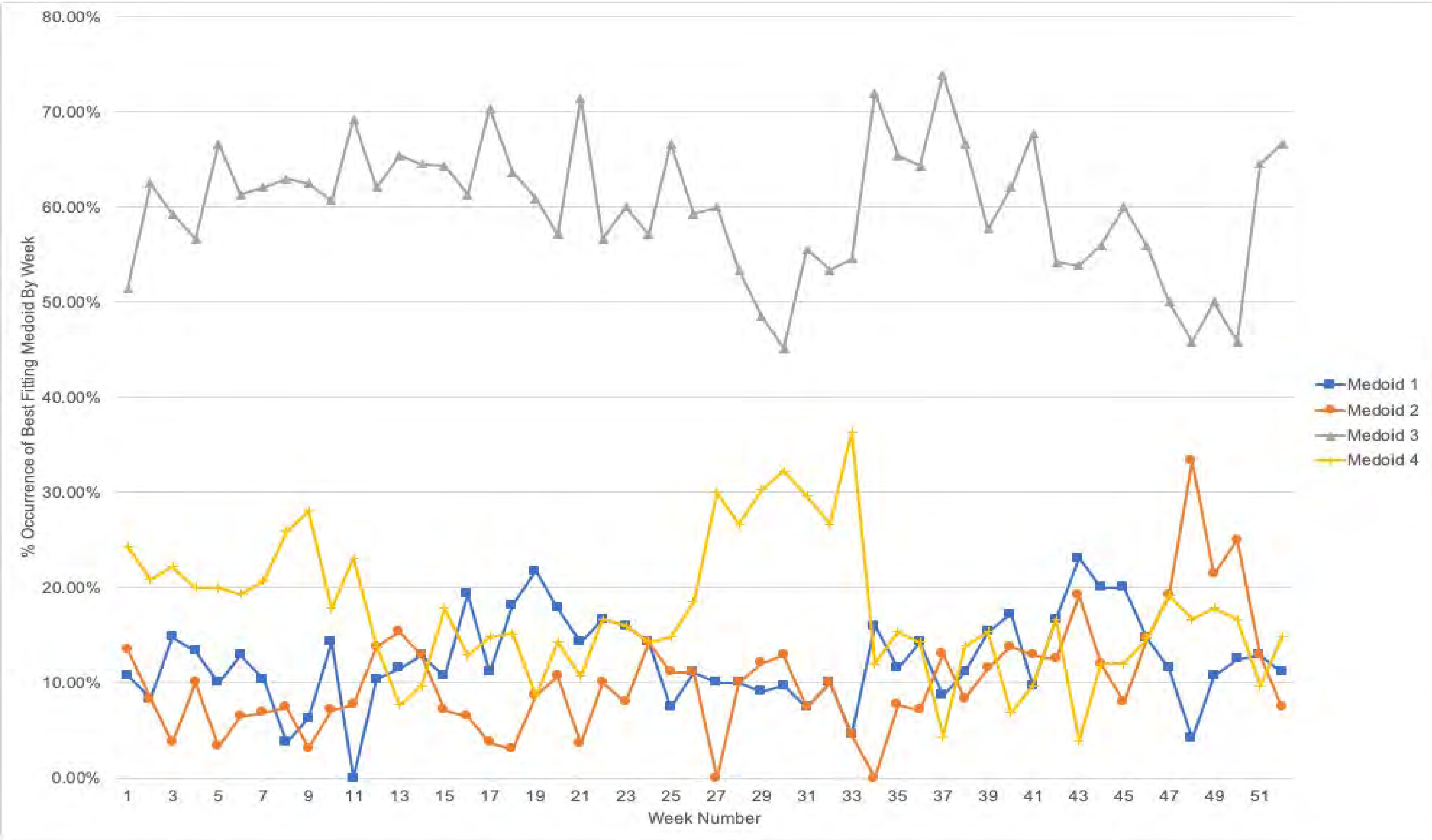


Figure 7.8. Seasonal variation of 2018 fuzzy clusters - Towns

7.4.3 Annual Distribution of Medoids for Major Towns

Figure 7.9 shows how the assignment of weekly clusters varies throughout the year for locations classified as Major Town Centres. Figure 7.9 again shows the seasonal fluctuations between Medoids 1 and 4. Both Medoids play a more significant role for Major Towns than with Towns and Medoid 3 has a reduced role, although both Medoids 1 and 3 appear to follow the same pattern. The latter observation suggests that the degree of weekly variation is an average between the two. Medoid 4 still has a summer influence, again suggesting that in the summer holiday period, weekdays see far more territorialisation than at other times of year.

The main observations are:

- There is a more seasonal shift with the medoid allocation than was evident for Towns.

- The pattern of summer holidays having increased territorialisation of weekdays and de-territorialisation of Saturdays compared to the rest of the year is evident.

- Outside of the Summer holidays, the weekday and Saturday corrections are influenced by both Medoids 1 and 3, suggesting the actual corrections lie between both.

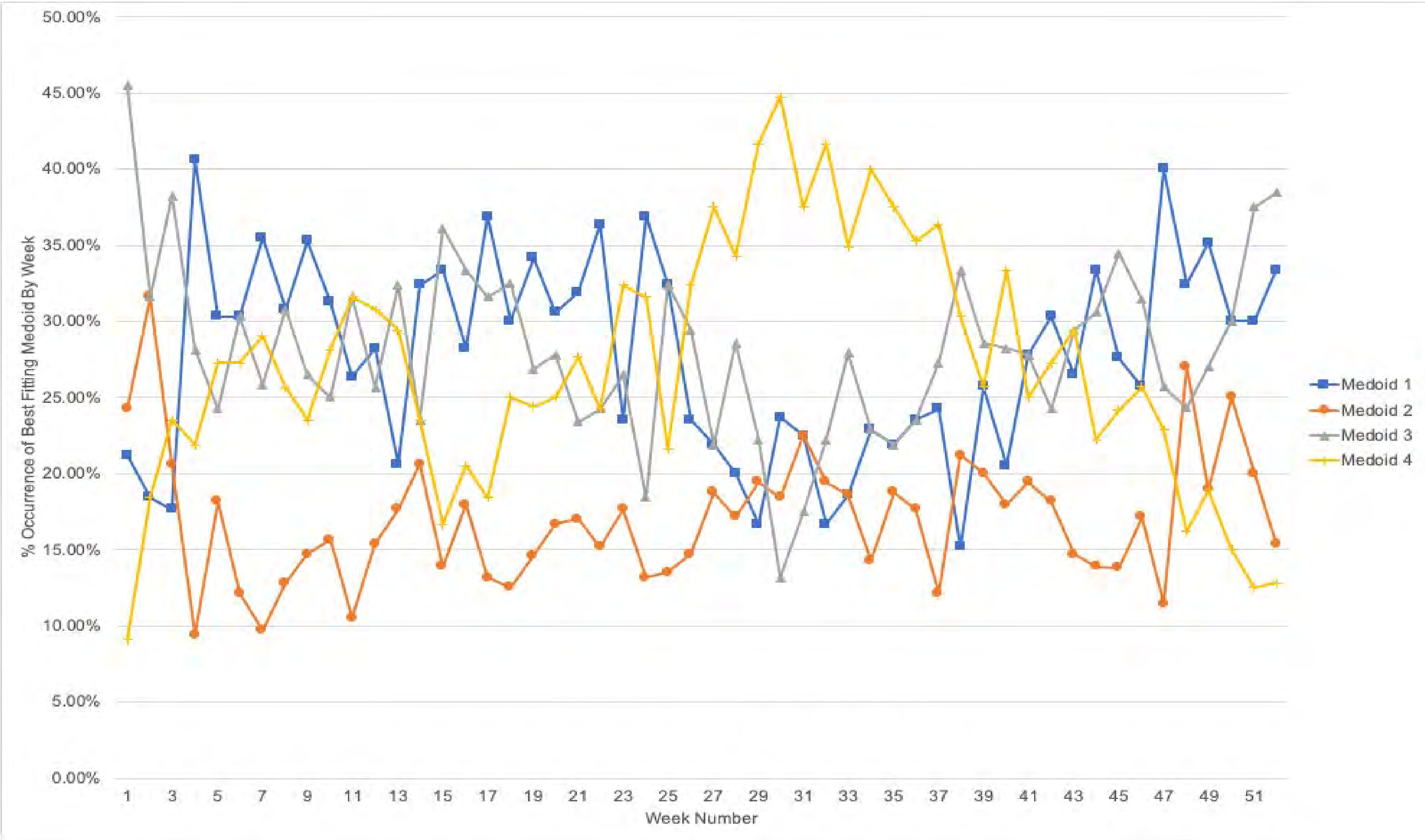


Figure 7.9. Seasonal variation of 2018 fuzzy clusters - Major Towns

7.4.4 Annual Distribution of Medoids for Sub-Regional Centres

Figure 7.10 below displays how the assignment of weekly clusters varies throughout the year for locations classified as Sub-Regional Centres.

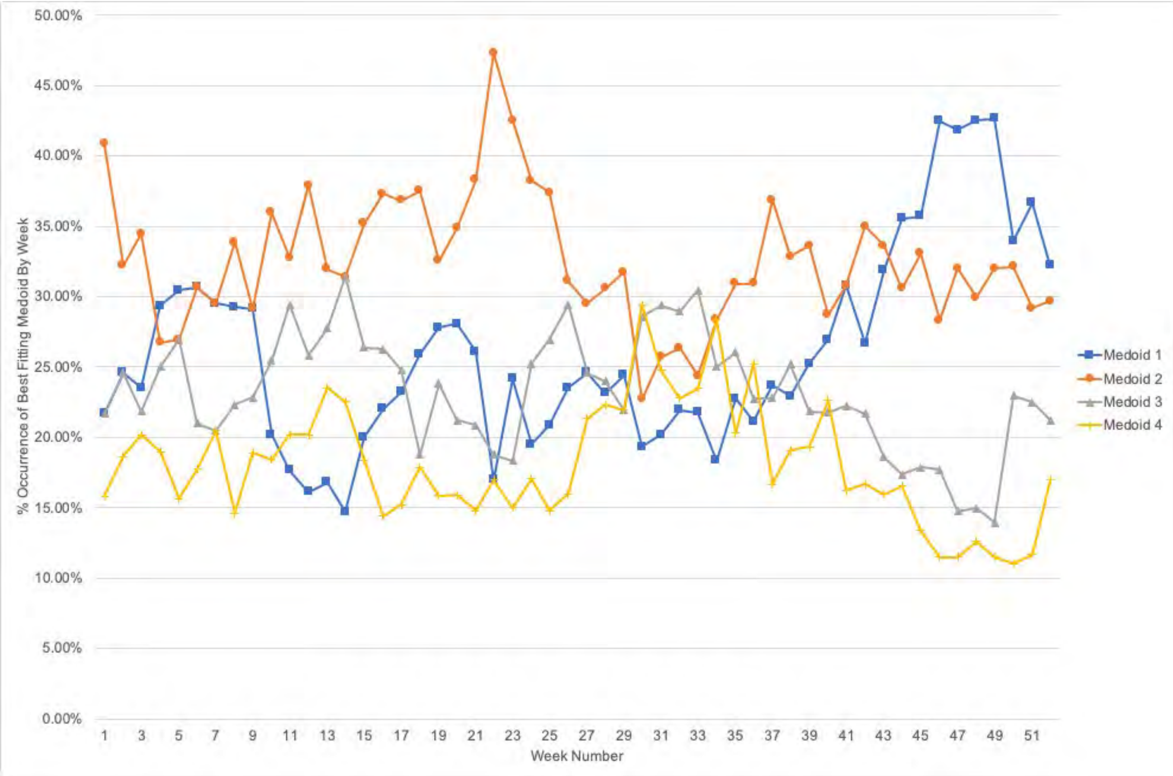


Figure 7.10. Seasonal variation of 2018 fuzzy clusters - Sub-Regional Centres

For Sub-Regional Centres, Figure 7.10 identifies that Medoid 2 is more significant until the Christmas period where both Medoid 2 and 1 dominate. There is less of a seasonal pattern than identified for the Major Towns and Figure 7.10 shows that the allocation of Medoids is roughly even across all 4 instances, suggesting problems with identifying a unique signature (collectively) for the summer period. The increased allocation of Medoid 1 later in the year can be anticipated to be a result of increased Christmas period shopping during this period.

7.4.5 Annual Distribution of Medoids for Regional Centres

Figure 7.11 displays how the assignment of weekly clusters varies throughout the year for locations classified as Regional Centres.

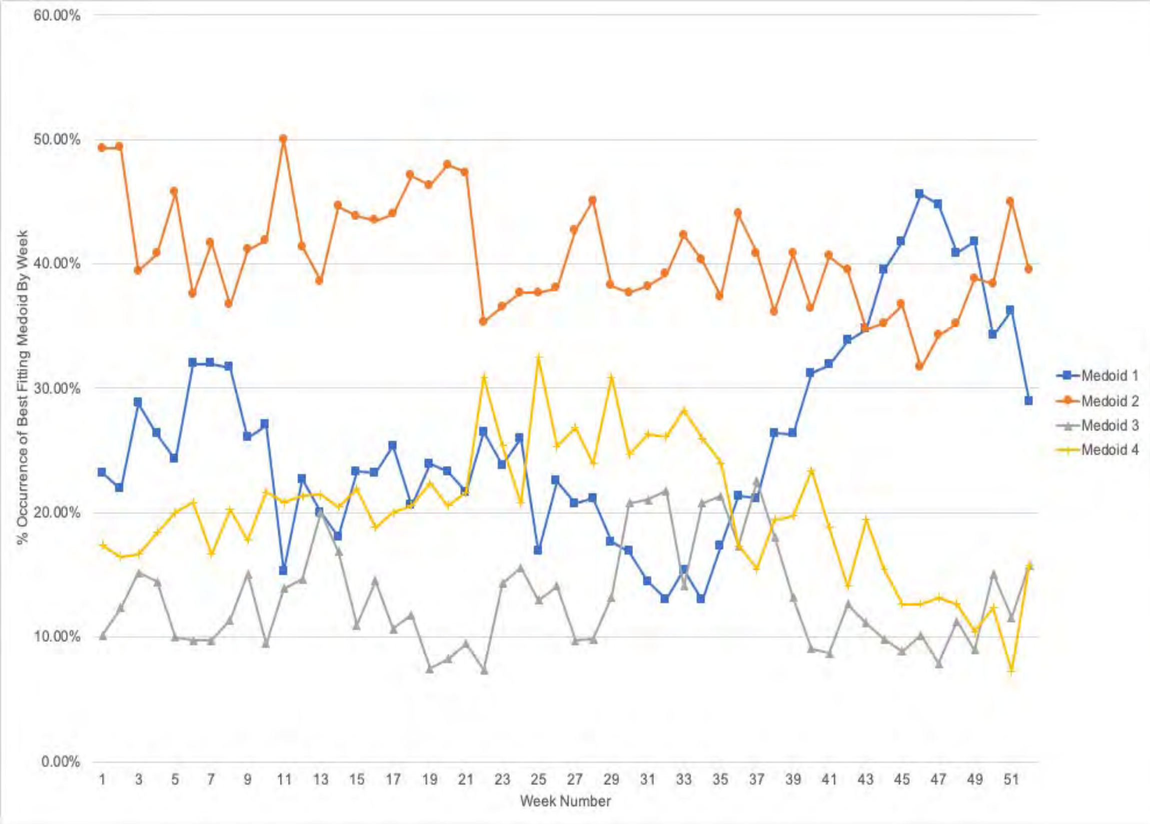


Figure 7.11. Seasonal variation of 2018 fuzzy clusters - Regional Centres

For the Regional Centres, Figure 7.11 shows a fairly constant allocation of medoids until the start of the Autumn period where Medoid 1 increasingly becomes much more dominant, replacing Medoids 3 and 4. This suggests that for regional centres, Saturdays and Sundays in this period (run up to Christmas) see a significant increase in footfall traffic – as would be anticipated.

7.4.6 Weekly Seasonal Changes

One of the questions identified, therefore is whether there is a reduction in the differentiation between Saturdays and weekdays in the summer months? To help answer this question, the following analysis was carried out using the imputed footfall data, rather than the weekly decomposed values, to ensure that any findings were independent of any influence from the STL algorithm used to create the weekly signatures.

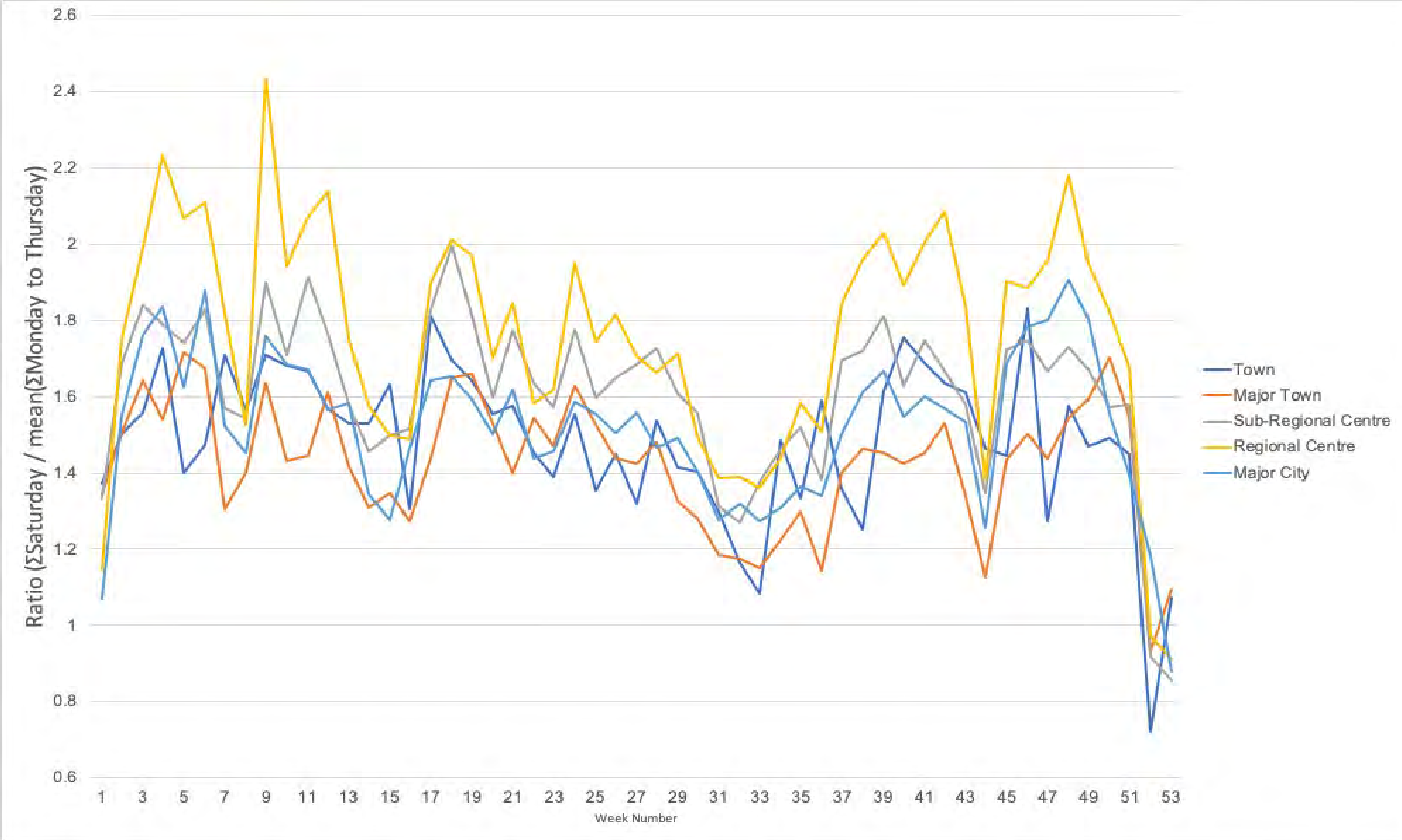


Figure 7.12. 2007 to 2009 weekly averaged footfall ratios of Saturday vs Weekday

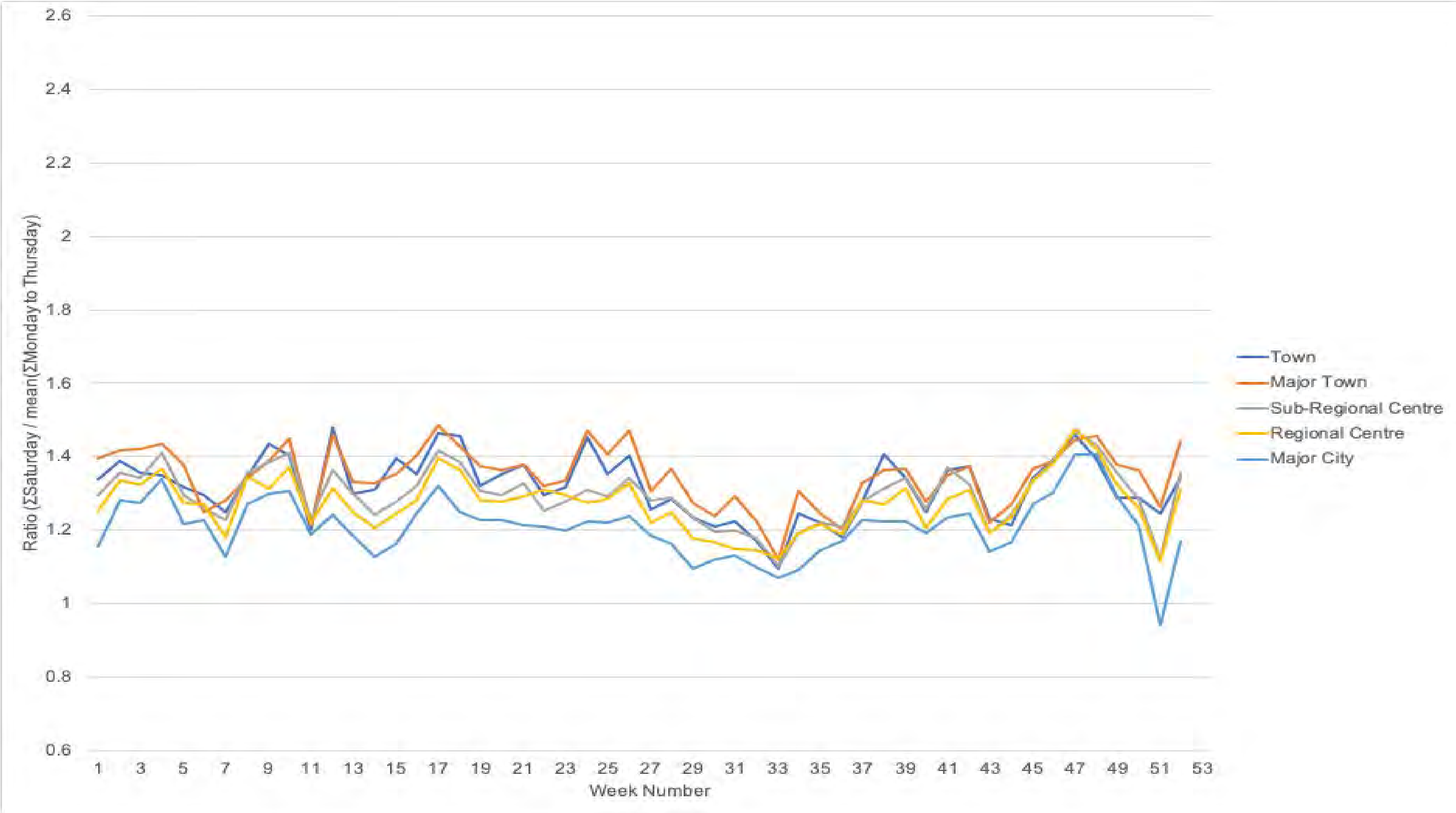


Figure 7.13. 2016 to 2018 weekly averaged footfall ratios of Saturday vs Weekdays

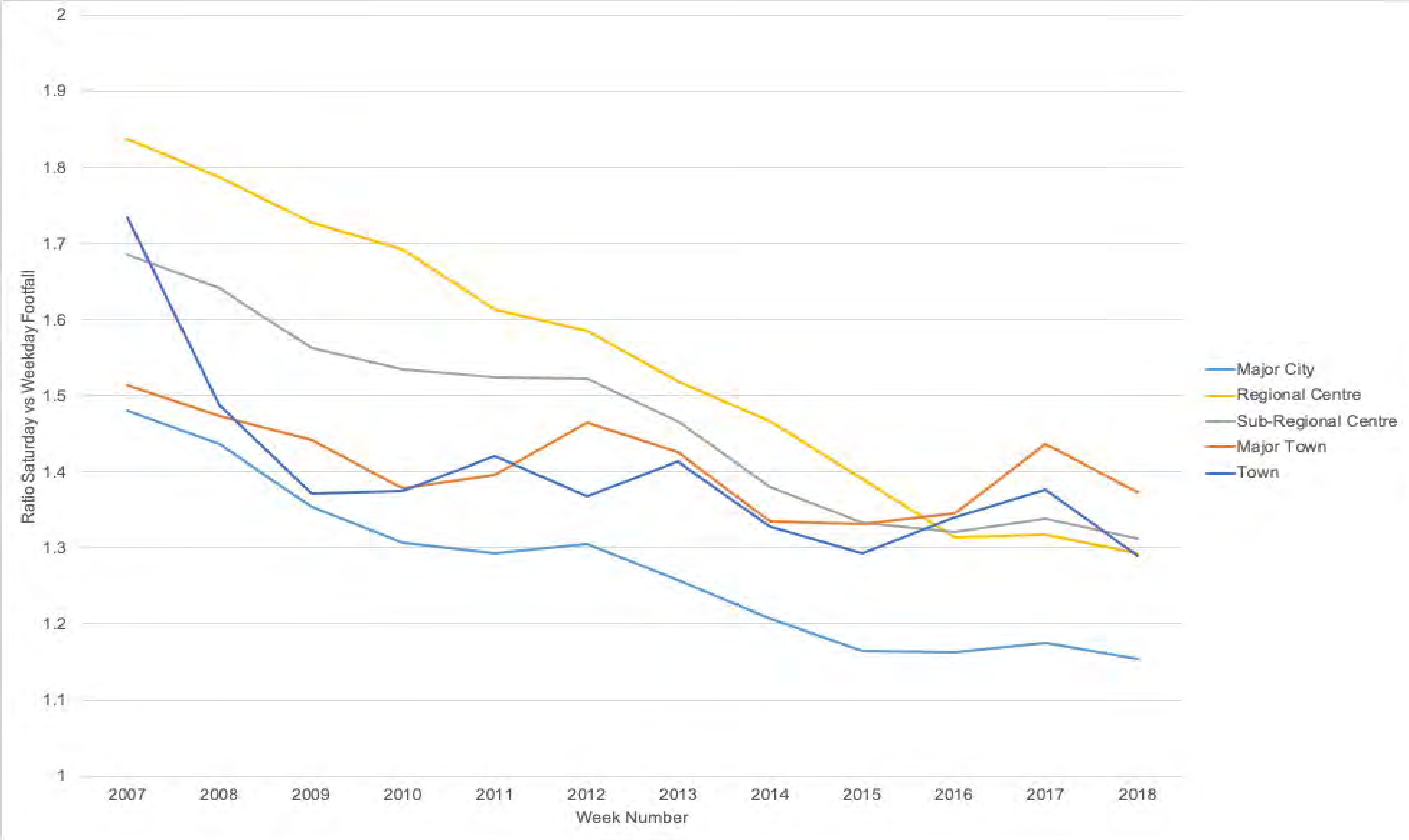


Figure 7.14. Annual averaged ratios of Saturdays vs Weekdays

Two sample periods were taken, 2007 to 2009 and 2016 to 2018. By taking results from both these periods, the intention was to smooth out individual annual patterns. The metric used is a ratio of Saturday footfall counts vs the average footfall counts for Monday to Thursday. Friday was not included as, based upon the weekly signatures, the cluster analysis suggests it has a profile that is different to the other weekdays. Specifically, the tendency for an increase in footfall in the late afternoon, evening, and night-time periods on Fridays, but not to the same degree as Saturdays. Figure 7.12 and Figure 7.13 show the changes to the ratios over the two periods and are segmented by urban classification type. Note that the vertical scale is the same for both graphs to facilitate comparison. The most obvious difference between Figure 7.12 and Figure 7.13 is the reduction in variability between the different urban classification types and the range of values. Regional Centres, which is confirmed in Figure 7.14, show the greatest reduction in the ratio value overall, a trend closely mirrored by sub-regional centres. Whereas Major Cities show the least decline, Towns and Major Towns have a more variable trend. Note that the initial value for towns in 2007 in Figure 7.14 is due to a very low representation of Town types in the 2007 data and so can be ignored.

Both Figure 7.12 and Figure 7.13 show reductions in the Saturday vs Weekday ratio of the Easter, Summer and Autumn holiday periods and this confirms the medoid signature findings that the differentiation between weekdays and Saturdays is reduced in the holiday periods. Both figures also show that the effect was greatest at the start of the data sampling period and has reduced over time.

Figure 7.15 and Figure 7.16 display weekly ratios of Saturday vs Sunday for each urban classification type. As with the comparison to weekdays, there is a general reduction in variability as the ratio values fall from the period 2007-2009 to 2016-2018.

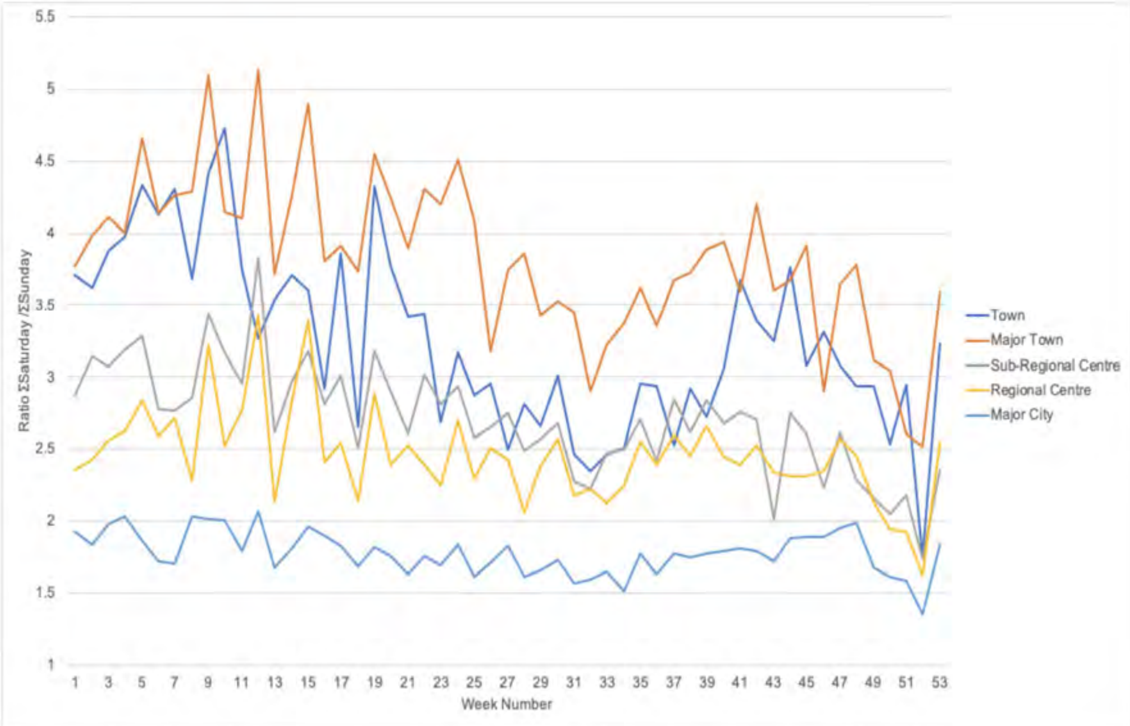


Figure 7.15. Ratio of Saturday vs Sunday 2007 to 2009

The ratio results for Major cities present the lowest ratio values and minimal seasonal variation, which matches the signature of Medoid 1 in Figure 7.5 for the 2018 cluster analyses - the most dominant medoid. Towns and Major Towns display the highest contrast between Saturdays and Sundays. Medoid 3 in Figure 7.5, has a large de-territorialisation correction for Sundays which is typically associated with Towns and to a degree Major Towns and is why the Saturday vs Sunday ratio values are greatest for Towns and Major Towns. Regional and sub-regional locations appear to be similar and sit between the other urban classification types. As already noted, all the ratios appear to reduce in value between the two time periods, with Major cities the least impacted and Major Towns and Towns the most. In terms of seasonal patterns, both periods suggest the greatest differentiation occurs at the start of the year with a more marked reduction of the summer period for Towns and Major Towns in the earlier period of 2007-2009 although, this is much less evident in the 2016-2018 plots.

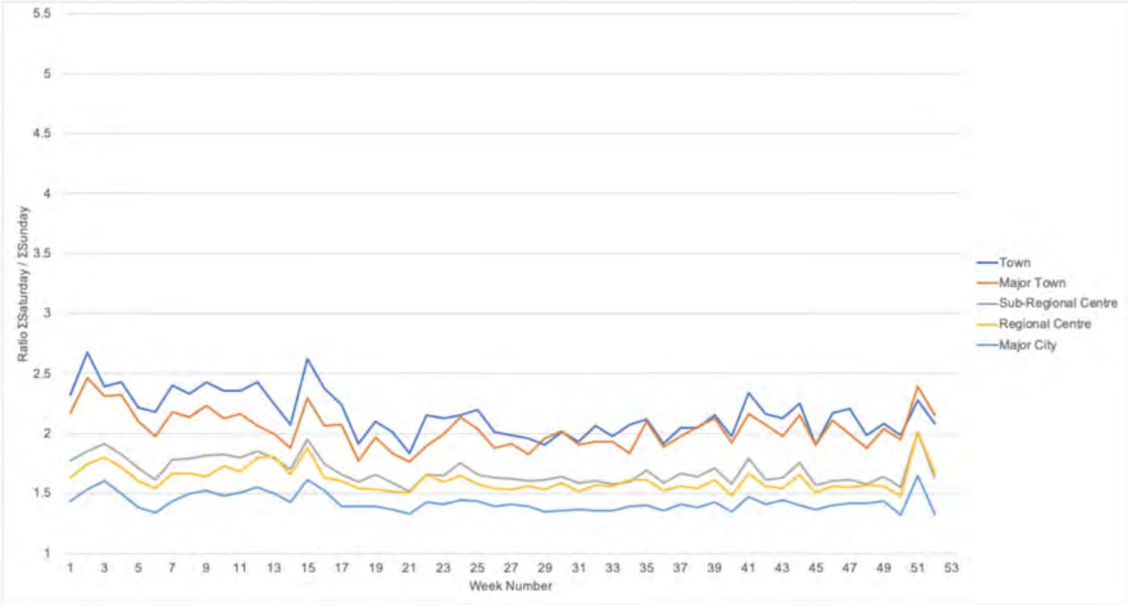


Figure 7.16. Ratio of Saturday vs Sunday 2016 to 2018

7.5 Summary

To answer the question regarding how places differ from each other, the weekly signatures indicate a relationship between the urban classification type and assigned medoid signatures. The most obvious characteristics of the weekly signatures relate to the days of Saturday and Sunday. For most locations, Saturday is the day of highest footfall and Sunday the lowest. For Major Cities, Sundays are likely to be much less a period of de-territorialisation than for Towns and Major Towns. The Saturday territorialisation period varies in intensity over the period of the year and for many locations; the differentiation between Saturdays and Weekdays is at a minimum during the period of the summer holidays and similar reductions can also be identified for Easter and holidays breaks. As the ratio of Saturday to Sundays and Saturdays to Weekdays has reduced from 2007 to 2018, it is evident that the territorialisation impact of Saturdays for all locations has reduced over time.

There are, however, much more subtle signals evident in the weekly medoid data with changes in the working week indicating a reducing de-territorialisation in the afternoons as the working week progresses. This makes the weekly medoids the most difficult to assess for the combined sensor locations but also suggests it is the most interesting. The adjustments for each day are effectively adjustments to the daily rhythms already identified in Chapter 8 and these adjustments then impact the annual rhythms detailed in Chapter 7. Table 7.8 p255 provides a summary of the dominant weekly rhythms identified.

The results all show a reduction in variability over the years that is associated (obviously) with the reductions in footfall. A process analyst might view this reduction as indication of improving, more predictable processes in operation (Brook, 2006) whereas for the town manager at each location, less variability has resulted in reduced footfall. For place, variability therefore is good (Jacobs, 1961; Gehl, 2010; Kärrholm and Wirdelöv, 2019).

8 Exemplar Results – Manchester

8.1 Approach for the Exemplar Analyses

In the previous chapters, the cluster analysis aimed to understand how places are changing using aggregated sensor data across all locations. In the following sections, the focus shifts to individual towns and cities where the attention is upon asking the following research question:

> *What can footfall offer as a measurement of how change occurs over time in a particular place?*

To perform this analysis and answer the above research question, exemplar cases were selected based upon the criteria listed below:

- To explore the diversity of assemblages that exist for any location, the exemplar place needed more than one footfall sensor present.
- At least 10 years of footfall data was required to ensure that the cluster analysis could pick out short-term and overall trends in the data as suggested by Richard et al. (2009).
- A location was required that demonstrated a diverse range of daily and weekly signatures (based upon the 2018 results for all locations). This was to demonstrate how sensor locations in the same place differ in relation to each other. In this case, Manchester was chosen.
- A location was required that demonstrated minimal variability between the daily and weekly signatures. This was to demonstrate sensitivity to small changes. In this case, Rotherham was chosen.

There were other locations that could also have been chosen. For example, Durham provided an excellent example of the term time annual signatures, where during the student holidays, footfall visibly drops. Cities other than Manchester could also have been selected, such as Leeds, Liverpool, or Nottingham. In the end, the exemplar analysis was limited to two cases as it was considered there was sufficient evidence to answer the research questions. However, the results, especially those for Manchester, present a practical use of the research design outputs and how these might be useful to place managers.

For the combined sensor fuzzy cluster results, a year-by-year approach to performing the analysis for each STL decomposed signature component (annual, daily, and weekly) was adopted. However, for the exemplar locations, since the data volumes were much smaller, all the available years of location sensors data could be extracted and processed with a single fuzzy cluster analysis for each of the STL component signatures. Consequently, it was possible to evaluate how the daily and weekly signatures changed (or not) over the years without the added confusion of interpreting results with different numbers of medoids for each year. As the data volumes were sufficiently small, this was possible for both the exemplars without computer memory problems being encountered. Thus, no sampling was necessary. However, the annual signatures were not processed this way as comparing periods was complicated, for example, by Christmas falling on different days of the week and Easter being over different weeks each year.

From the weekly and daily combined results came the idea of investigating changes to the fuzzy cluster allocations over the period of a year. With the exemplar results, since the cluster analyses were processed for much longer periods of time, one of the presentational tools this study used to evaluate the changes to fuzzy cluster allocations was run charts. Run charts are a time-series with the median shown as a horizontal line and provide an objective way of understanding how the fuzzy cluster allocation changes over time with minimal mathematical complexity (Perla et al., 2011). As Perla et al. (2011) note, the run chart provides a means of assessing time ordered data in a way that summary statistics ignore. Run charts are a valuable tool in process improvement (Anhoej, 2015), although for this study their use is simply to show how fuzzy cluster allocations evolve and change over time. Run charts are used for both the exemplar daily and weekly results that follow and were developed using the R package ggplot2 (Wickham, 2016) from the graphical outputs provided by R package qicharts2 (Anhoej, 2020).

8.2 Manchester

Manchester was chosen as an exemplar due to the variety of different signatures identified between the different footfall sensors. All the sensors for the centre of Manchester are within the BID area (CityCo & ManchesterBID, 2020). The footfall results for Manchester are provided by four sensors, identified in Figure 8.1. The sensors located at: King Street; Market Street; and New Cathedral Street provided data from the start of 2007. The fourth sensor located at the Exchange by the Arndale Centre became available in 2014. All the sensors for the centre of Manchester are within the CityCo and Manchester BID area (CityCo & ManchesterBID, 2020).

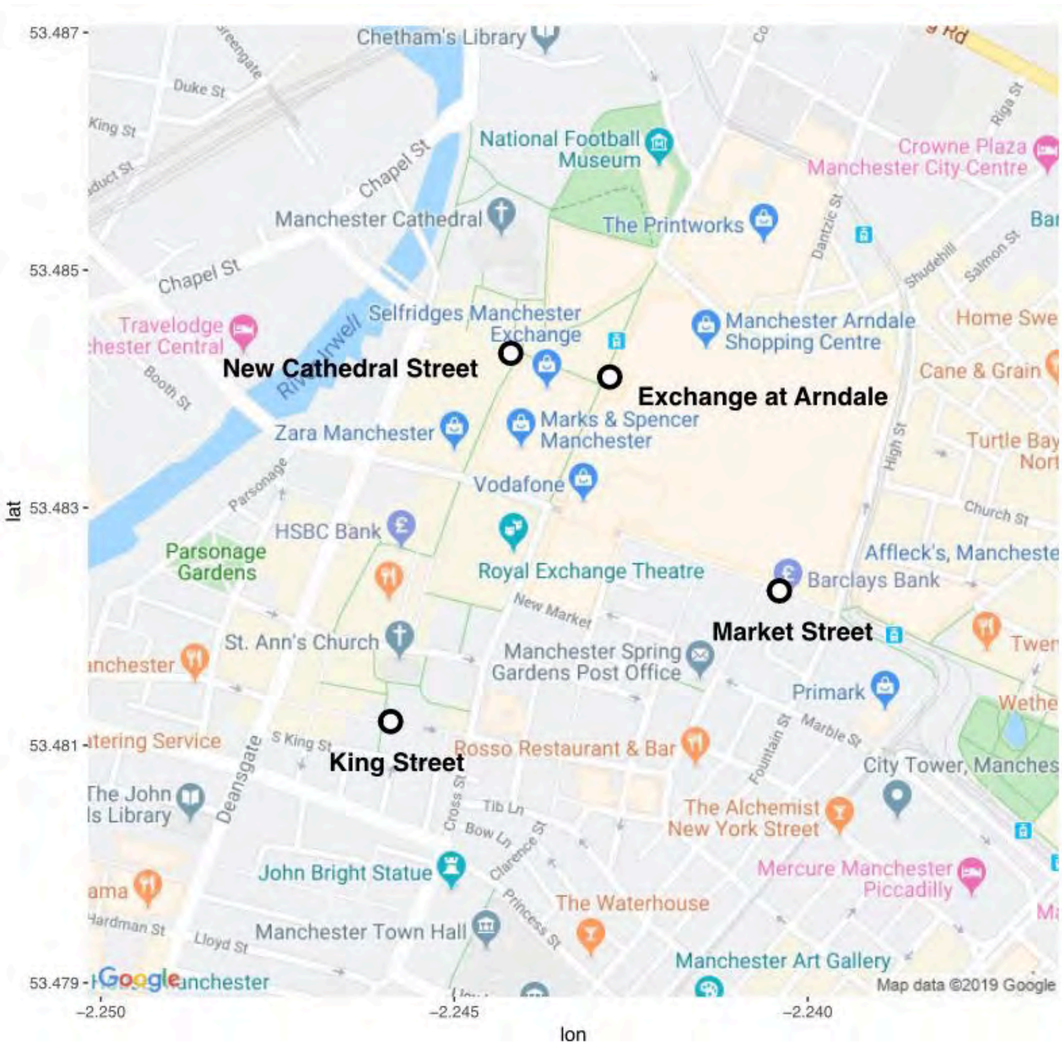


Figure 8.1. Footfall sensor locations in Manchester

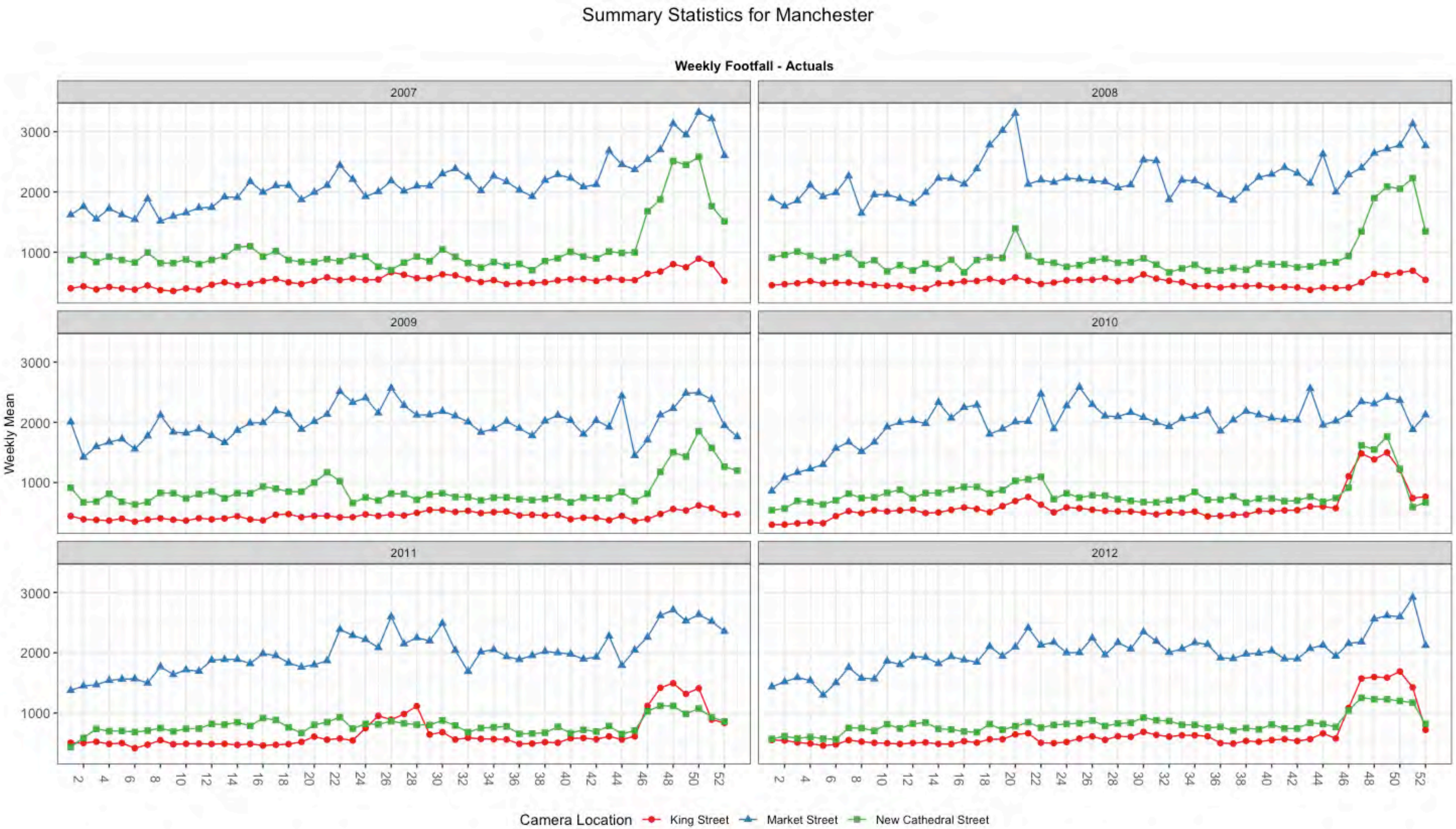


Figure 8.2. The mean weekly imputed footfall for each of the Manchester centre sensors for the period 2007 to 2012

Summary Statistics for Manchester

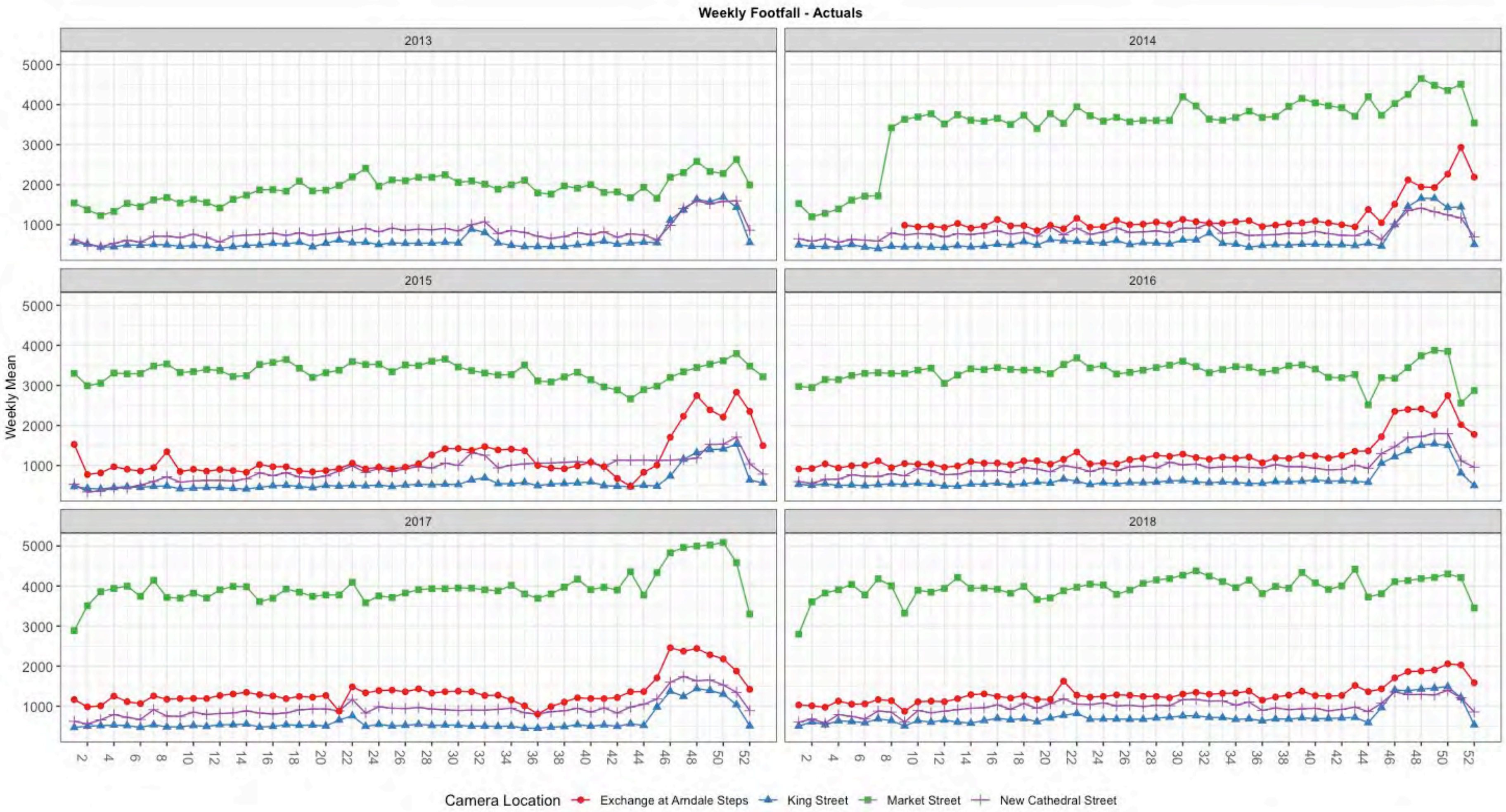


Figure 8.3. The mean weekly imputed footfall for each of the Manchester centre sensors for the period 2013 to 2018

Table 8.1. Annual Analysis Types from the collective annual cluster analyses

Year	King Street	Market Street	New Cathedral Street	Exchange at Arndale Centre Steps
2007	MF-Xmas + Mixed	MF-Xmas + Mixed	MF-Xmas	-
2008	MF-Xmas + Mixed	Mixed + MF-Xmas	MF-Xmas + Mixed	-
2009	MF-Xmas + Mixed	MF-Xmas + Mixed	MF-Xmas	-
2010	MF-Xmas	Mixed + MF-Xmas	MF-Xmas	-
2011	MF-Xmas + Mixed	MF-Xmas + Mixed	MF-Xmas + Mixed	-
2012	MF-Xmas	Mixed + MF-Xmas	MF-Xmas	-
2013	MF-Xmas	MF-Xmas + Mixed	MF-Xmas	-
2014	MF-Xmas + Term Time	Not Definable	MF-Xmas + Mixed	-
2015	MF-Xmas + Term Time	Mixed + MF-Xmas	MF-Xmas + Mixed	MF-Xmas + Mixed
2016	MF-Xmas	MF-Xmas + Mixed	MF-Xmas + Mixed	MF-Xmas
2017	Not Definable	Mixed + MF-Xmas	MF-Xmas + Mixed	Mixed + MF-Xmas
2018	MF-Xmas	MF-Xmas + Mixed	MF-Xmas + Mixed	MF-Xmas

Both Figure 8.2 and Figure 8.3 show how the mean weekly imputed footfall amounts have changed over time. For most years, all the sensors display an increased territorialisation for the Christmas period, whereas for much of the rest of the year footfall was relatively constant, identifying the locations as a mixture of multi-functional use and Christmas period shopping, the MF-Xmas annual analysis type identified in Chapter 7 (see Table 5.13 on page 194 for a summary of the annual analysis types). This is evidenced in Table 8.1 where most locations show that MF-XMAS is the dominant annual analysis type. Yet the pattern is not constant from year to year and in some years, for example 2018 at the Market Street sensor location, no increased territorialisation is evidenced at Christmas. Note the sudden jump in footfall amounts for Market Street in 2014, which coincides with a year when no specific fuzzy allocation of an annual medoid could be identified – see Table 8.1.

Reviewing the annual analysis types in Table 8.1, the fuzzy cluster analysis predominantly assesses each sensor as having a MF-Xmas analysis type, and in addition, there is also a degree of seasonality identified, which sometimes is more dominant than the Christmas peak period (see Market Street). The weekly mean results in Figure 8.3 show that Market Street in 2018 has no indication of a Christmas peak in footfall whilst the annual cluster assigns the MF-Xmas analysis type as the dominant type. Despite there being no Christmas period peak, the overall steady state of the footfall throughout the year still best matches the MF-Xmas type. Ideally therefore, the Christmas period would be considered as an independent rhythm to the rest of the year.

The following sections take the same approach used for analysing the yearly combined sensor results by firstly performing a cluster analysis on the decomposed daily and weekly signatures. Note that the annual signature analysis was not rerun. The choice of the optimal number of medoids for both the daily and weekly cluster analyses is detailed in Appendix E – Exemplar Results.

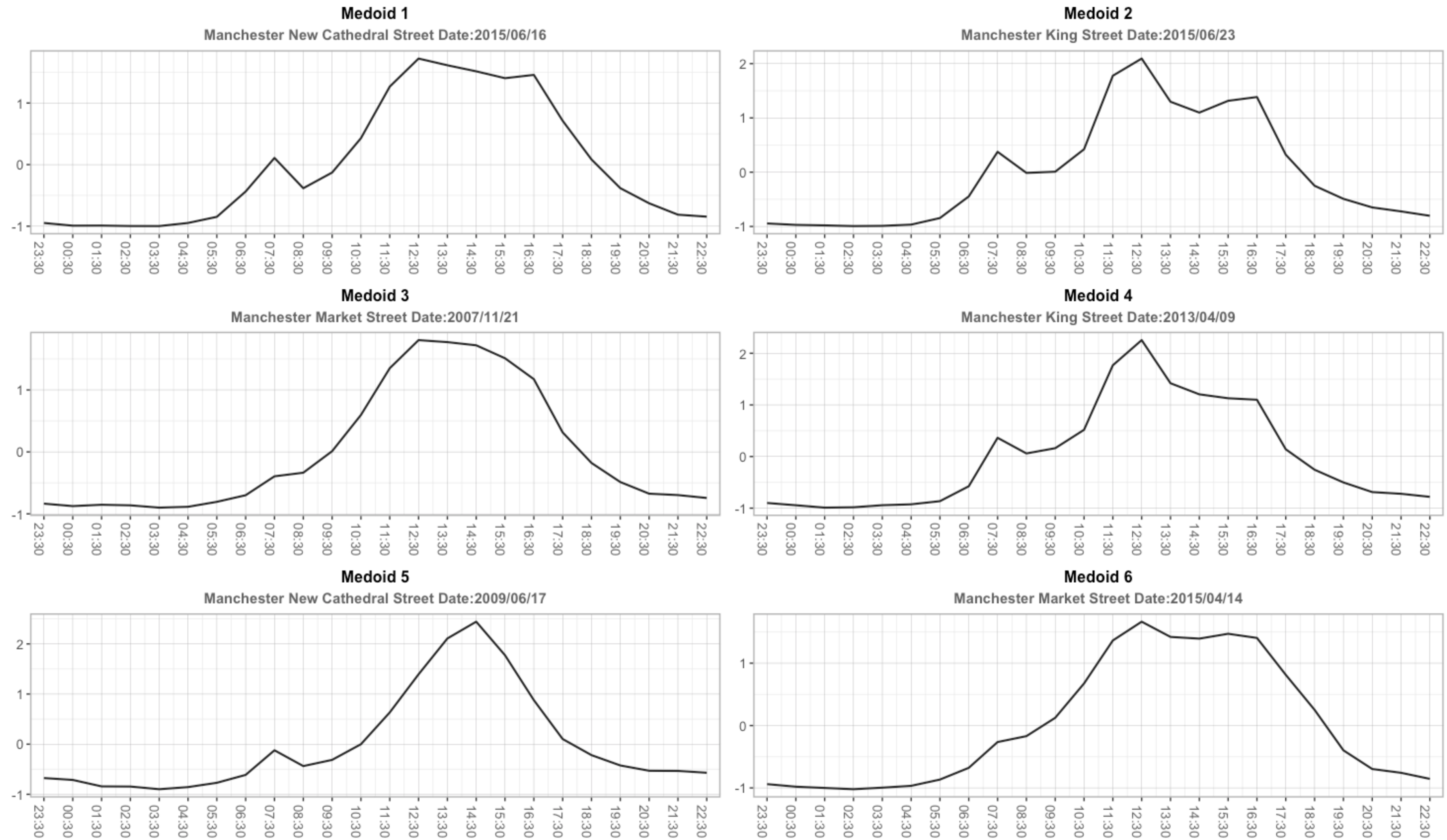


Figure 8.4. Daily Medoids for Manchester footfall sensors – 2007 to 2018

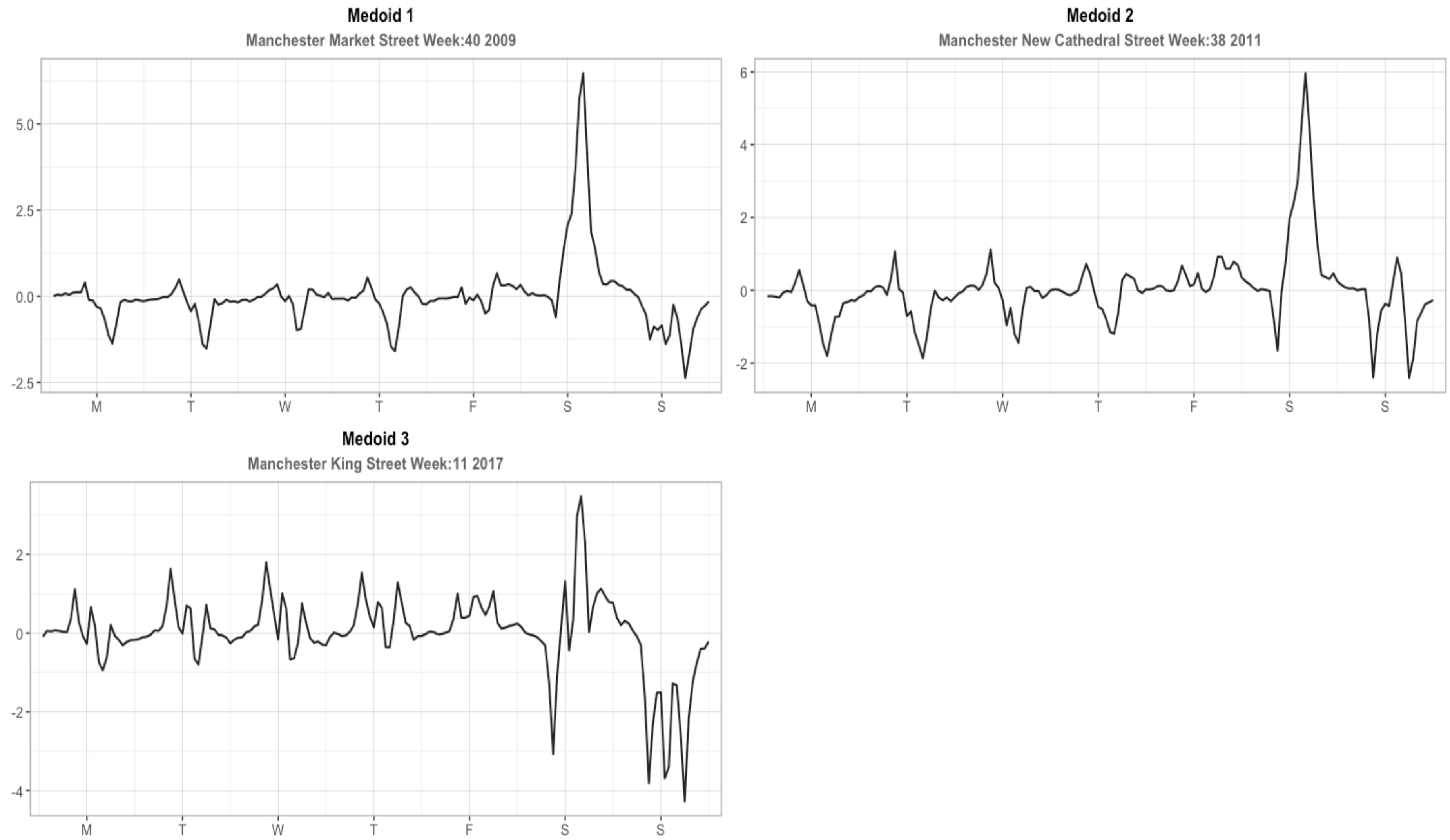


Figure 8.5. Weekly Medoids for Manchester footfall sensors - 2007 to 2018

8.3 Daily Analysis Results

Figure 8.4 displays the medoids that represent each fuzzy cluster for the period of analysis between 2007 and 2018. As Manchester is a Major City, as was found for the collective results, the daily 24-hour period signatures (remember that the medoids do not represent individual days of the week) extend beyond the midday period into late afternoon and early evening. However, there is no night-time territorialisation picked out apart from Medoid 5, and this is minor. Figure 8.4 also indicates early morning (07:00 to 08:00), lunchtime (12:00 to 13:00) and end of the working day (16:00 to 17:00) peaks in all the medoids except for Medoid 5 which has a peak in the afternoon between 14:00 to 15:00. The Medoids in Figure 8.4 suggest that there is a combination of working day rhythms with footfall registering for the start of the working day, lunchtimes and going home. These rhythms are very evident in Medoids 2 and 4. Medoids 1 and 6 suggest that the working day pattern is modified by an intensification in territorialisation in the afternoon period. Medoid 6 also suggests that the period after the initial morning peak as viewed in Medoid 1 also has a period of territorial intensification. Medoid 5 presents a separate pattern with the morning peak still identifiable, but the lunchtime and evening peaks are replaced by a period of territorial intensification in the afternoon. The medoids identified by the analysis reflect those identified by Lugomer and Longley (2018).

8.4 Weekly Analysis Results

Figure 8.5 displays the weekly medoids (168 hours of data from Monday to Sunday) that represent each fuzzy cluster for the period of analysis between 2007 to 2018. As with the annual collective results, there is a large positive correction for Saturdays in all 3 Medoids. However, Medoid 3 provides a smaller correction and, during the week periods also has positive corrections to the morning and afternoon periods. Also note that there is no large correction for Sundays in Medoids 1 and 2, whereas Medoid 3 has a more intense de-territorialisation. Medoid 1 includes periods of de-territorialisation in the afternoons for Mondays to Thursdays. Medoid 2 has a similar pattern but with a larger range of corrections and positive adjustments to morning footfall during the weekdays. The next sections investigate how the fuzzy allocation of the medoids changes over time for each of the footfall sensors for both daily and weekly clusters.

8.5 King Street Footfall Sensor Analysis

The following sections present the results for King Street in Manchester. Located on the Southern boundary of the Manchester BID area, this street is associated with the finance industry and the more upmarket retail apparel brands (VisitManchester.com, 2020).

8.5.1 Daily Cluster Analysis Results

Figure 8.6 displays the run chart of the fuzzy cluster allocations for the Manchester daily signature medoids for King Street. The run chart immediately identifies that King Street is dominated by Medoids 2 and 4 with Medoid 4 being gradually replaced by Medoid 2 during a transition period of 2011 to 2015 and therefore an increased afternoon peak footfall period between 16:00 and 17:00. This immediately highlights a benefit of using fuzzy cluster analysis as it can identify transitions between the medoids, and seasonal variation as displayed by Medoid 3 during the Christmas period. In Figure 8.4, the identified daily medoids for Manchester show that Medoids 2 and 4 are very similar, with Medoid 2 having more of an afternoon peak in territorialisation than Medoid 4. The results also indicate that during the Christmas period, the daily medoid profile changes from having morning, lunchtime, and end of working day peaks in footfall to more of an extended period of afternoon territorialisation (Christmas shopping) as displayed by Medoids 3,5 and 6. By providing a smoothed plot of the changes in the fuzzy allocations, medoids 3 and 6 could be viewed as having only a minor contribution running up to Christmas. However, the actual values indicate (in grey) that all three Medoids dominate totally with Medoid 3 having up to 75% assignment between 2010 and 2013 and then is replaced by Medoid 6 from 2014. The fuzzy allocations therefore can provide very specific time-bound views of territorialisation at each location.

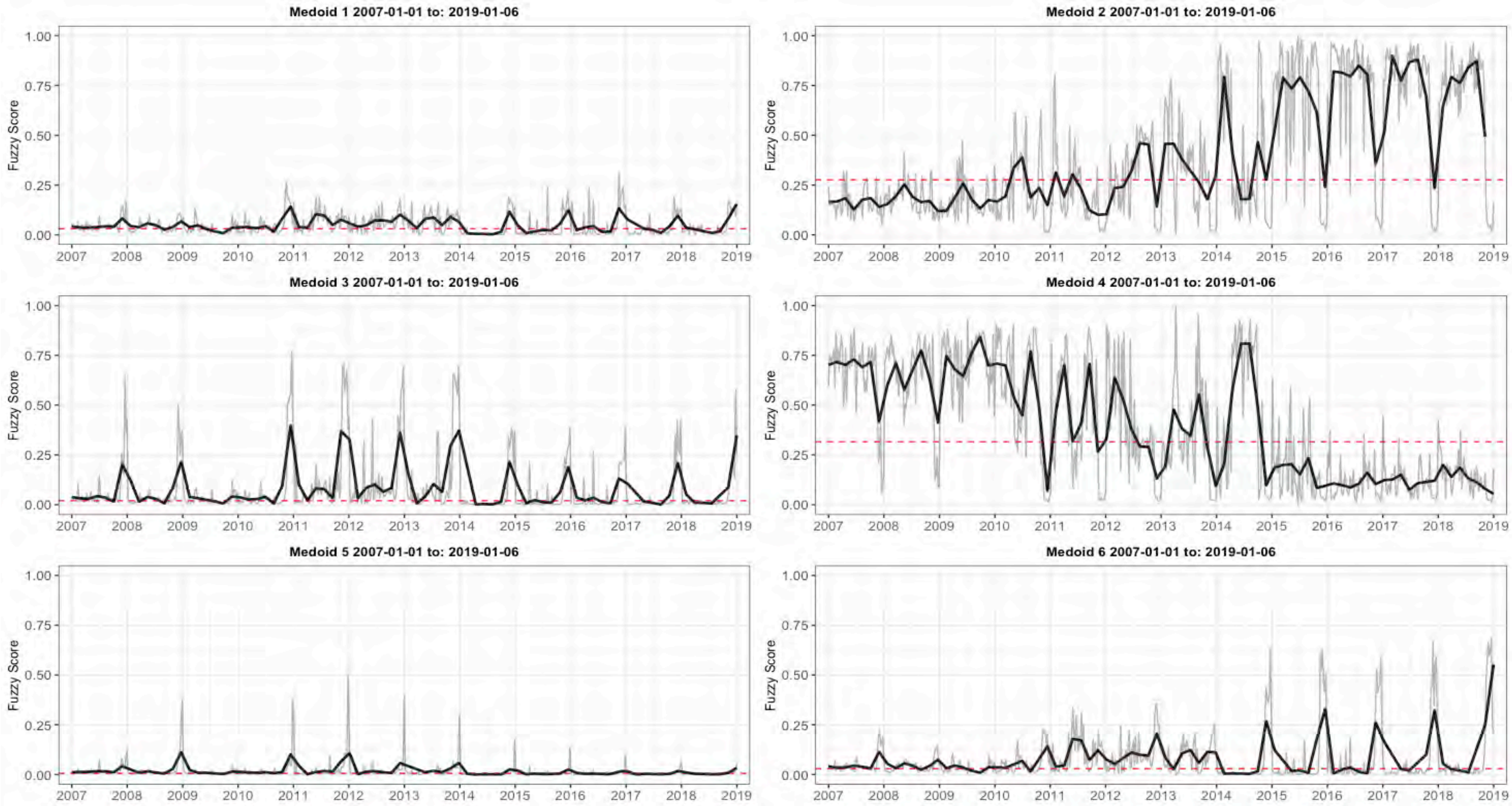


Figure 8.6. Run chart for King Street of the daily medoid fuzzy allocation

The results emphasise that King Street is dominated by working day rhythms and during the Christmas period, the street becomes additionally territorialised by Christmas shopping pedestrians. Note that King Street is the location for the French themed Christmas market stalls (Manchester Christmas Markets, 2017). The run chart also shows a change in street activity with the increase of afternoon activity evident after 2015 with this change happening over a transition period from 2011. The value of the run chart in monitoring changes in analysis cluster allocations over time is very evident. It also helps identify those medoids which have no influence most of the year, such as Medoids 1 and 5, apart from very short periods such as over the Christmas period. The run chart is therefore picking up seasonal changes and structural changes over-time in the footfall activity.

8.5.2 Weekly Cluster Analysis Results

Figure 8.7 displays the run chart of the fuzzy cluster allocations for the Manchester weekly signature medoids for King Street. Figure 8.7 picks out the period of transition also identified in the Daily Signature analysis between 2011 to 2015. In this case though, Medoid 3 dominates before and after this period in the non-Christmas periods and to a lesser degree the summer holiday period.

The dominance of Medoid 3 means that King Street, whilst Saturdays are still the peak footfall day, the differentiation between weekdays and Saturdays is minimised compared to Medoids 1 and 2 and that the footfall corrections suggest a more working and commuter focused location. However, during the Christmas period, Medoid 3 is replaced by Medoids 1 and 2 suggesting an increase in optional activities such as shopping. During the transition period between 2011 and 2015, Medoid 3 reduced in significance and was replaced by both Medoids 1 and 2, suggesting that during this period there was an increase in the territorialisation of the location on Saturdays and Sundays compared to outside this period.

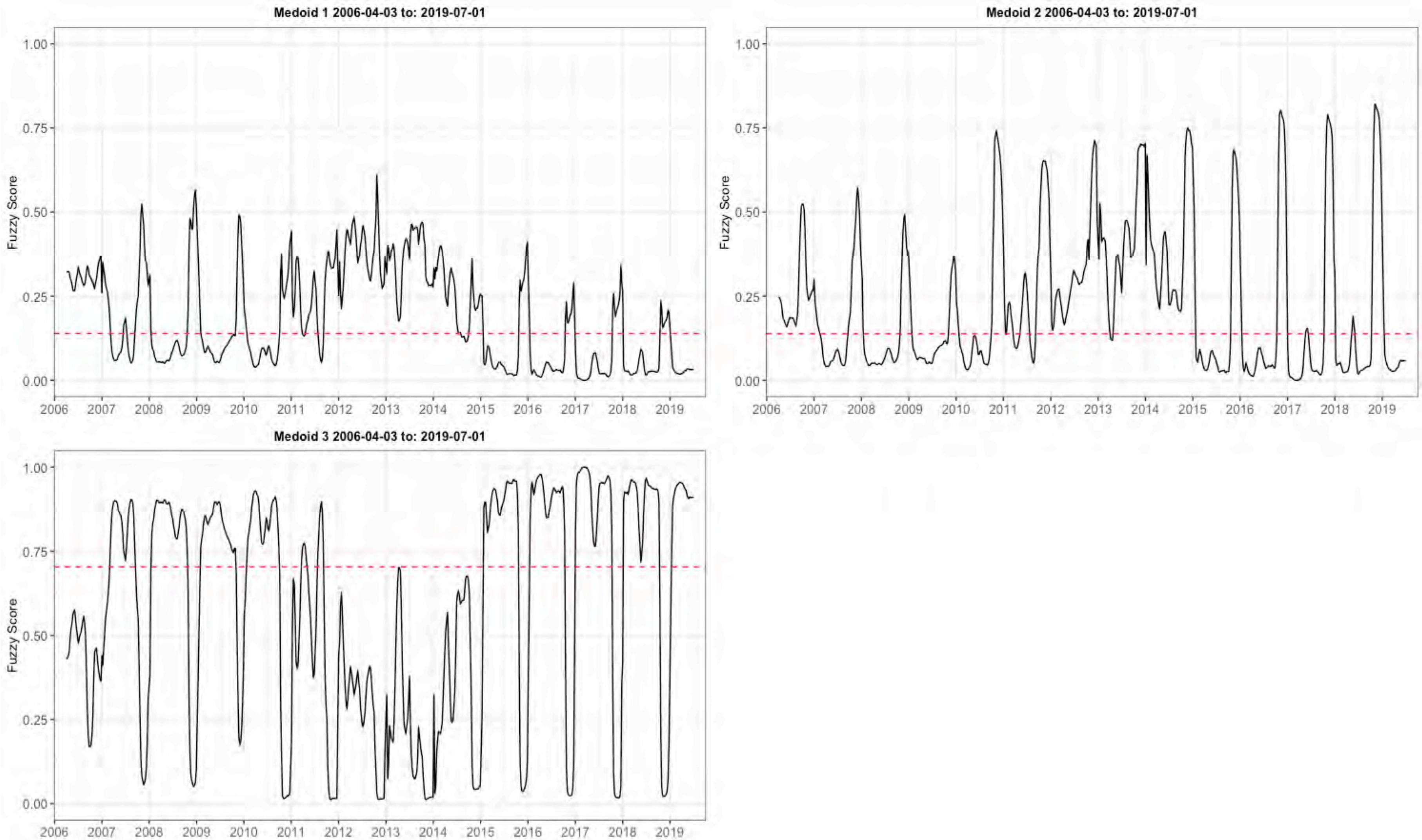


Figure 8.7. Run chart for King Street of the weekly medoid fuzzy allocations

8.5.3 Cluster Validation

By plotting hourly footfall imputed values over a year and by month, the findings from the cluster analysis can be verified to ensure the patterns identified are real and not random patterns generated by the different algorithms used by this study. The period between 2011 and 2015, where Medoids transition between 2 and 4, is a period where weekend footfall for King Street is much higher, as can be seen in Figure 8.8, validating the increased assignment of weekly medoids 1 and 2. Figure 8.8 shows though that the significantly higher weekend footfall began in 2010, which Figure 8.6 suggests was due to changes in the daily signatures over the Christmas shopping period from November to December.

Looking at Figure 8.9, the plot confirms the working week pattern (for 2018) with morning, lunchtime, and end of working day peaks in footfall clearly visible. Also notable is the increase in footfall on Saturdays and to a lesser degree the weekdays over the build up to Christmas. Finally, over the Christmas period, there is more territorialisation of King Street in the evenings than at other times of the year.

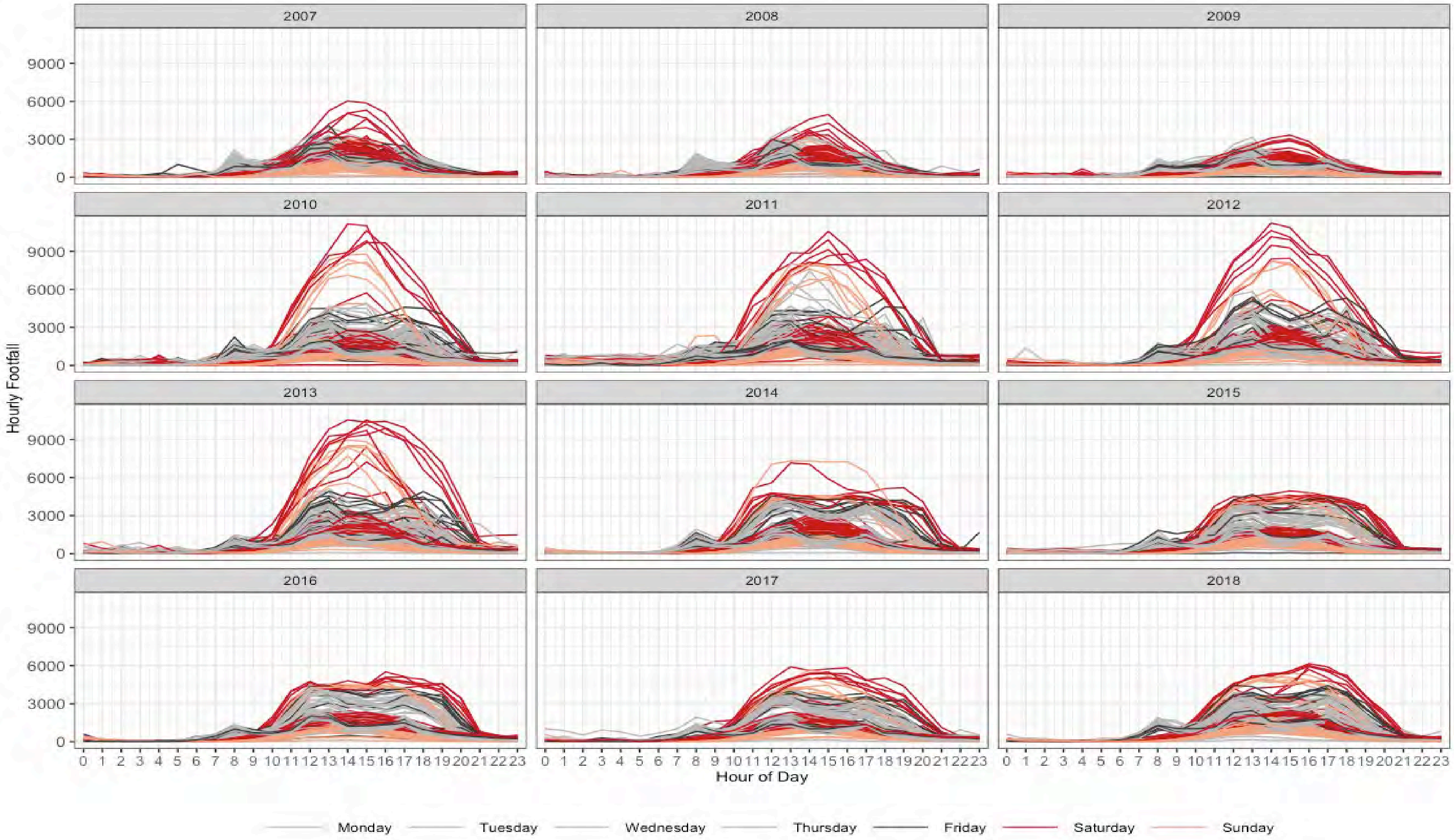


Figure 8.8. Hourly plots of imputed footfall for King Street from 2007 to 2018

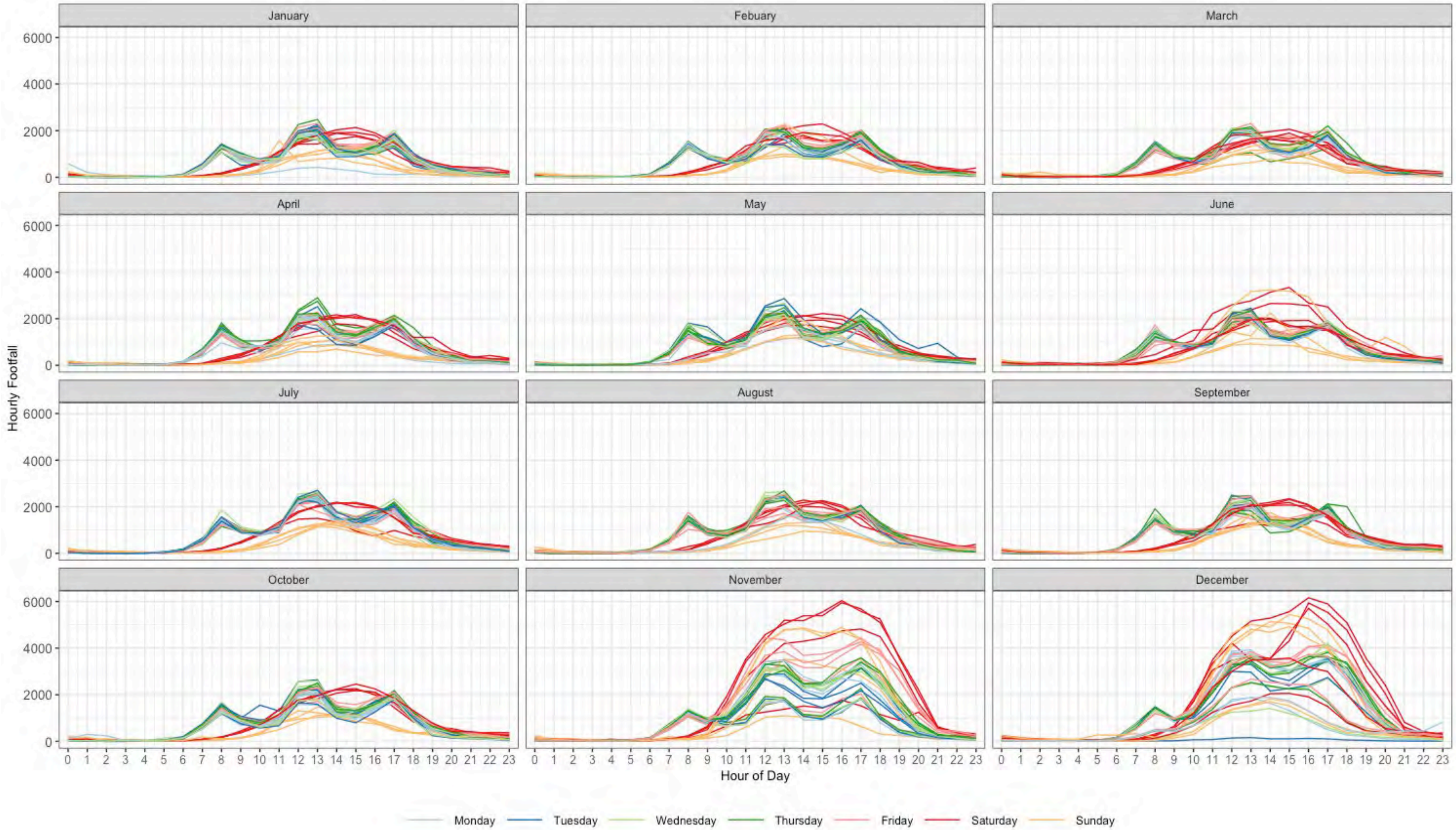


Figure 8.9. Hourly plots by month of footfall for King Street for 2018

8.6 Market Street Footfall Sensor Analysis

The following sections analyse the results for Market Street in Manchester. Located at the heart of the Manchester BID area, this street is Manchester's key area for high street shopping (VisitManchester.com, 2020).

8.6.1 Daily Cluster Analysis Results

Whereas King Street suggests that the dominant daily 24-hour rhythms are based around the working day, Market Street is more aligned to the daily rhythms of King Street at Christmas. Medoids 3 and 6 (Figure 8.4) dominate with a peak of territorialisation at lunchtime followed by this period extending into the afternoon and reducing in intensity into the early evening. For Market Street, Figure 8.10 shows that Medoid 3 dominates until 2014 when the jump in weekly footfall volumes occurs - see Figure 8.3. After this sudden change, Medoid 6 dominates with an increased period of footfall into the afternoon and decreasing in intensity at a slower rate into the evening than presented by Medoid 3. This suggests the increase in footfall noted in the weekly mean values can be attributed to increased afternoon and early evening activity.

8.6.2 Weekly Cluster Analysis Results

In Figure 8.11, Market Street, up to 2014, shows a weekly signature where Saturdays were the key shopping day of the week. After 2014, with weekly Medoid 3 becoming more influential, this suggests a decrease in the Saturday versus weekday differential. Note that after 2014, Medoid 2 also becomes more prominent with (to contradict the last statement), a more differentiated Saturday versus weekday weekly pattern. This apparent contradiction in the Medoid allocations is addressed in the next section.

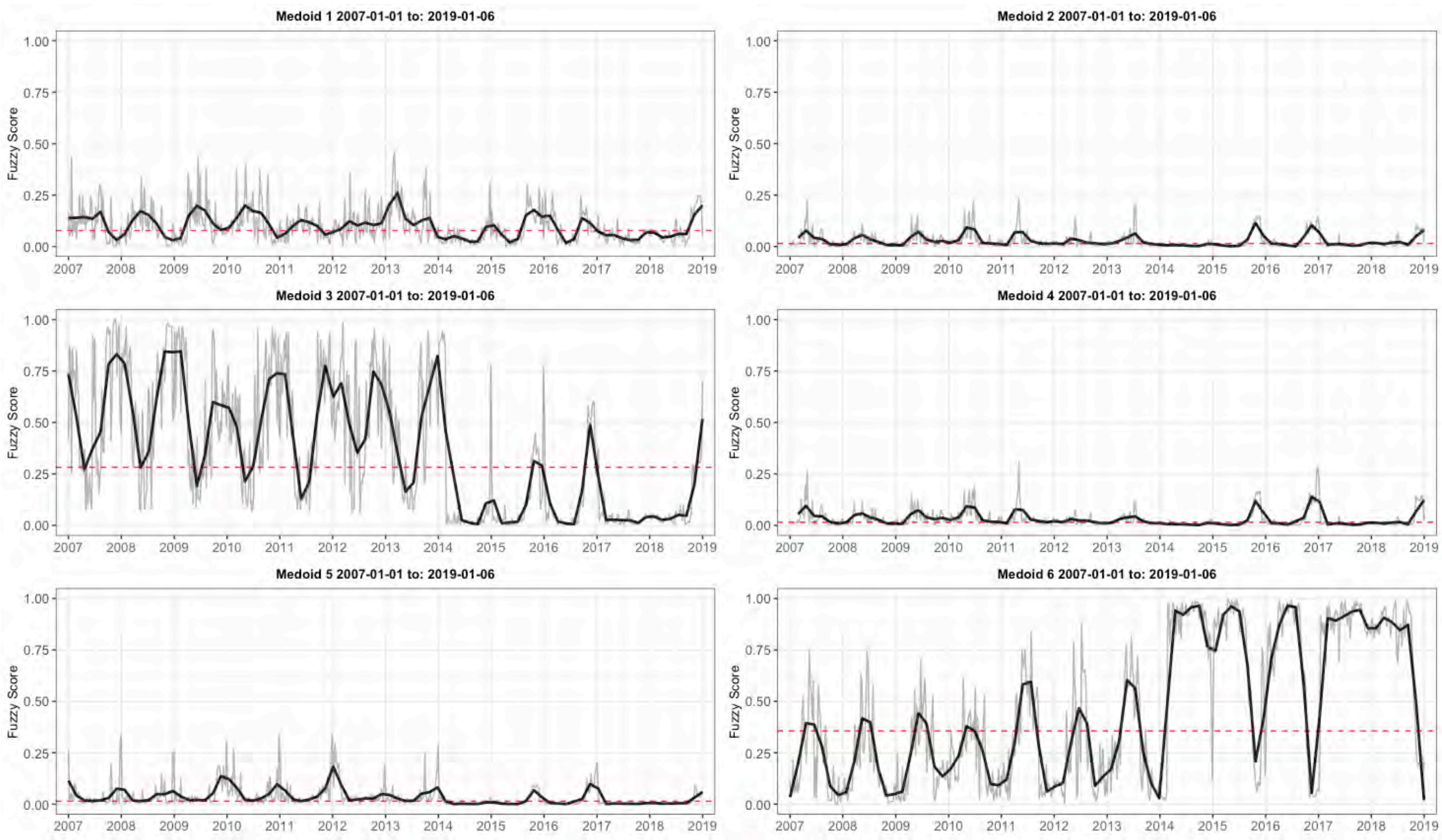


Figure 8.10. Run chart for Market Street of the daily medoid fuzzy allocations

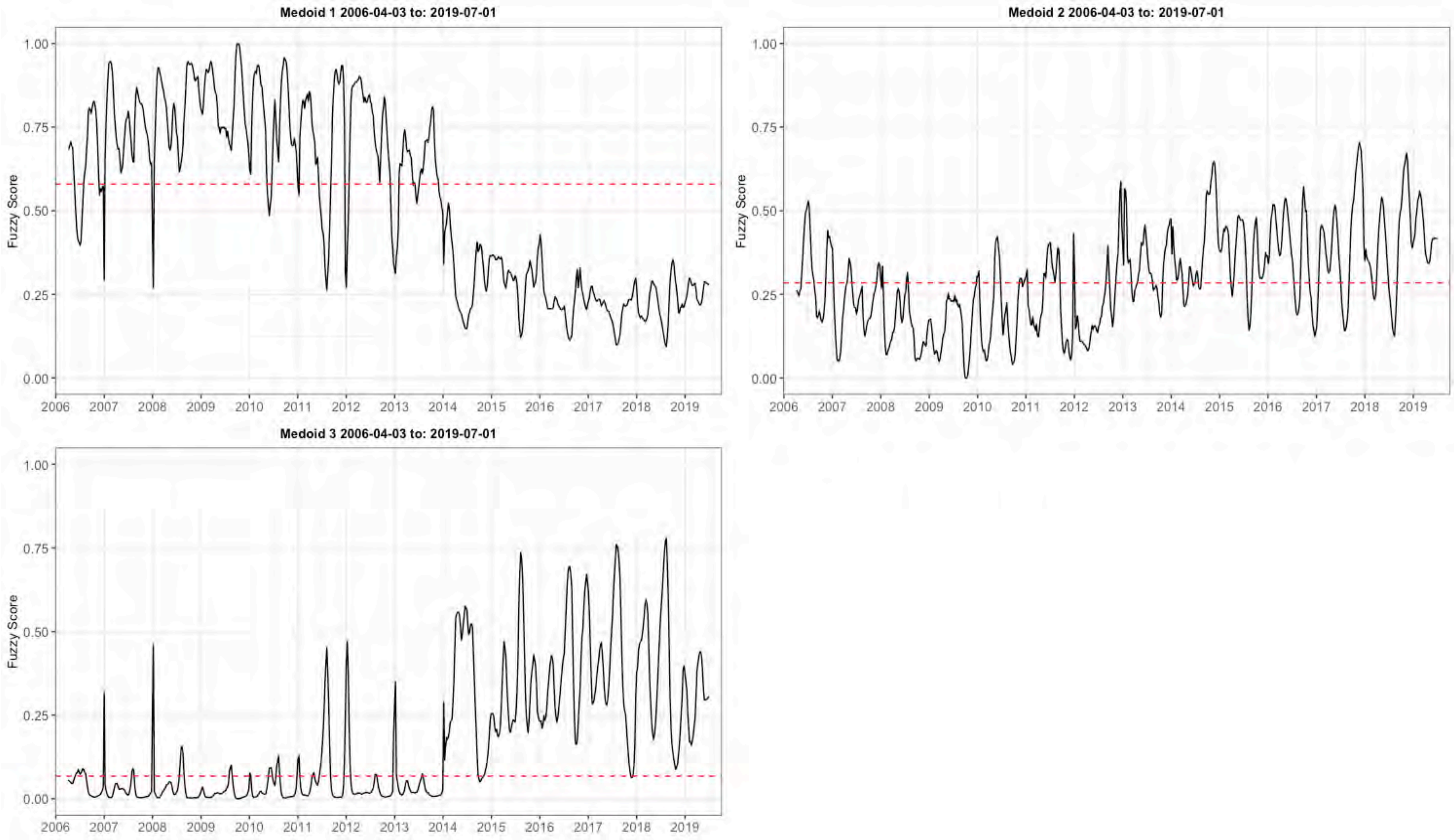


Figure 8.11. Run chart for Market Street of the weekly medoid fuzzy allocations

8.6.3 Cluster Validation

Figure 8.12 displays hourly plots for each day in a year and picks out weekday vs weekend days. The plots show a clear reduction in the influence of Saturdays year on year. However, as already discussed, from 2014, footfall levels increase considerably, suggesting that although Saturdays de-territorialise, the other days of the week must increase in intensity of territorialisation to account for the footfall increase. This is suggested to be the case as Medoid 3 from the weekly cluster analysis becomes more influential.

The results for individual years can be used to check the above findings. Comparing Figure 8.13 to Figure 8.14, the plot for 2007 displays a greater level of footfall for Saturdays, yet by 2018, this distinction has essentially vanished. The weekdays have the distinctive three periods of territorialisation intensity around the start of the working day, lunchtime, and end of the day whereas Saturdays follow the daily signature patterns of Medoids 3 and 6 - having a lunchtime intensification of territorialisation that continues often to a peak in the afternoon. This evidences why Medoid 3 becomes more prominent but also, for some months, Saturdays still have the highest peaks in footfall that helps explain why weekly Medoid 2 also has a degree of influence.

Unlike King Street where the changes in fuzzy cluster allocation presented a transition over time, for Market Street and the daily cluster allocations, a more sudden change in medoid is identified between 2014 and 2015. The fuzzy medoid allocations are therefore able to identify periods of change over time, and sudden shifts in behaviour.

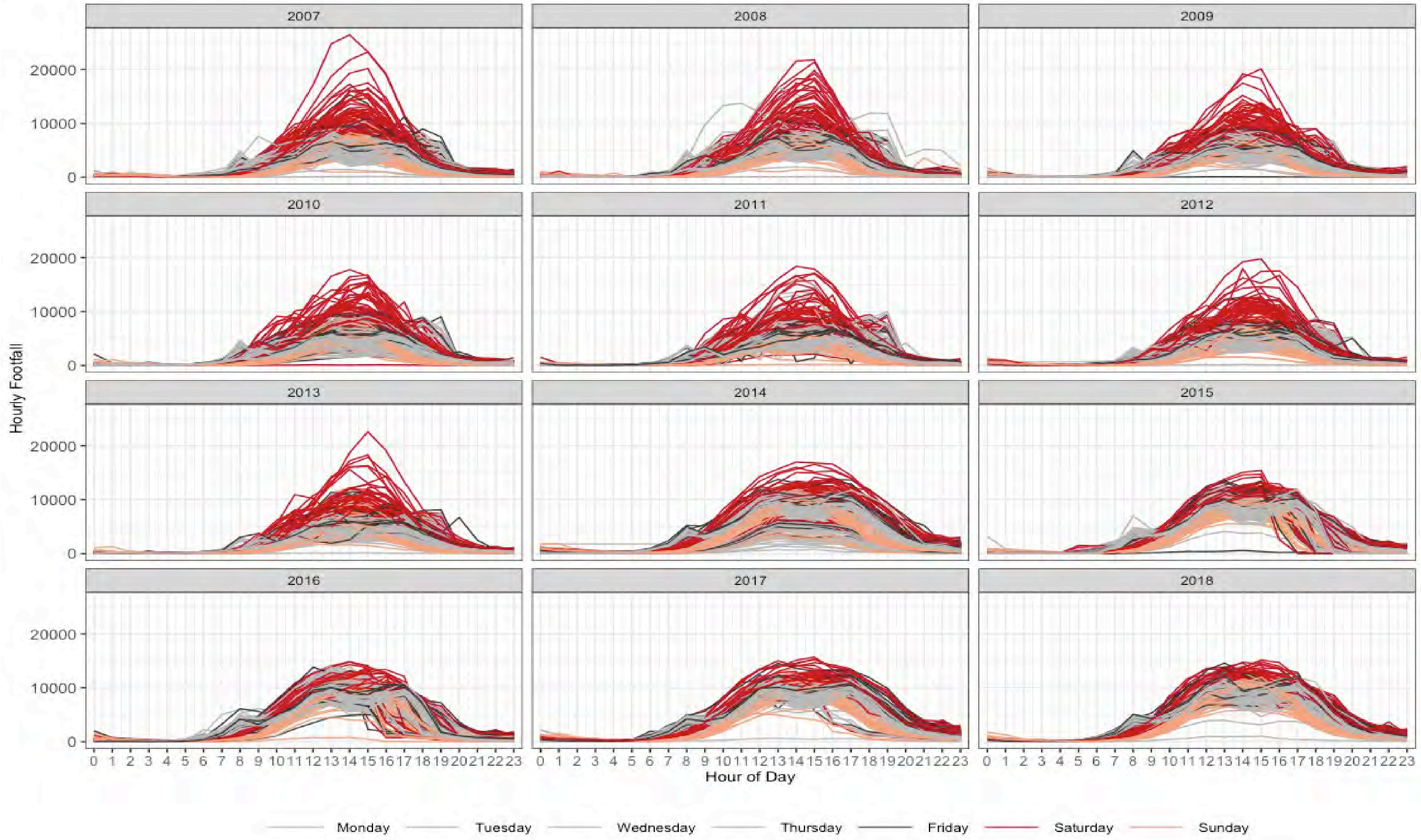


Figure 8.12. Hourly plots of footfall for Market Street from 2007 to 2018

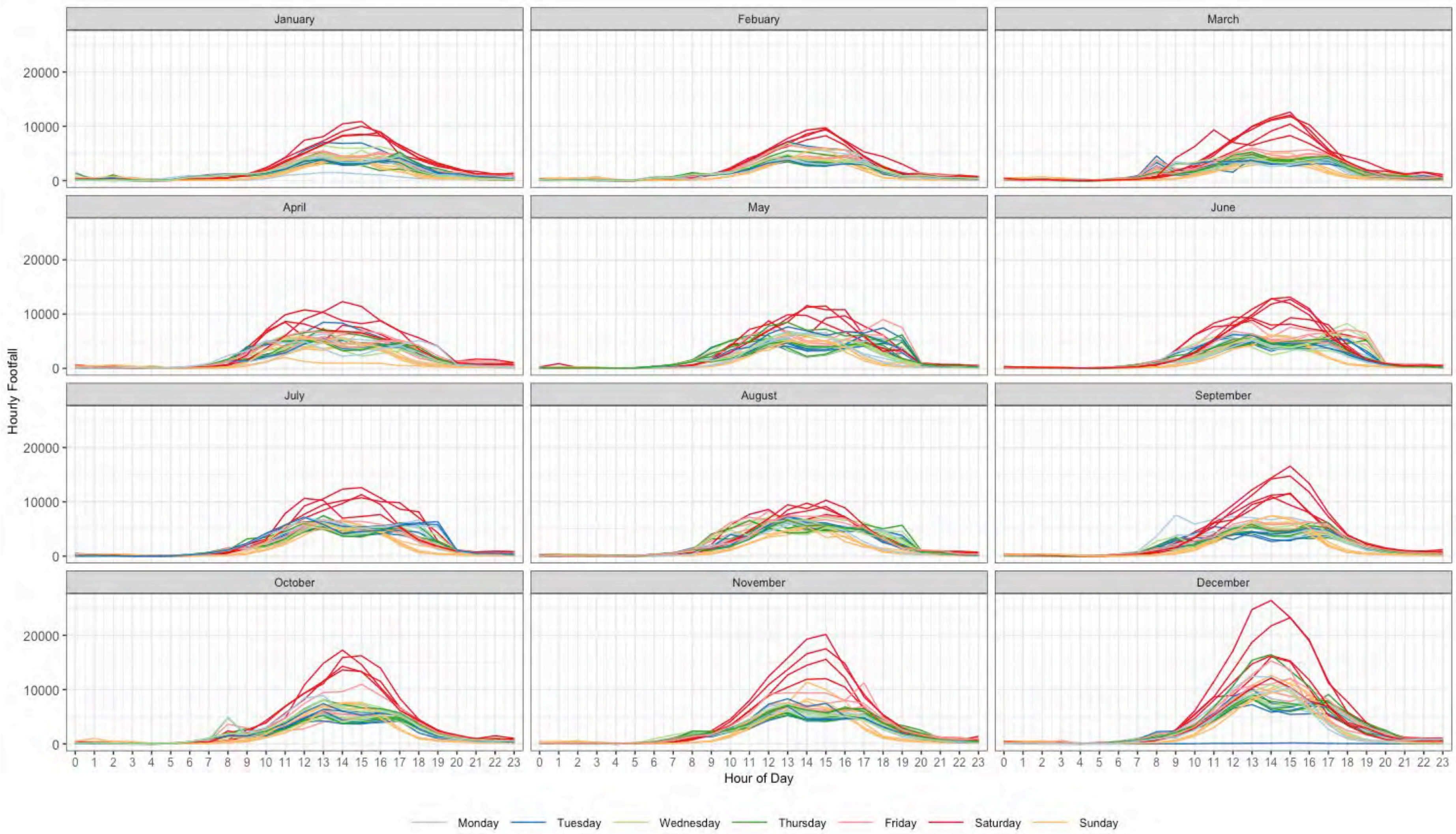


Figure 8.13. Hourly plots by month of footfall for Market Street for 2007

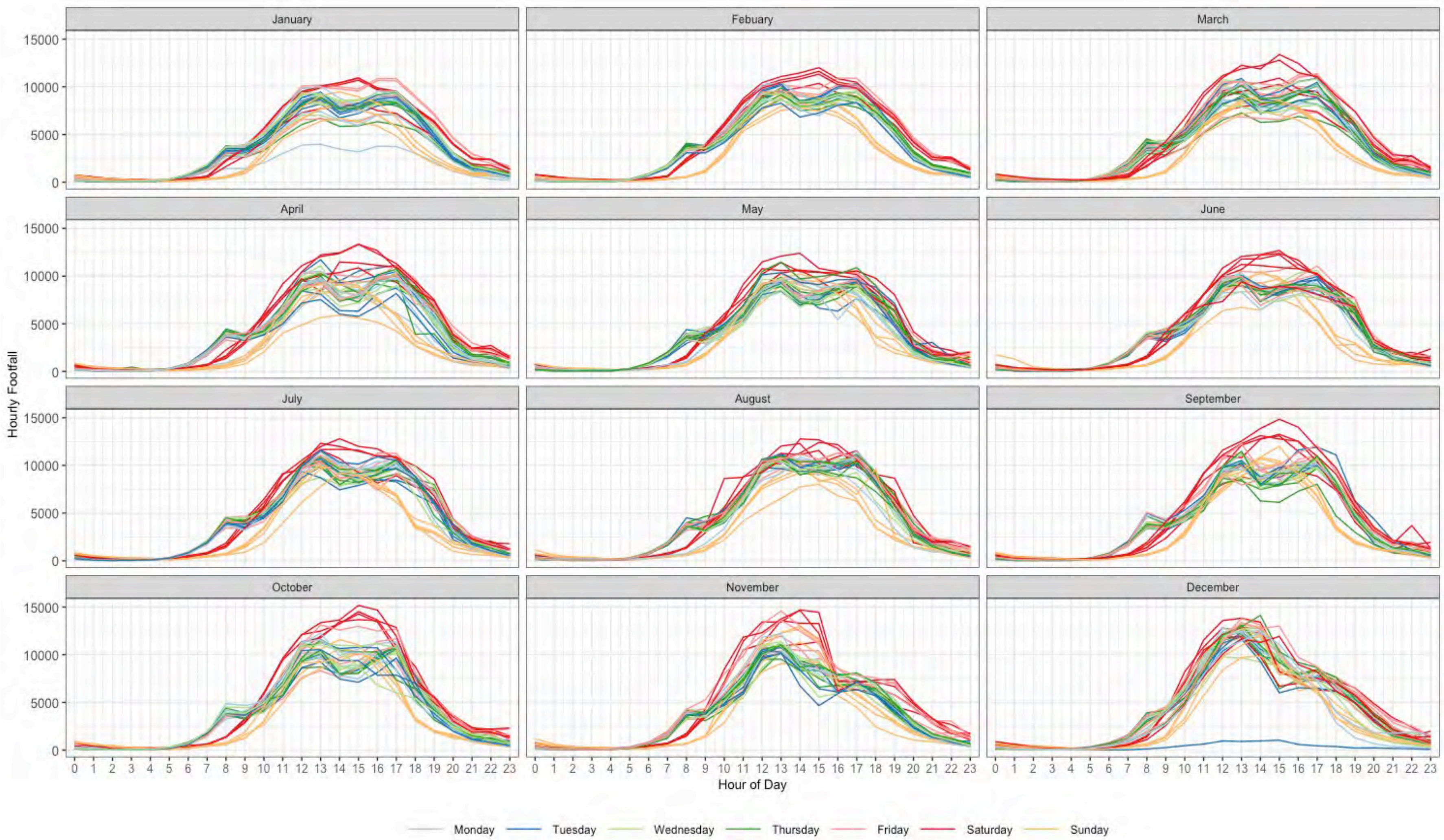


Figure 8.14. Hourly plots by month of footfall for Market Street for 2018

8.7 New Cathedral Street Footfall Sensor Analysis

The following sections analyse the results for New Cathedral Street in Manchester. On the west side of the Manchester BID area, this pedestrianised retail street includes branches of Marks and Spencer, Selfridges, Harvey Nichols, Louis Vuitton, Reiss, Zara and the largest Ted Baker and Hugo Boss stores outside London (Manchester City Council, 2020a).

8.7.1 Daily Cluster Analysis Results

Figure 8.15 shows the run chart of daily fuzzy allocations for New Cathedral Street. The reason for choosing Manchester as an exemplar was due to the variation in results and New Cathedral Street provides a different daily rhythm to both King and Market Streets. In this case, Medoids 1 and 5 (up to 2009) appear most dominant. There is an apparent seasonal rhythm to the allocation of the medoids, with both Medoids 1 and 5 (up to 2009) showing a dominance outside the Winter months (except for 2010 and 2011). An evident change in the cluster allocations occurs between 2010 and 2011, where Medoid 5 becomes much less significant. After 2011, during the Christmas period, there are small contributions from Medoids 2,3,4 and 5 (the latter from 2011 onwards). The initial dominance of Medoid 5 identifies New Cathedral Street as a place with a peak intensity of territorialisation in the afternoon. From 2011 and the increased allocation of Medoid 3 suggests this initial afternoon peak becomes extended over the afternoon period or, the peak footfall period associated with Medoid 5 is reduced. Figure 8.16 shows the changes in footfall differences hour to hour on Saturdays and there is a very noticeable change in the intensity of footfall change between the afternoon peaks before 2011 and the lack of them afterwards. Medoid 5, as a daily signature is quite unique as this signature did not appear when all locations were processed collectively, identifying that performing the cluster analysis for individual places is required to pick up individual place rhythms.

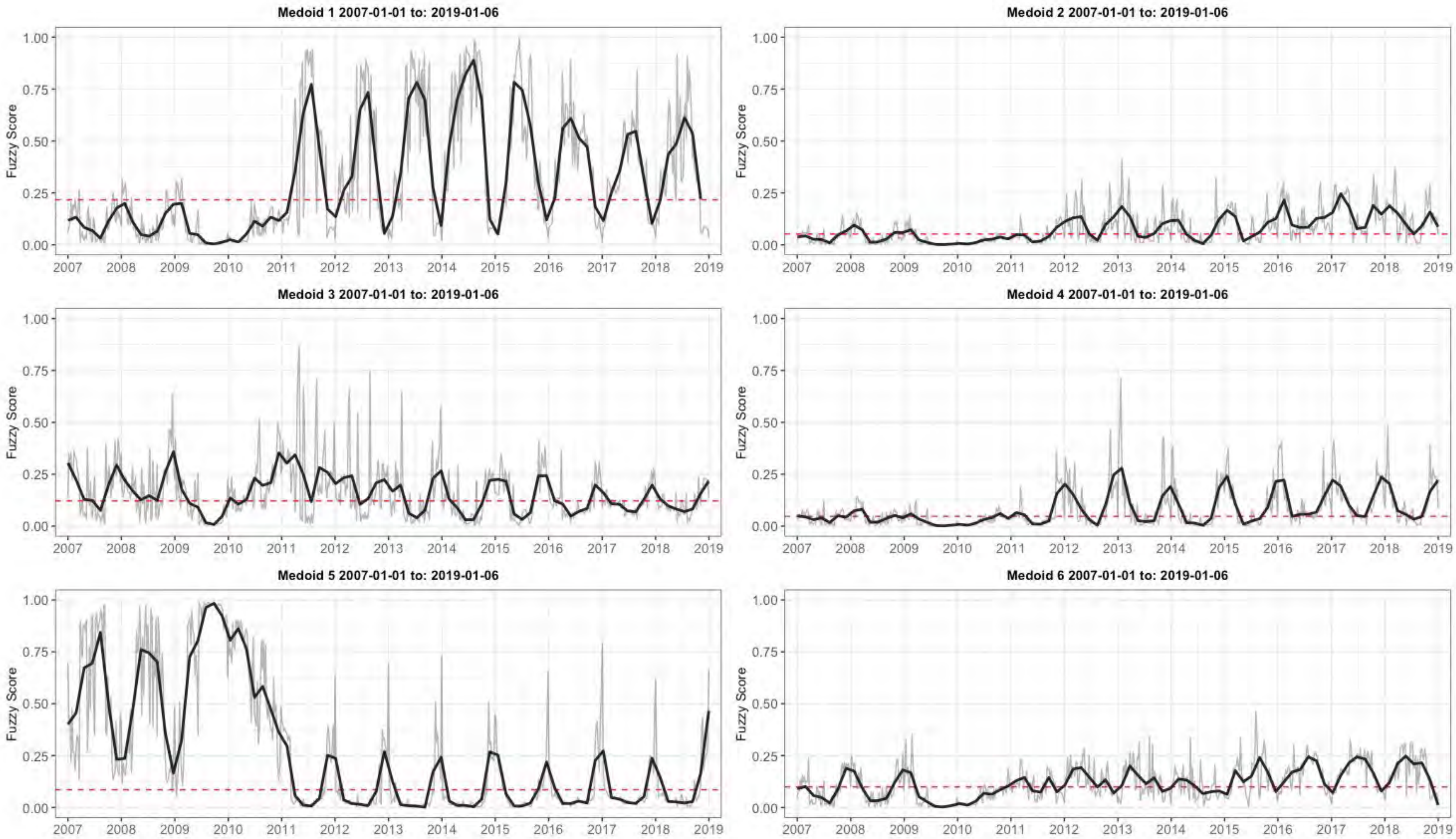


Figure 8.15. Run chart for New Cathedral Street of the daily medoid fuzzy allocations

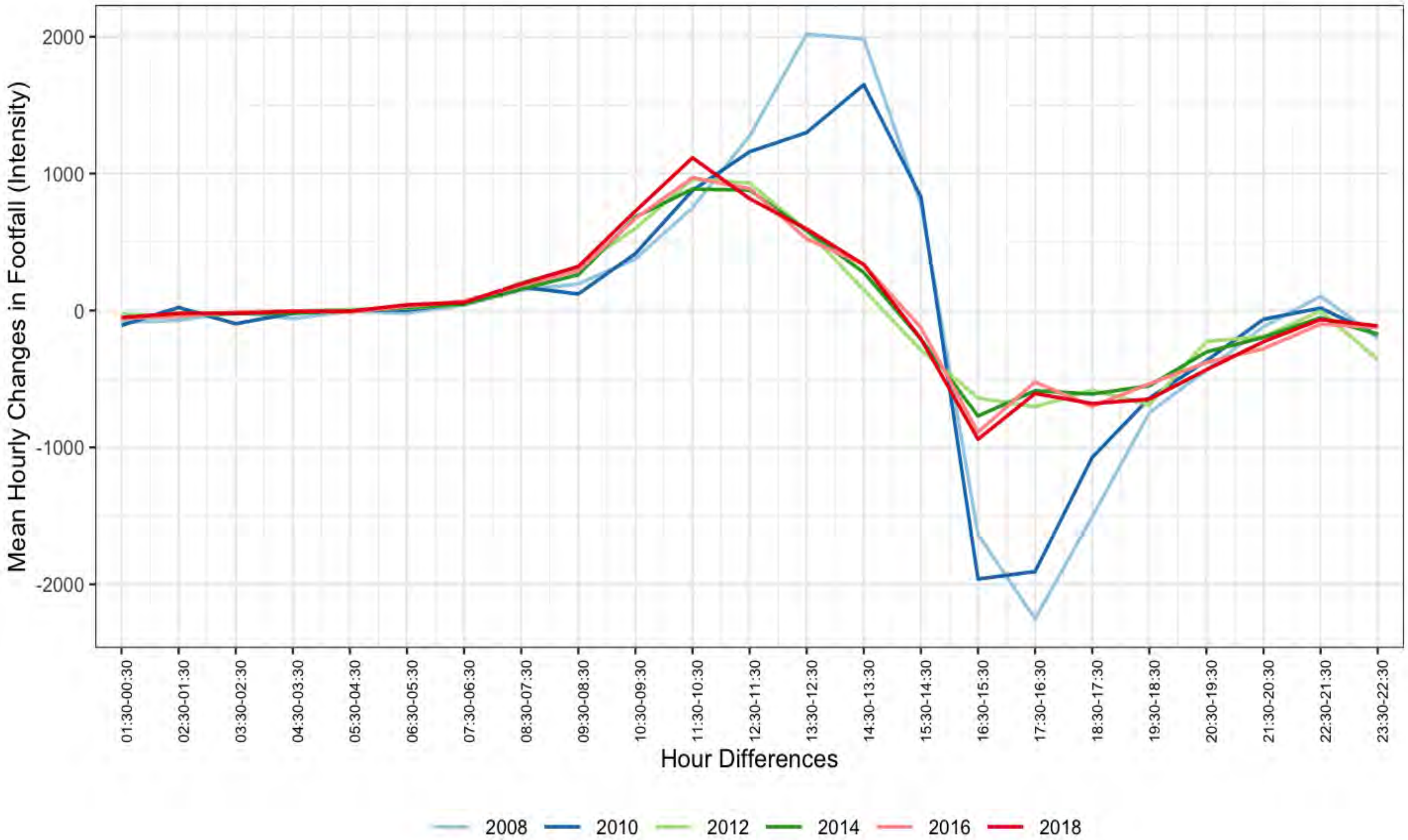


Figure 8.16. Intensity Plot of changes in the hourly differences for footfall on Saturdays - New Cathedral Street

8.7.2 Weekly Cluster Analysis Results

In Figure 8.17, the weekly signatures can be seen to change at the same time as the daily signatures change. In the initial period, Medoid 1 is dominant with small adjustments to the weekday daily rhythms. After 2011, Medoid 2 is more dominant still with a noticeable Saturday peak but also more variability adjusting the weekday day signatures. Medoid 3, apart from individual days around Christmas, for example 2008 and an increasing but minor allocation from 2016, has little influence. This suggests that New Cathedral Street is dominated by Saturday footfall volumes but this effect, with the transition from weekly Medoid 1 to 2, has become reduced.

8.7.3 Cluster Validation

As with the previous sensors, looking at the hourly footfall plots provides a visual validation of the cluster and fuzzy allocation findings. Figure 8.18 below shows how the overall patterns of footfall have changed from 2007 to 2018. The change in the daily and weekly signatures corresponds with the large reduction for Saturday (mainly) footfall volumes which peaks as suggested by Medoid 5 (daily signatures) around 15:00. However, Figure 8.18, apart from showing the hourly pattern expected from the Daily Signature allocation of Medoid 5 with the afternoon peak, also appears to show a weekday signature like King Street.

Figure 8.19 confirms this finding. By removing the results for Saturdays and Sundays and the Christmas period months of November and December, Figure 8.19 shows that like King Street, there is a working week pattern evident in the footfall data - although the afternoon peak in footfall still occurs for different days of the week for each month. What is of interest is that the working day footfall rhythm (apart from the morning peak commuter period) was not identified by the cluster analysis algorithm, suggesting that the most dominant features in the signatures are identified but not some of the more subtle features. To illustrate this last point, Figure 8.20 presents the monthly hourly plots for 2007 and clearly, the Saturday footfall is significant enough that the signal from other days of the week is difficult to view – and therefore for the cluster analysis to identify.

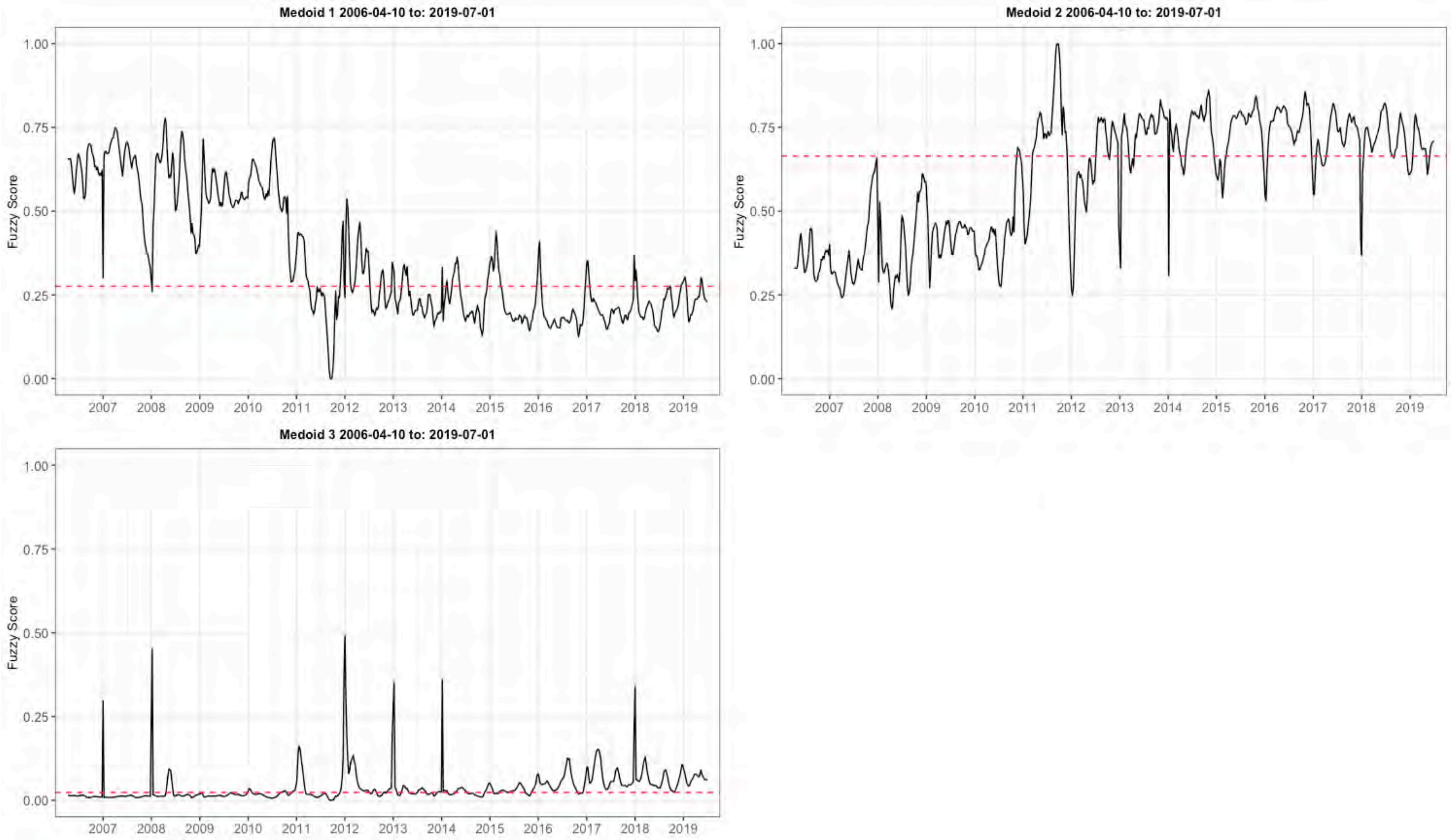


Figure 8.17. Run chart for New Cathedral Street of the weekly medoid fuzzy allocations

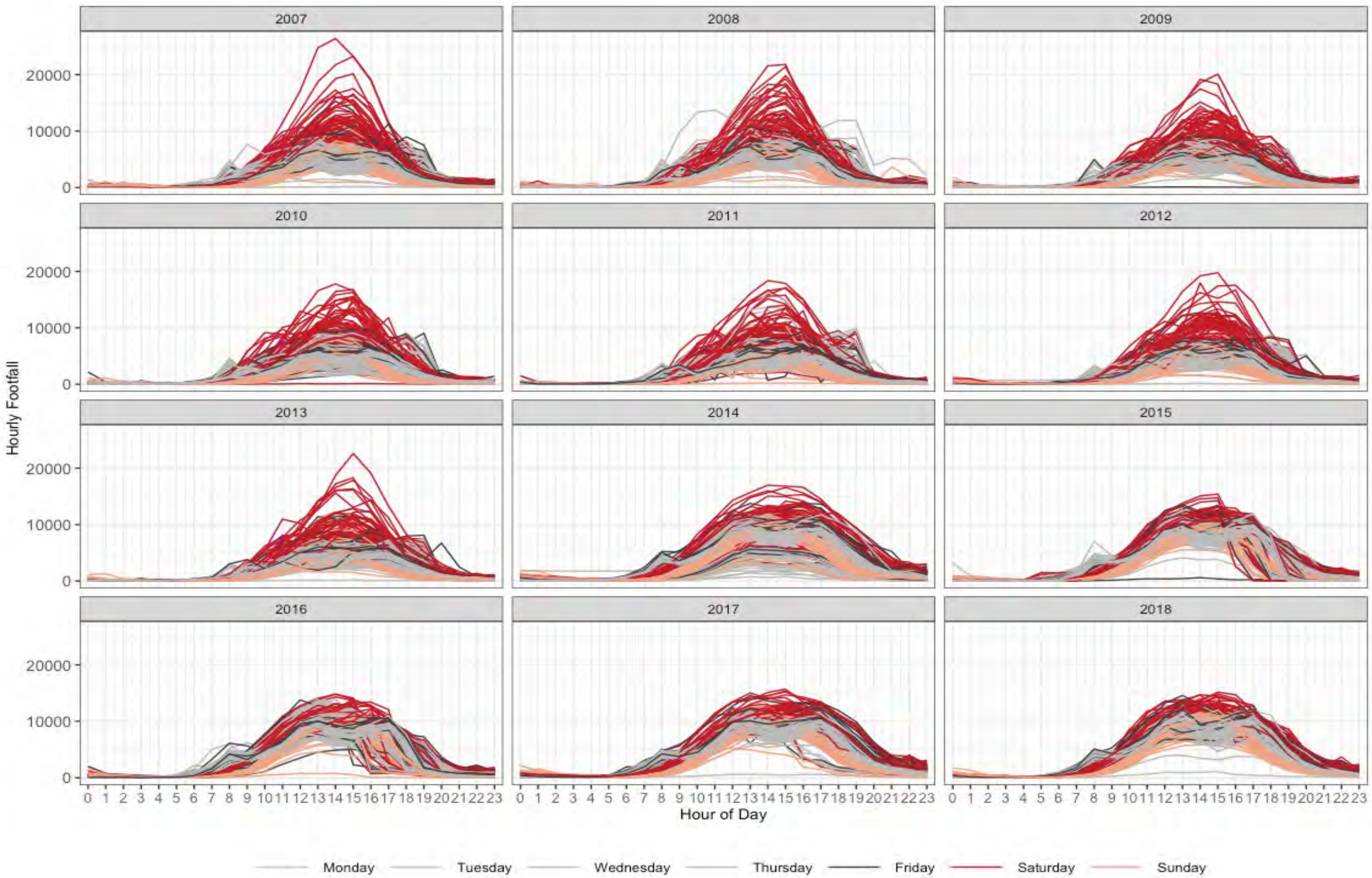


Figure 8.18. Annual hourly plots of footfall for New Cathedral Street

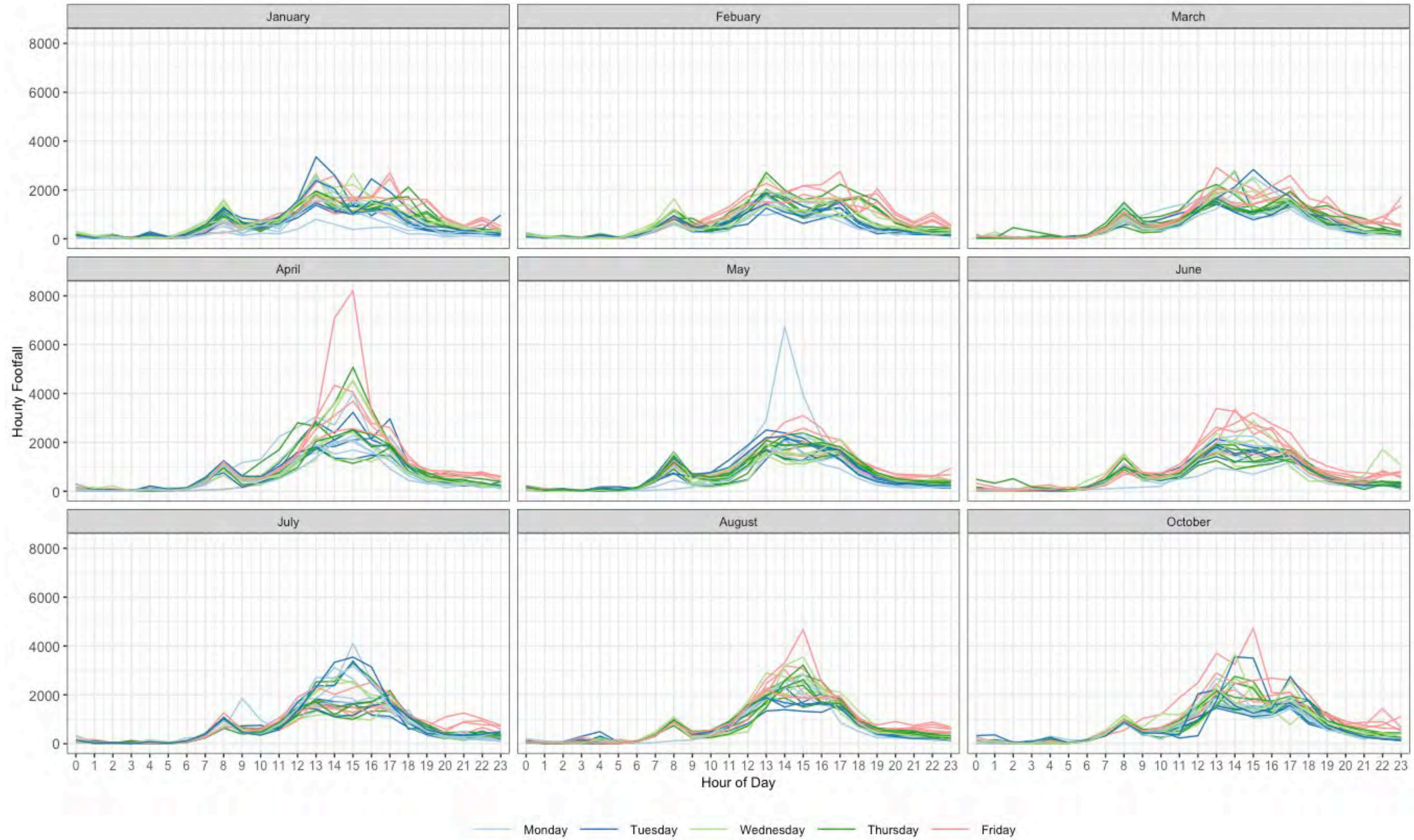


Figure 8.19. Hourly plots for New Cathedral Street with Saturday and Sunday removed and results for November and December

Figure 8.20. Hourly plots for New Cathedral Street for 2007

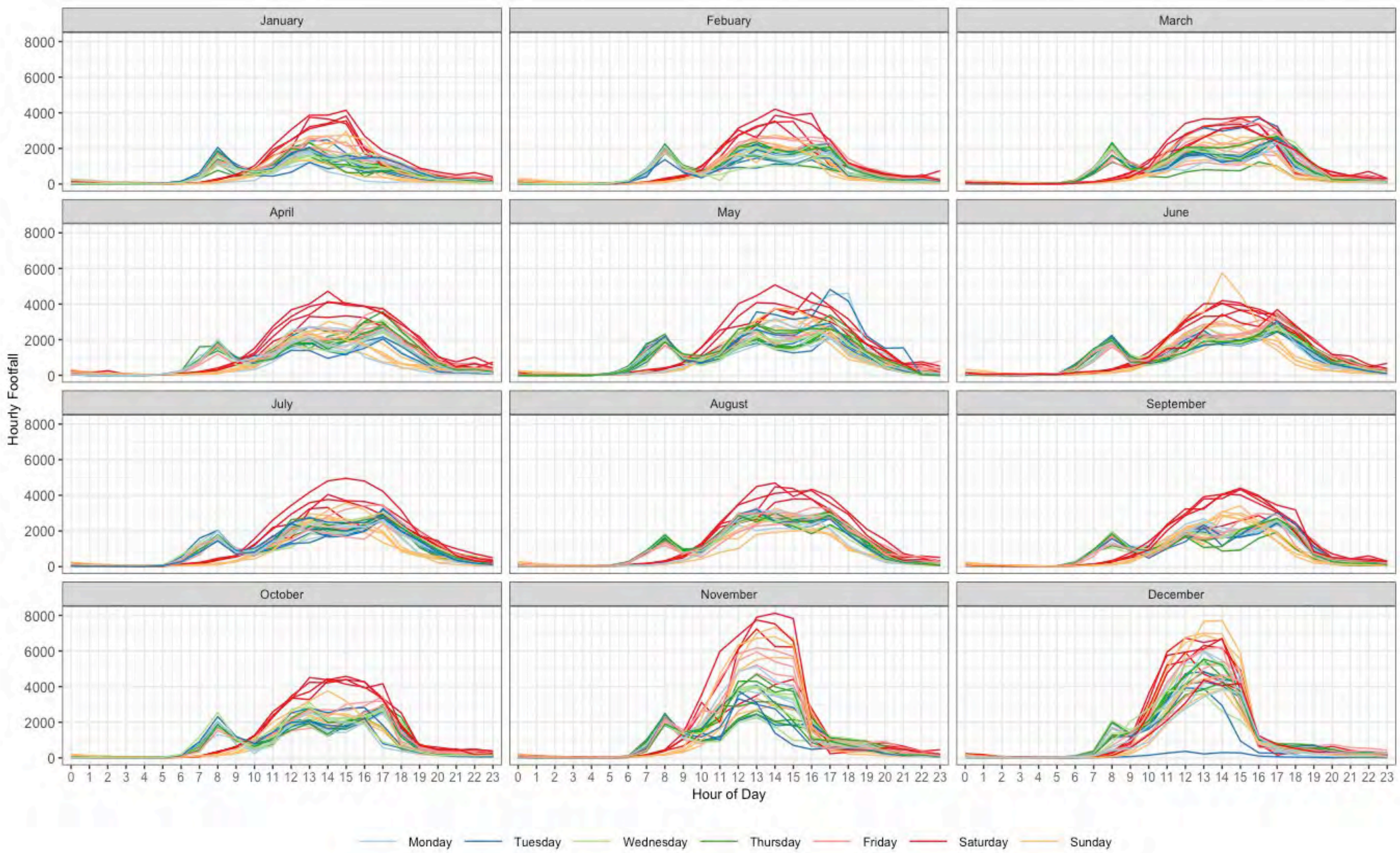


Figure 8.21. Hourly plots for New Cathedral Street for 2018

By 2018, Figure 8.21 shows that the differential between Saturdays and weekdays is much reduced. Also, the working week pattern is more visible, and this probably accounts for why Medoid 2 from the weekly signatures becomes more dominant after 2011 due to the increased weekday component accounted for by this Medoid.

Thus, New Cathedral Street shows that the cluster analysis is good for identifying dominant patterns but care with the interpretation is needed and requires that supporting evidence from the hourly footfall plots should always be used to make sure that less significant patterns are not missed. For example, missing the weekday pattern versus Saturday peak where there is a very large difference in footfall volumes. The results illustrate the value of looking at the changes between hours to also pick out changes over time as displayed using the Intensity Plot in Figure 8.16.

8.8 Exchange Square Footfall Sensor Analysis

The footfall sensor for Exchange Square is located by the entrance to the Arndale Shopping Centre and was operational from 2014. Exchange Square is a major public space located in the heart of the shopping district bordered by the Arndale Centre, the Corn Exchange, Selfridges and Harvey Nichols as well as being located close to designer shops and the Printworks entertainment complex. Exchange Square is part of the pedestrianised route from Victoria Station and has a Metrolink station (Manchester City Council, 2020b).

8.8.1 Daily Cluster Analysis Results

Figure 8.22 provides the run chart fuzzy results for the Exchange at one of the Arndale Shopping Centre exits. The lack of allocation of Medoids 2 and 4 indicate no distinct working week rhythm exists. However, as Medoid 1 is assigned significance, the working week signature within this Medoid that is combined with an afternoon period of territorialisation suggests complexity in the footfall rhythms for this location. As seen with New Cathedral Street, this is shown to be a result of distinctly different signatures for weekdays vs weekends.

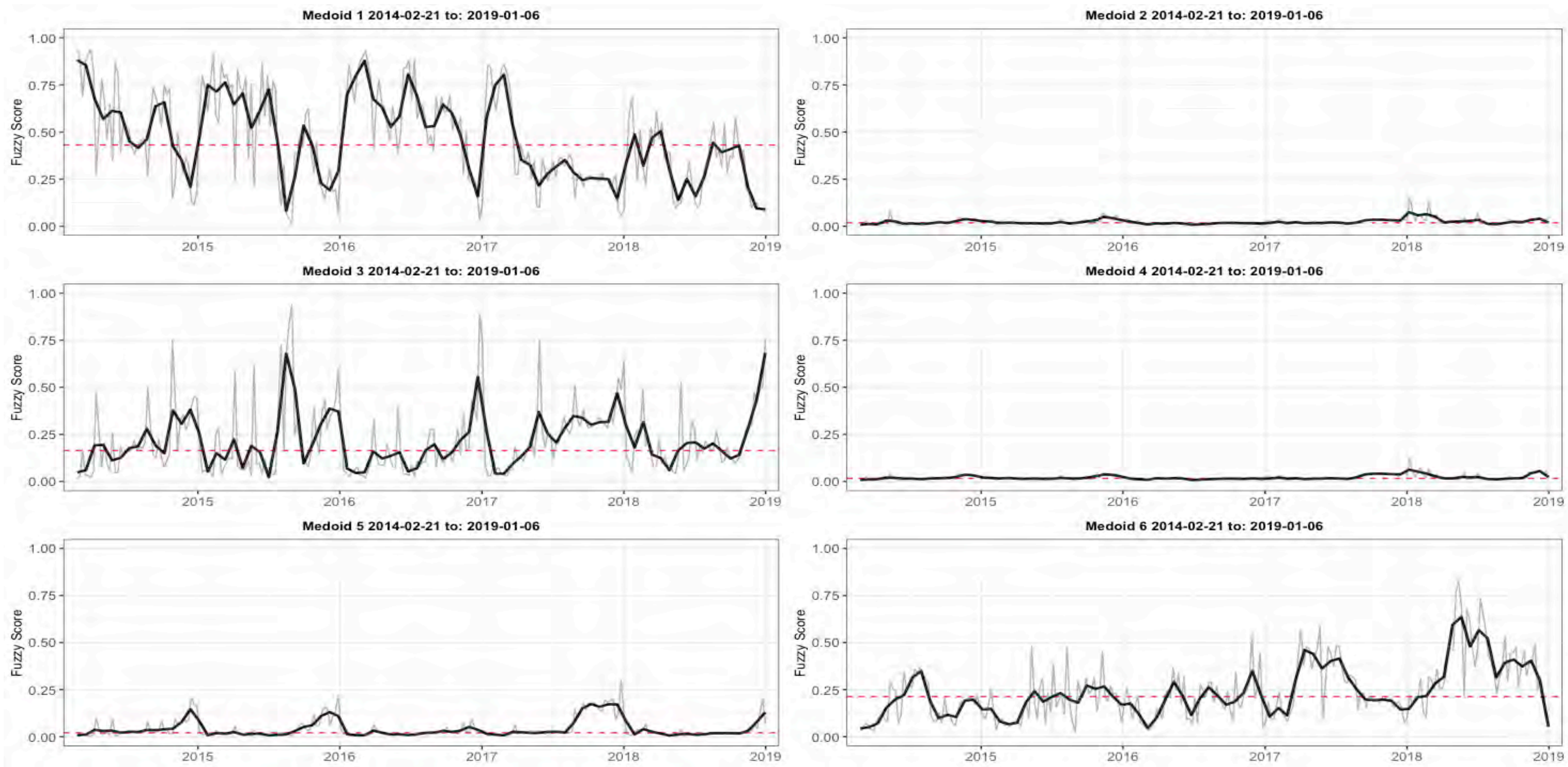


Figure 8.22. Run chart for Exchange Square of the daily medoid fuzzy allocations

8.8.2 Weekly Cluster Analysis Results

Figure 8.23 identifies that for the weekly signatures, Medoids 1 and 2 dominate. Although Medoid 2 is the most dominant, the two medoids appear to have cycles when one or the other is more representative of the footfall patterns. Both indicate the importance of Saturdays to this location as found with New Cathedral Street and it should be noted that both locations are very close to each other.

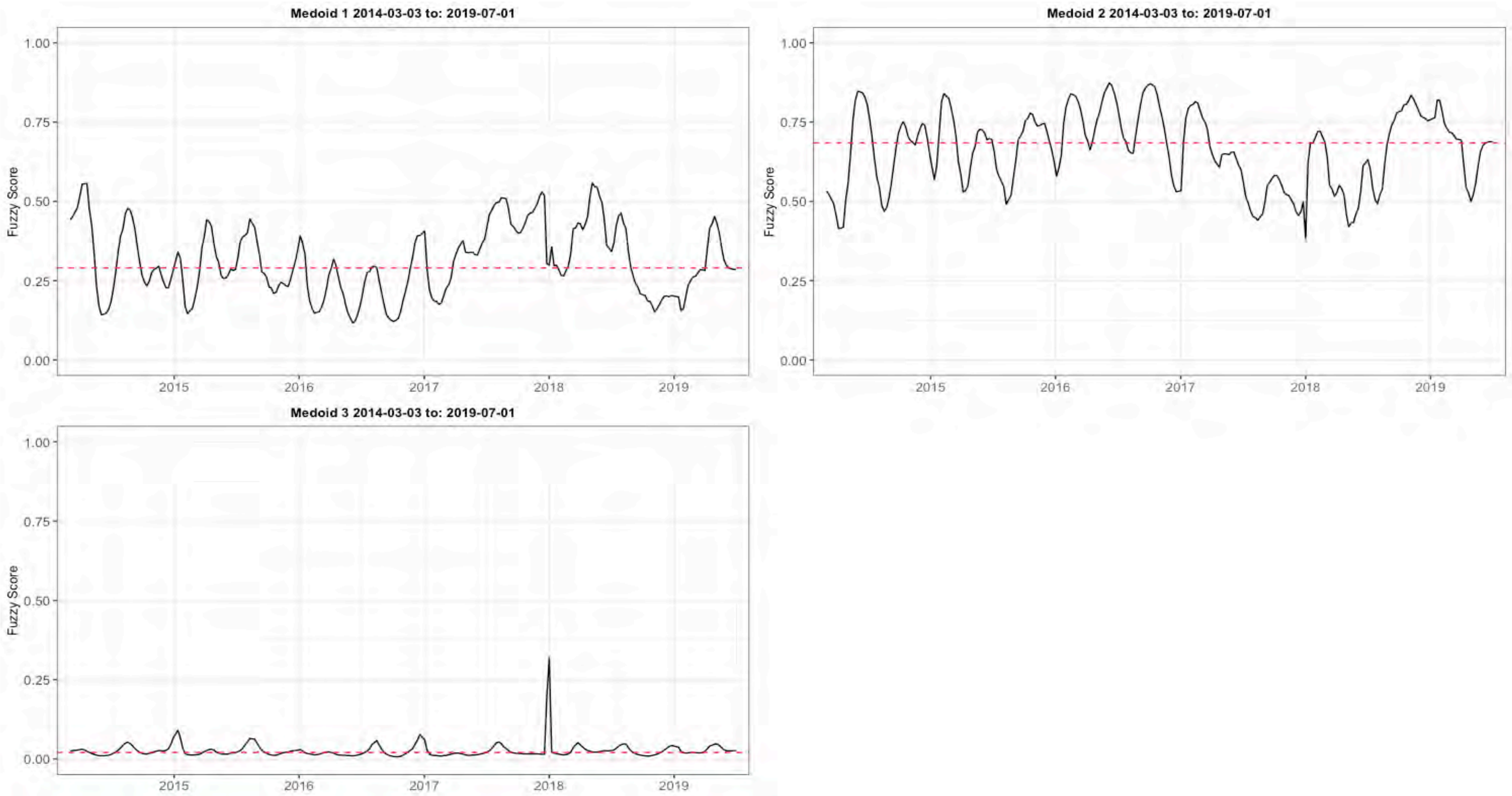


Figure 8.23. Run chart for Exchange Square of the weekly medoid fuzzy allocations

8.8.3 Cluster Validation

Figure 8.24 plots the hourly distribution of footfall over the period of data availability for this location. The Saturdays leading up to Christmas are evident, especially for 2017. For the years 2014 to 2016, the night-time levels of footfall have dropped significantly, indicating a reduction in the territorialisation intensity at this time.

Figure 8.25 shows that the high night-time footfall in this area of Manchester was taking place in November and December, a period when there were several all-night music events in Manchester on a Friday/Saturday. For example, see https://www.facebook.com/events/219106328475064/ - hosted by Rong Events.

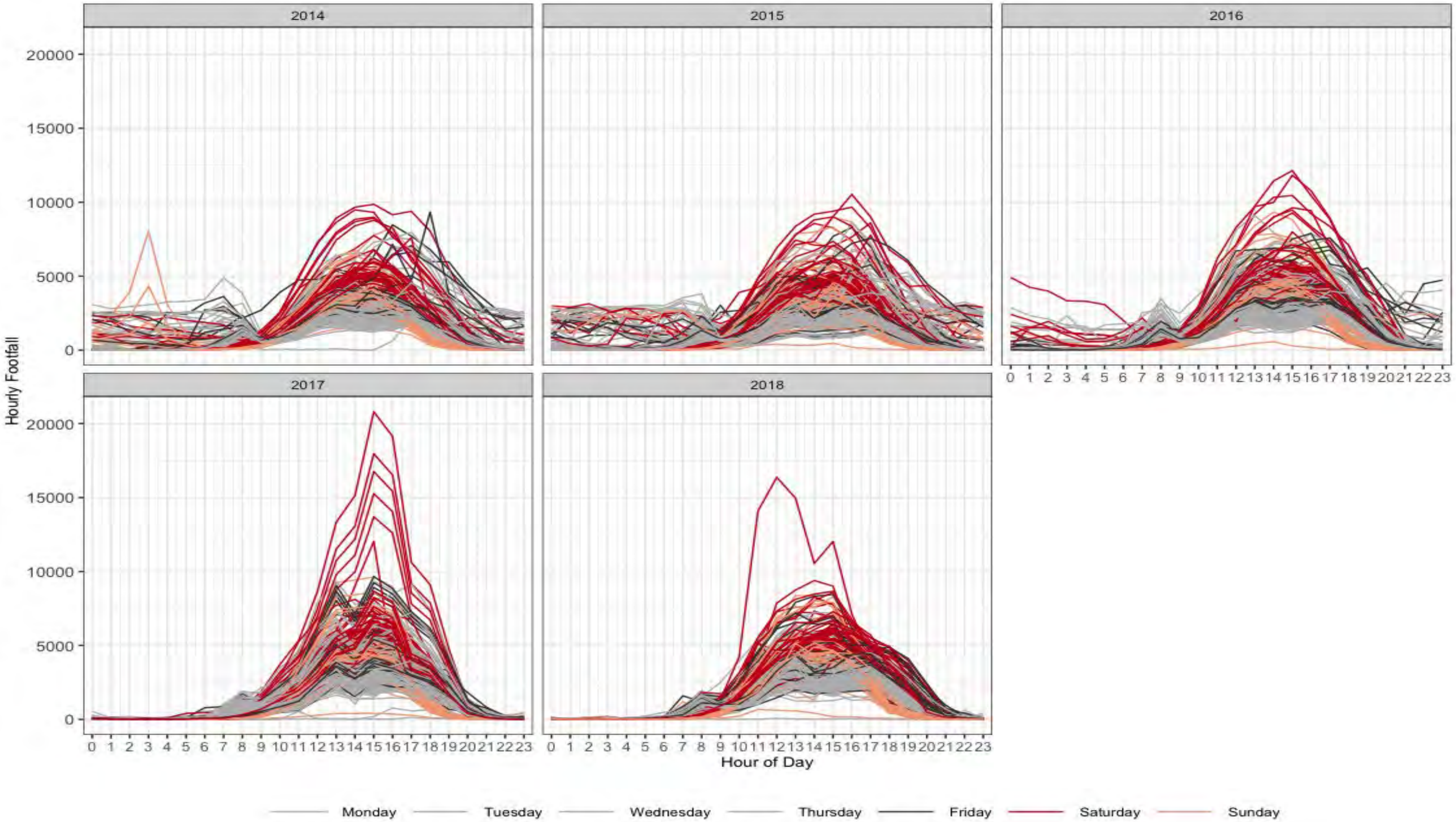


Figure 8.24. Hourly plots for Exchange Square - 2014 to 2019.

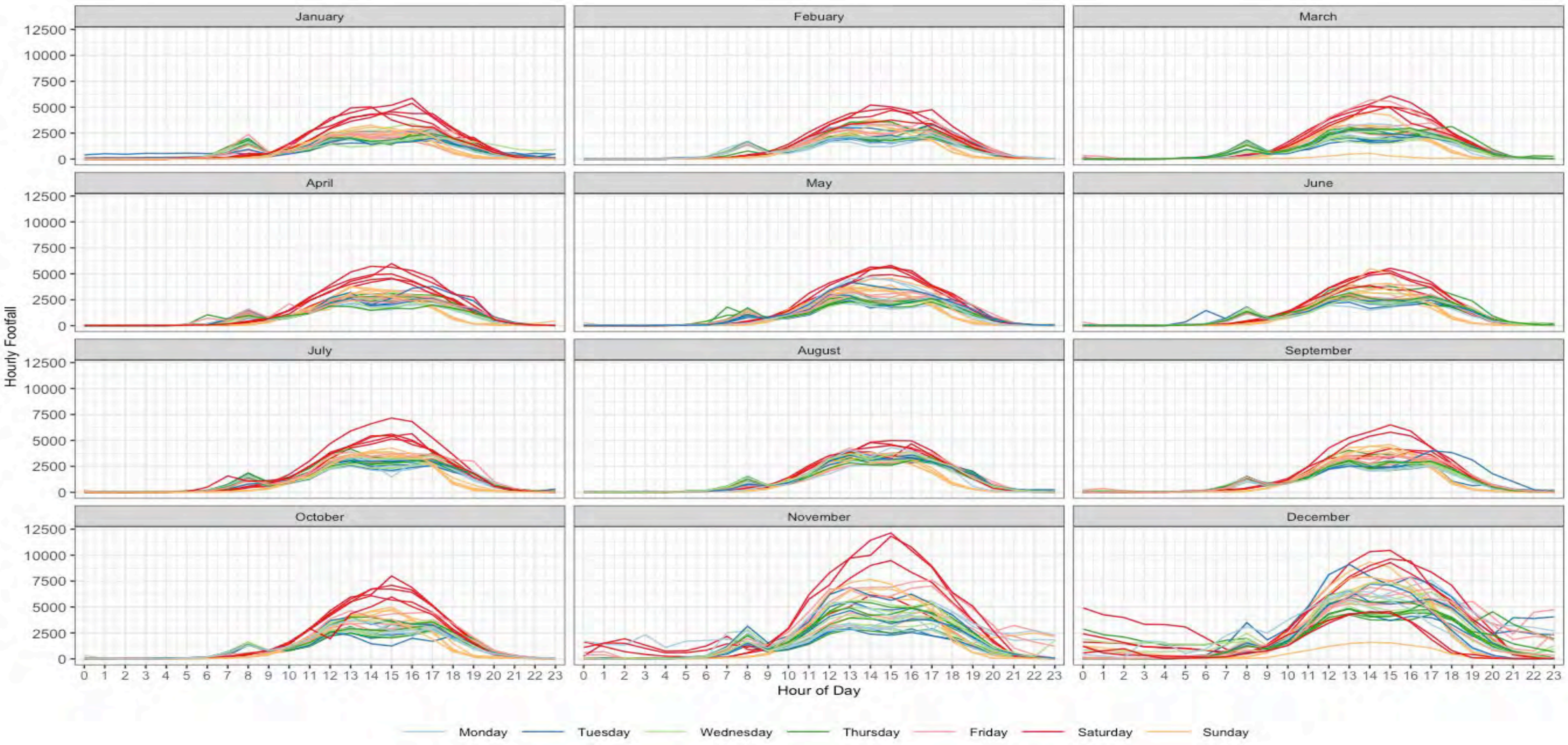


Figure 8.25. Hourly plots at Exchange Square during 2016

8.9 Summary of Results

The run charts of the fuzzy cluster weightings assigned to each medoid provides a useful tool to see how each sensor location evolves over time. When combined with actual plots of footfall data, the changes identified by the cluster algorithms can be better understood and helps gain confidence in the cluster results and their interpretation. Although the Manchester footfall sensors are in the centre of the city centre, the different locations presented different rhythms which all changed over the period of analysis. All the locations demonstrated evidence of the working week rhythms but for some of the more shopping orientated locations, additional afternoon shopping rhythms were superimposed upon this. What the analysis shows is the reducing differential between Saturdays and weekdays, a finding also picked out for the combined sensor results in Chapter 9. Not surprisingly, the cluster algorithm is able to identify the significant rhythms in the data, but not the minor rhythms as identified for New Cathedral Street. This highlights the need for the cluster medoids plots and associated run charts to be supported by the hourly plots of footfall to identify the more subtle signals in the footfall time-series. Finally, no changes to the fuzzy clustering parameterisations were required, nor was there a need to switch away from using the STL decomposed daily and weekly data components.

Manchester was chosen as an exemplar because overall, the footfall sensors indicated a range of daily and weekly signatures. So, the next exemplar, Rotherham is chosen as the opposite is true as all the sensor signatures indicate very little difference between them.

9 Exemplar Results – Rotherham

The footfall results for Rotherham, identified with an urban classification of Major Town, are provided by six sensors, identified in Figure 9.1. The sensors located at: High Street; Corporation Street; Effingham Street; All Saints Square and College Street provided data from the start of 2007. The sixth sensor located at Effingham Square, became available in 2016. All the footfall sensors for the centre of Rotherham are located at the request of Rotherham Council (RMBC, 2020).

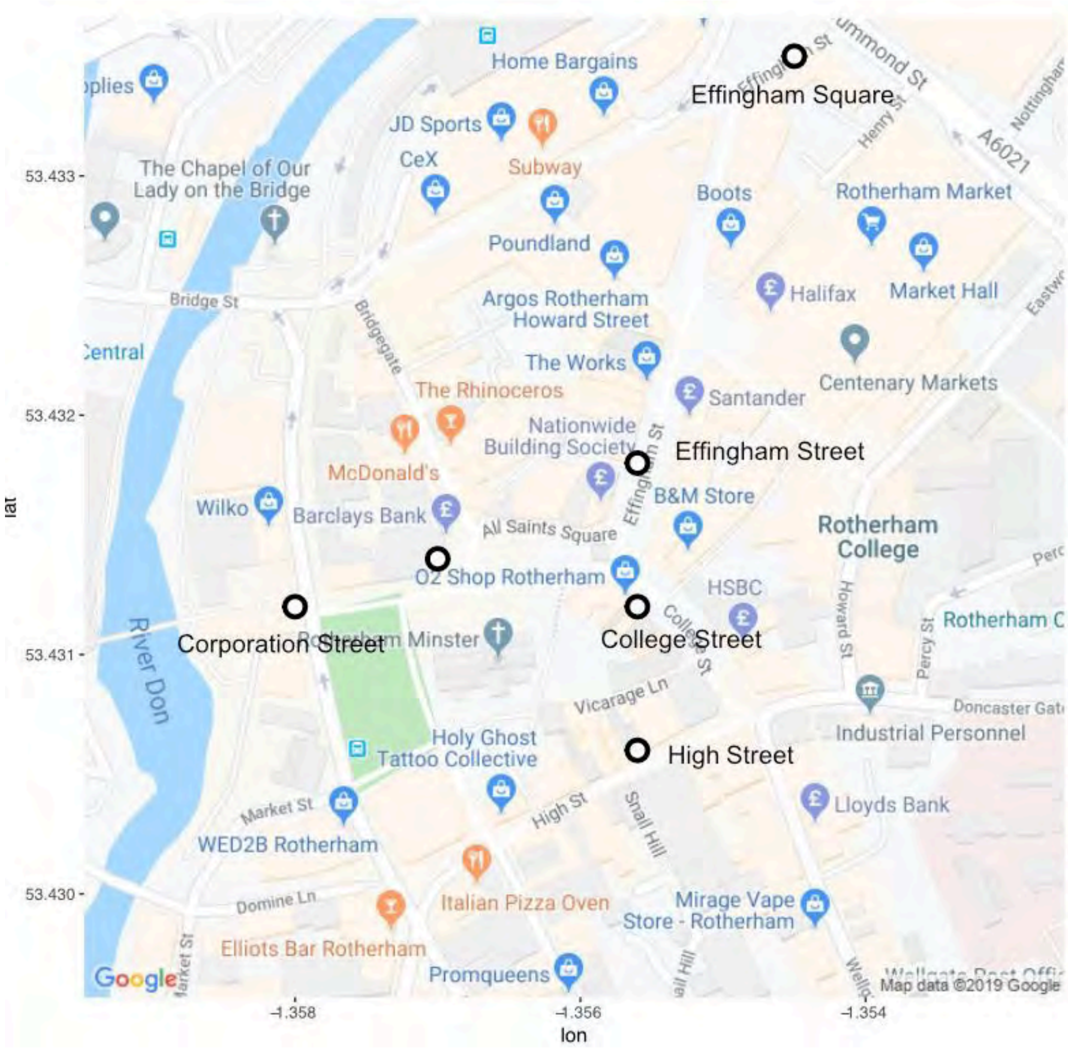


Figure 9.1. The location of the six footfall sensors in the centre of Rotherham

Both Figure 9.2 and Figure 9.3 show how the mean weekly footfall amounts have changed over time with an overall reduction in footfall apparent in Figure 9.4. Between 2011 and 2012, the identifiers for the footfall sensors for College Street and All Saints Square switch and although this is clearly a problem if looking at individual time-series trends for the cluster analysis, as the unit of analysis is a discrete period (individual day, week, or year), this was not considered to have a bearing on overall results. However, it does indicate the importance of using time-series plots for picking out such issues with the data.

All Saints Square is an important location of territorialisation through all the years and Effingham Street indicates a decline in footfall between 2008 and 2010. Figure 9.4 shows that generally, footfall declines over the years and College Street displays reducing seasonality over the years. Figure 9.4 shows that the days of highest footfall traffic in Rotherham are Saturdays, Fridays, and Tuesdays, whilst Sunday has much lower footfall. The much-reduced Sunday footfall supports the findings for town/major town weekly clusters identified in the combined location analysis in Chapter 9.

As with the results for Manchester, the following sections take the approach of analysing the daily and weekly rhythms. The analysis begins by processing results using the STL decomposed daily and weekly signature components. However, the fuzzy cluster analysis failed to provide valid results due to the lack of differentiation between medoids – see Appendix E: Section 16.1 Manchester for the results. Hence, the clustering approach needed to adapt to find ways of increasing the ability to identify changes between the sensors and over time.

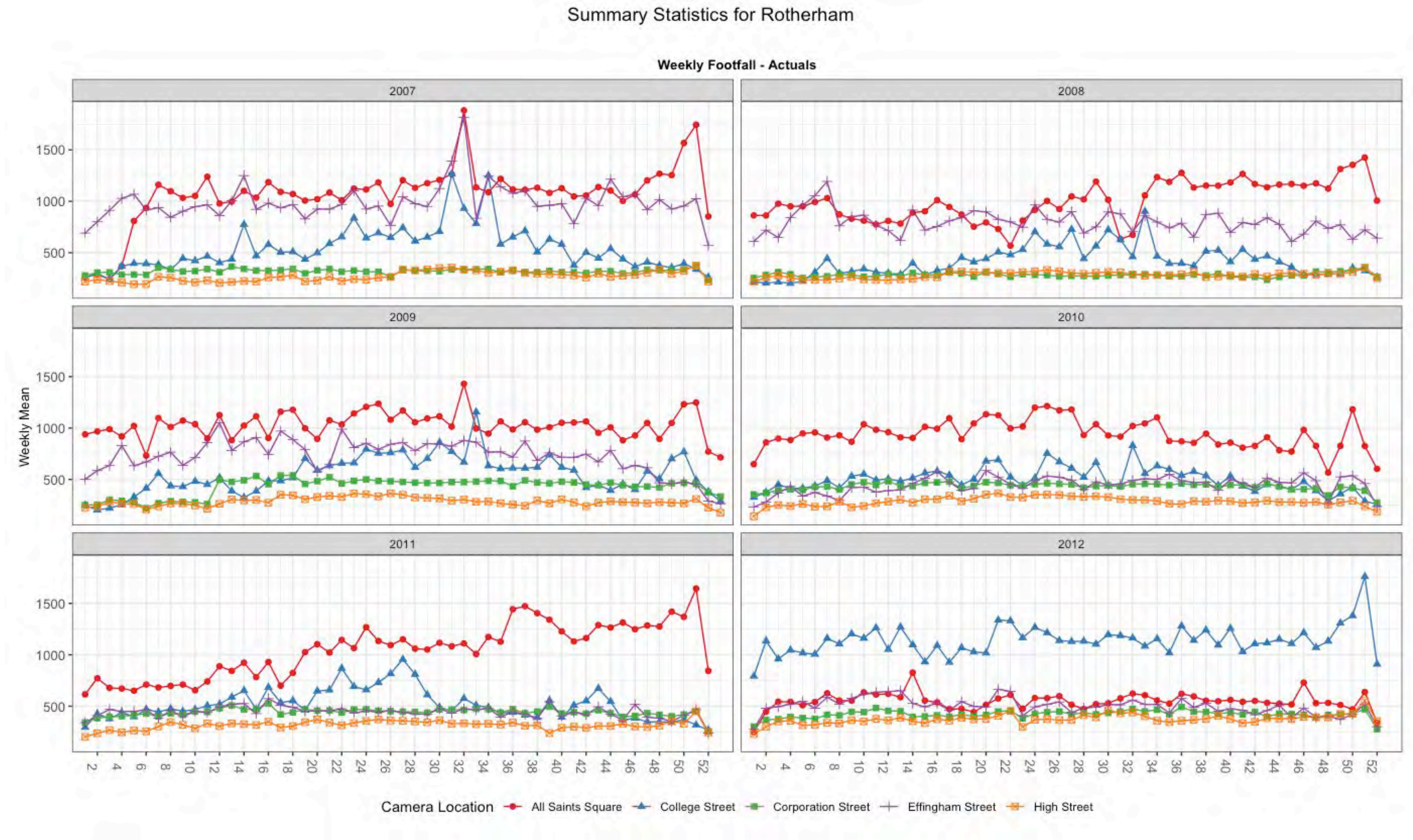


Figure 9.2. Mean weekly footfall for Rotherham town centre sensors for the period 2007 to 2012

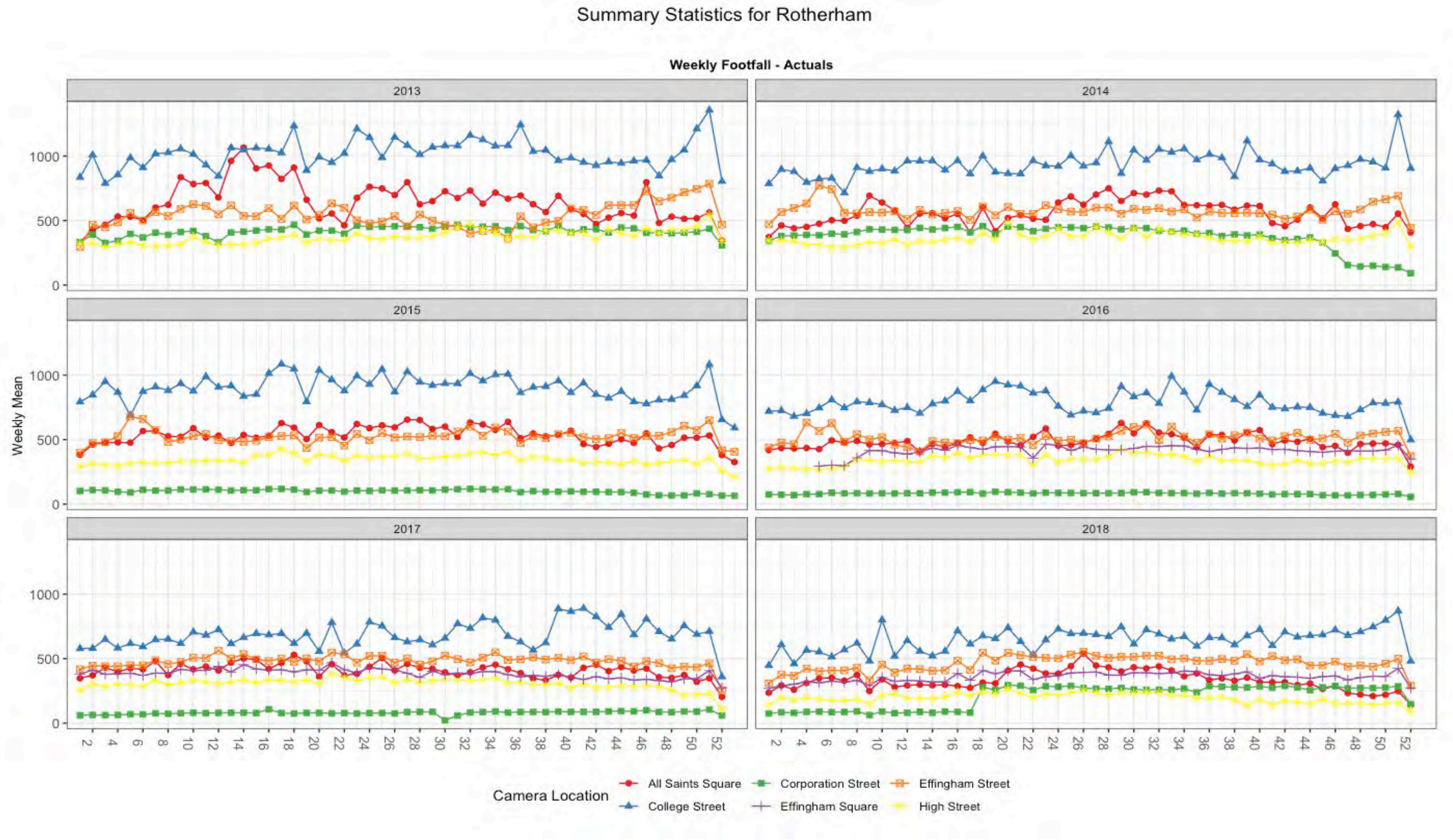


Figure 9.3. Mean weekly footfall for Rotherham town centre sensors for the period 2013 to 2018

Figure 9.4. Mean annual footfall for Rotherham by day of week

Table 9.1. Annual Analysis Types assigned to Rotherham footfall sensors

Year	All Saints Square	College Street	Corporation Street	Effingham Street	High Street	Effingham Square
2007	Mixed + Seasonal	Mixed + Seasonal	Mixed + Seasonal	Mixed + MF-Xmas	Mixed	-
2008	Mixed	Mixed	Mixed	Mixed	Mixed	-
2009	Mixed	Mixed + Seasonal	Mixed + Seasonal	Mixed + MF-Xmas	Mixed + Seasonal	-
2010	Mixed + Seasonal	Seasonal + Mixed	Seasonal + Mixed	Seasonal + Mixed	Mixed + Seasonal	-
2011	Mixed	Seasonal + Mixed	Seasonal + Mixed	Not Defined	Mixed	-
2012	Mixed + Seasonal	Mixed + Seasonal	Seasonal + Mixed	Mixed + Seasonal	Mixed	-
2013	Mixed	Mixed + Seasonal	Mixed + Seasonal	Mixed + MF-Xmas	Mixed + Seasonal	-
2014	Mixed + Seasonal	Mixed + Seasonal	Mixed + Seasonal	Not Defined	Mixed + Seasonal	-
2015	Mixed	Mixed	Mixed	Mixed + Term Time	Mixed	-
2016	Mixed + Seasonal	Mixed + Seasonal	Mixed + Seasonal	Mixed + MF-Xmas	Mixed + Seasonal	-
2017	Mixed + MF-Xmas	MF-Xmas + Mixed	MF-Xmas + Mixed	MF-Xmas + Mixed	Mixed + MF-Xmas	Mixed + MF-Xmas
2018	Mixed	Mixed	Mixed	Not Defined	Mixed	Mixed

Table 9.1 presents the annual analysis types assigned to each sensor in Rotherham. The predominant signal from the annual cluster analysis is that the annual rhythms of Rotherham show a mixture of Seasonal and Mixed signatures and that these can vary from year to year, with some years having more of a

summer peak (Seasonal analysis type) versus a mixture of the Seasonal and MF-Xmas peaks (mixed analysis type). From 2015 onwards, a change in the annual signatures can be identified with the MF-Xmas type becoming more dominant whilst the Seasonal type is assigned less. This matches the general trend found in the annual cluster patterns where the Seasonal rhythm diminishes over the study period.

9.1 Decomposed Daily and Weekly Analysis Results

The fuzzy cluster analysis began using the STL derived decomposed signature values for the weekly and daily signatures. In both cases, the fuzzy cluster analysis was unable to derive valid cluster results. The cluster validation indices for both, see Appendix E p472, show no agreement and, the Radviz diagrams for both were unable to distinguish between the clusters.

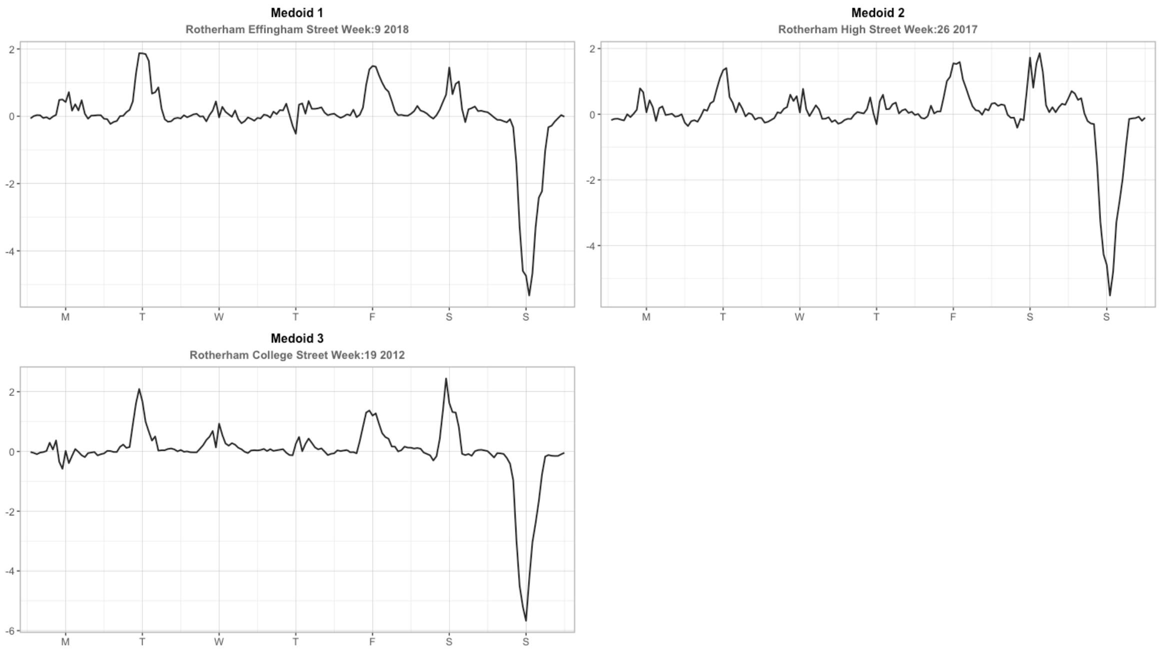


Figure 9.5. Weekly medoids for the Rotherham sensors where k=3

However, the weekly results still highlighted some interesting results. Figure 9.5 above displays the weekly medoids that represented each fuzzy cluster. All three medoids indicate the de-territorialisation of Rotherham on Sundays. All three show that Friday has a significant addition of footfall along with Saturday. What all three medoids pick out though very well is the increase in footfall on Tuesdays, the day when the outdoor market takes place in Rotherham (RMBC, 2020) with 95 stalls available in Effingham Street, Effingham Square, Upper Millgate and the top of Bridgegate (RTC, 2020). Small adjustments are apparent for other weekdays but the main days where territorialisation intensity occurs are Tuesdays, Fridays and Saturdays and Sunday is a day of very significant de-territorialisation. This reflects the annual mean results displayed in Figure 9.4 above. Although the weekly decomposed signatures provide more significant clusters than the daily signatures, the cluster validation indices still failed to suggest a valid number of clusters. This was due to a lack of distinction between the Medoids so in the following sections, options are explored to increase the sensitivity of the fuzzy clustering process.

9.2 Imputed Footfall Data Daily Signature Results – Option 1

The first option explored was to drop the decomposed daily signatures provided by the STL algorithm and use the imputed footfall values (original footfall values with missing data values imputed) directly. The objective, therefore, of this analysis was to validate if the STL seasonal decomposition process used to generate the daily, weekly, and annual components from the footfall data was desensitising the daily fuzzy analysis results. The fuzzy analysis was therefore processed using the footfall daily values which were also standardised for each 24-hour period. See Appendix E: Section 16.2 Rotherham for the validation of the number of medoids chosen.

Figure 9.6 presents the medoids for the daily results derived from the imputed data. Except for Medoid 6, all the other medoids present a daily signature that reaches peak intensity of footfall late morning up till lunchtime. This follows the expected patterns already identified for locations categorised as Towns and Major Towns. In plotting the changes to the medoid allocations over time for each sensor location, no clear patterns were identifiable except for the High Street. Figure 9.7 provides the results for the High Street where Medoid 6 picks out early hours footfall on Sunday mornings especially over the non-Winter period and is investigated in section 9.4 below.

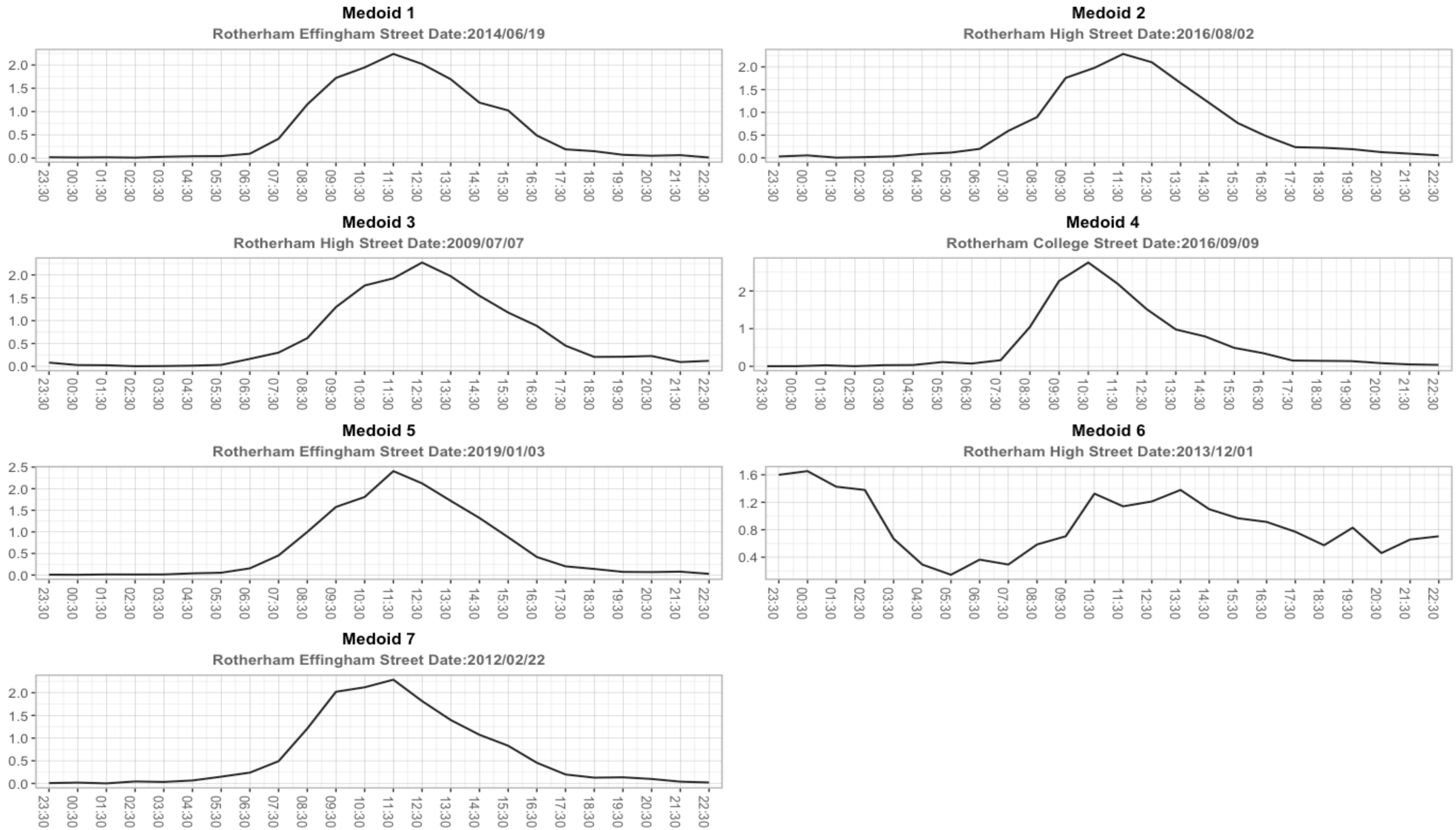


Figure 9.6. Daily medoids using the imputed daily footfall totals for Rotherham where k=7

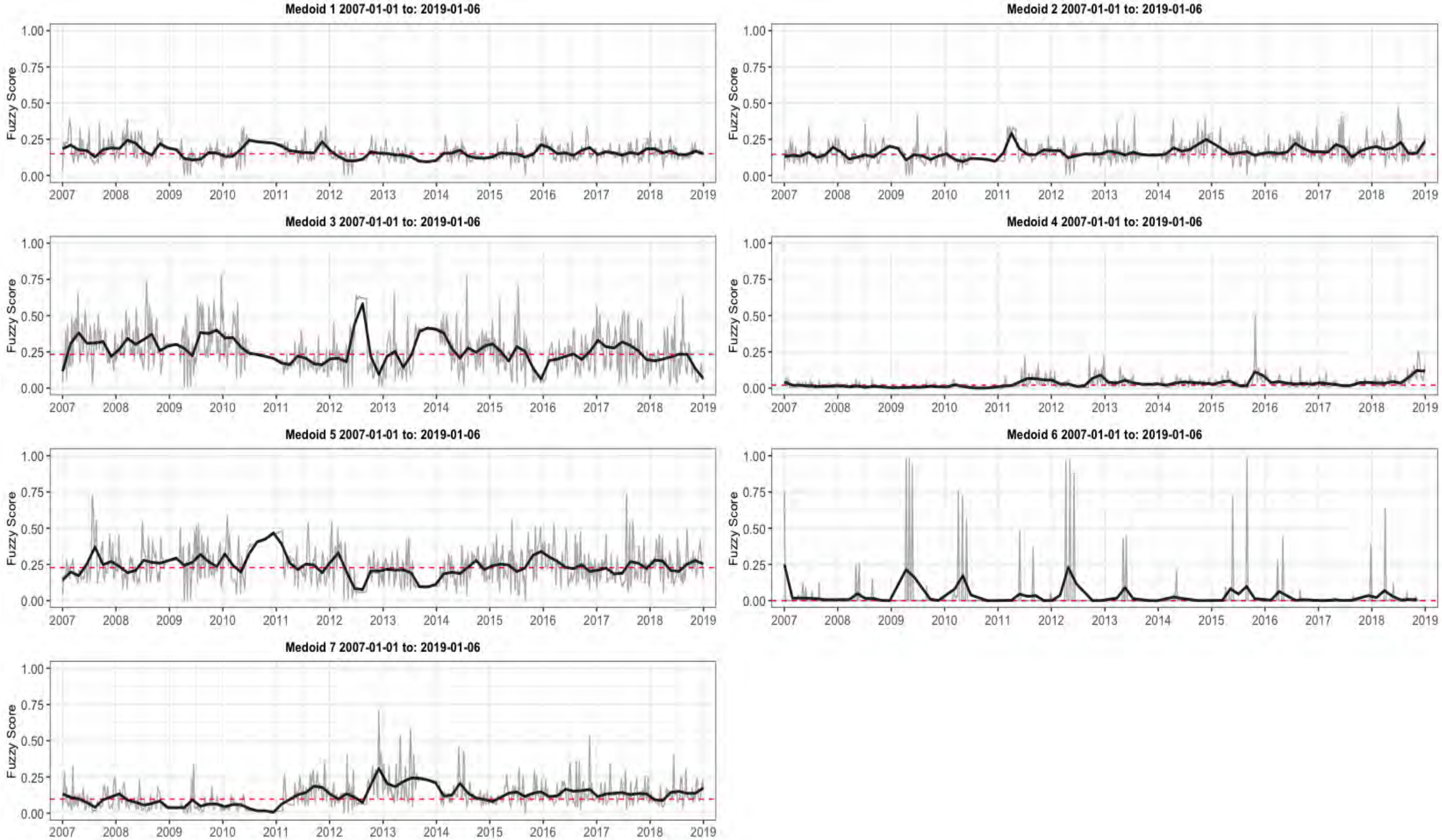


Figure 9.7. Run chart for medoid allocations at High Street

9.3 Imputed Footfall Data Daily Signature Results – Option 2

Using the imputed footfall data again, the fuzzy analysis was re-run but this time with the distance time warping distance switched off and replaced with Euclidean distance. The consequence of doing this prevents the merging of time-series with slight phasing differences resulting in a greater distinction between different 24-hour periods of data. Thus, should there be systematic changes in the shape of the time series such as the peak of lunchtime shifting from midday to an hour earlier, these should be identified more easily. Again, the results were standardised and the validation of the number of medoids selected (k=7) is provided in Appendix E: Section 16.2 Rotherham.

The results in Figure 9.8 reflect those displayed in Figure 9.6 although the Sunday medoid pattern is not present for the second option results. However, the biggest difference becomes apparent when the run charts showing how the fuzzy allocations change over time for each sensor are plotted. For the fuzzy results using the Euclidean distance, the run charts pick out much more detail in the change of the medoid allocations. For example, in Figure 9.9, there is a clear change from Medoid 6 to an assortment of Medoids 1,2,5 and 7, the significant feature being the shift of the peak footfall period moving by an hour from midday to before 12:00. Figure 9.10 showing the results for Corporation Street indicates a similar pattern. The results suggest that when the fuzzy analysis results using the decomposed footfall components present results that fail to distinguish between sensor locations, the sensitivity of the analysis can be improved by using the imputed footfall data and by switching to using Euclidean distance for the creation of the distance matrix for daily cluster analysis.

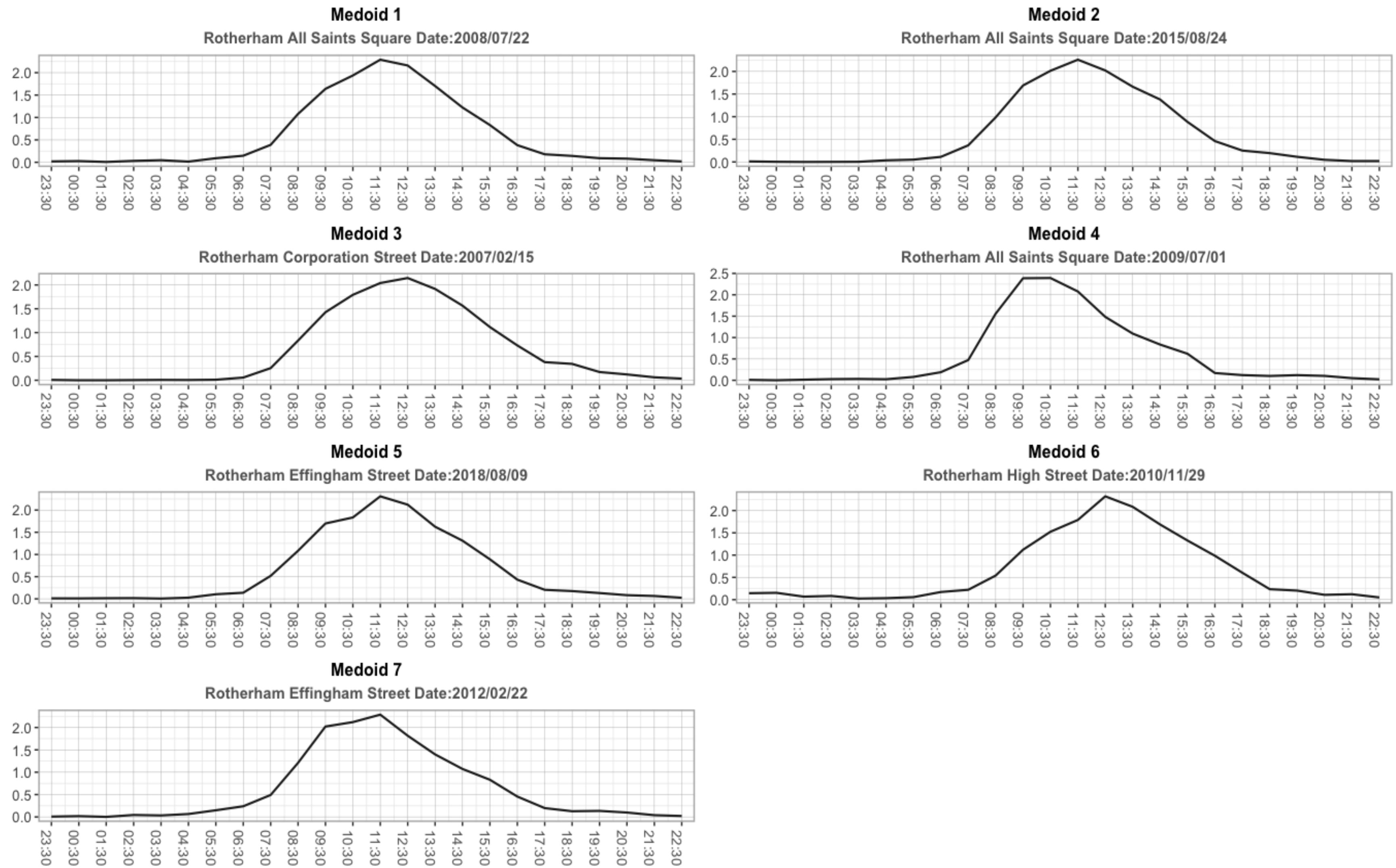


Figure 9.8. Daily medoids using the imputed daily footfall totals and Euclidean distance for Rotherham where k= 7

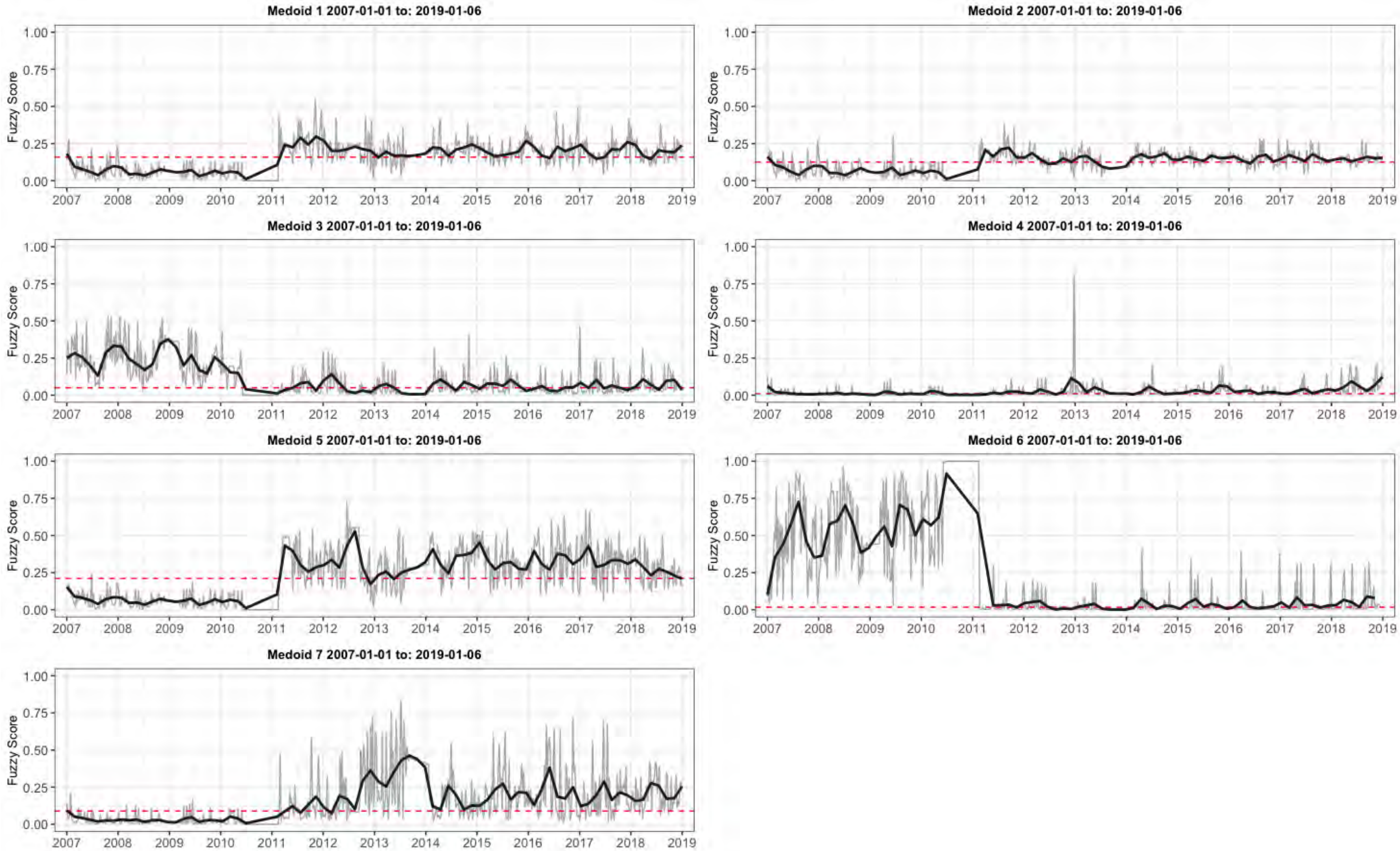


Figure 9.9. High Street Run Chart for the Euclidean Fuzzy Analysis – Rotherham

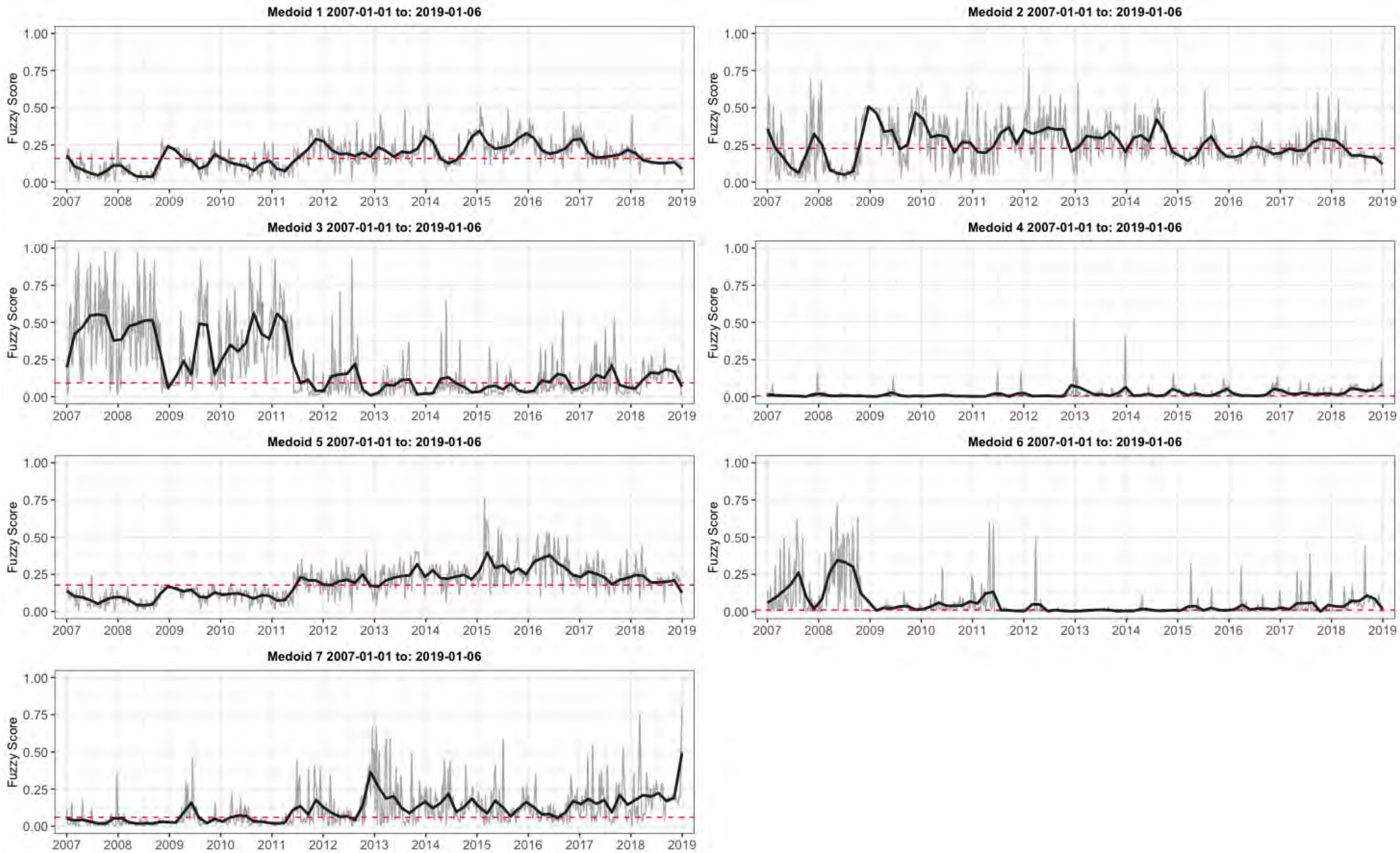


Figure 9.10. Corporation Street Run Chart for the Euclidean Fuzzy Analysis – Rotherham

9.4 High Street Footfall Sensor Analysis

The following sections look at the results for High Street in Rotherham. High Street is pedestrianised and located in the heart of the main shopping area for Rotherham, and although a retail area, there is also a focus on niche shops, entertainment and leisure for this street (RMBC, 2020).

9.4.1 Option 1 Results – Imputed Daily Values not STL decomposed values

From the option 1 results (imputed daily footfall - not STL decomposed values), Figure 9.11 displays how the allocation of each of the medoids changes over time for each day of the week. There are some clear breaks in the fuzzy allocations (suggestive of algorithmic nuances rather than real changes), for example between 2011 and 2012 on Thursdays and Saturdays. However, the most noticeable change is on Sundays where Medoid 6 displays a reduced allocation from 2015 onwards. Figure 9.12 displays the daily plots for the High Street and how these have changed from year to year. Overall, the reduction in the amplitude (the intensity of territorialisation) of footfall is apparent. Tuesdays (green) are an important day for generating footfall, confirming the weekly signature findings and Sundays can be seen to have the lowest overall footfall levels recorded. Returning to Medoid 6 and Figure 9.12, the plot also appears to pick out that the early hours of Sunday show decreasing footfall amounts (these are admittedly small changes) when comparing 2018 to years before 2016.

Table 9.2 illustrates how levels of footfall for the hours 23:30 to 02:30 have changed for High Street in Rotherham. Note the peak in footfall around 2012 followed by a steady reduction since that time which only materialises as a change in cluster allocation from 2015 onwards. The results suggest that the fuzzy cluster algorithm has successfully identified the change in early Sunday morning levels of footfall after the maximum recorded in 2012.

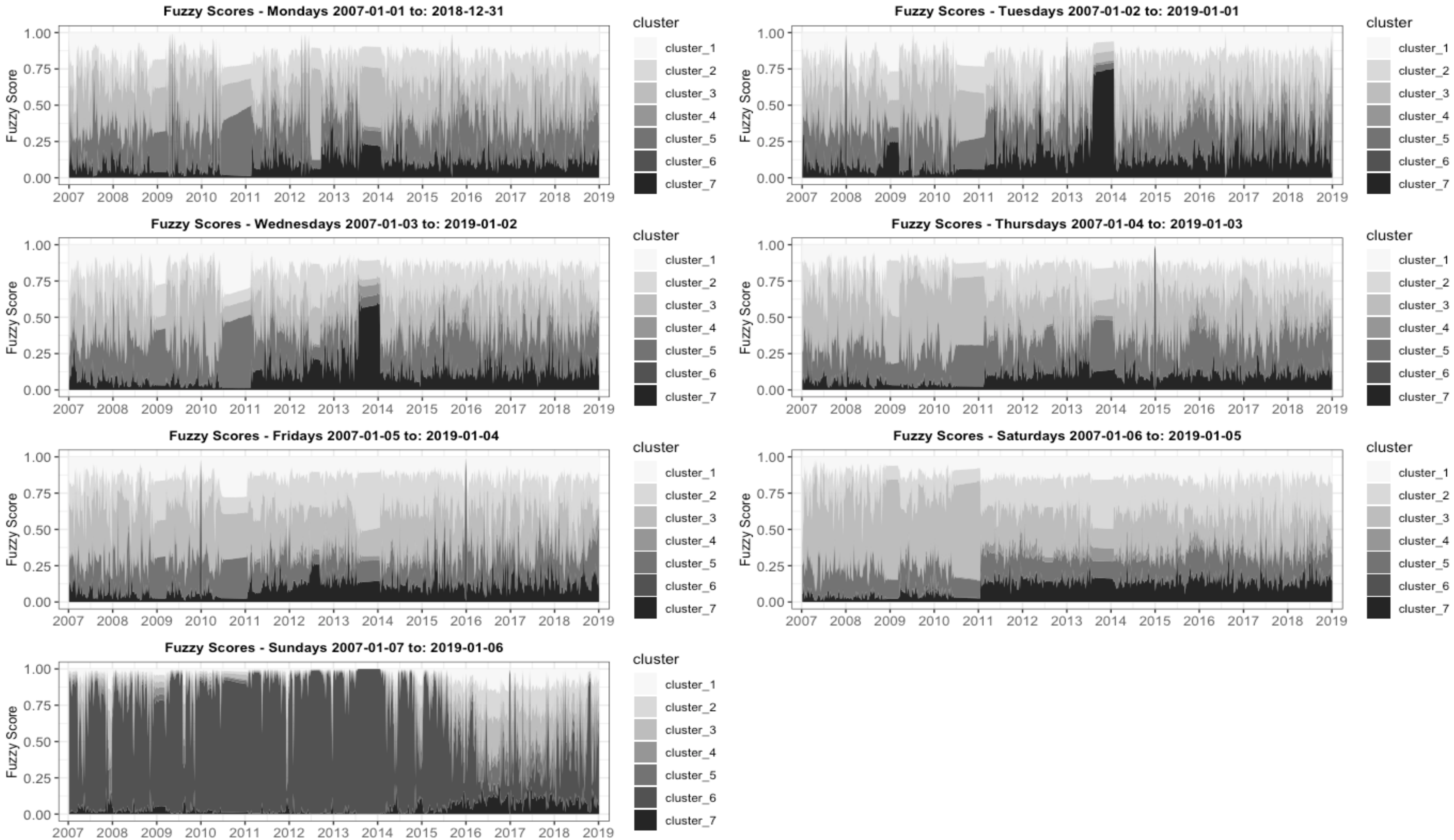


Figure 9.11. Imputed Daily Analysis Fuzzy Scores for each day of the week at High Street from 2007 to the end of 2018

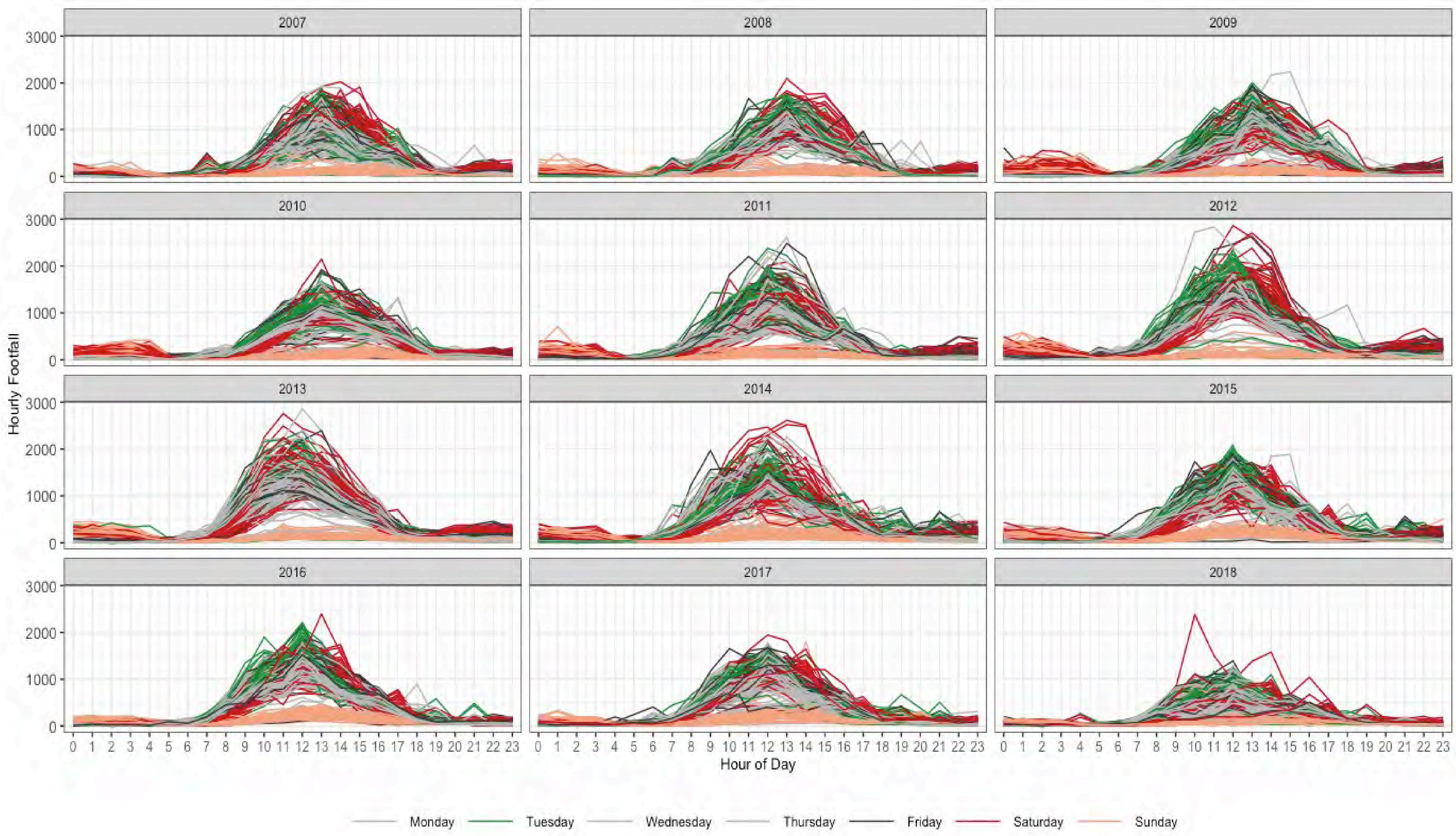


Figure 9.12. Plot of the daily footfall profiles from 2007 to the end of 2018 - note outdoor market days on Tuesdays (green).

Table 9.2. High Street mean footfall for 23:30 to 02:30 on Sunday mornings.

Years	January	February	March	April	May	June	July	August	September	October	November	December	Grand Total
2007	2071	1694	1414	1236	981	909	2548	2119	2720	1710	1997	2584	21983
2008	2255	1439	2242	2084	1660	2698	1946	2219	1849	2513	2492	3693	27090
2009	1999	1822	2422	3633	4025	3421	3755	2291	1595	2240	4052	3983	35238
2010	3528	3381	3254	2484	3574	2932	2914	3080	1526	2165	2331	2129	33298
2011	2705	3229	2603	2839	3953	2756	3197	2867	2253	4544	2243	2656	35845
2012	4326	3545	4905	5057	3976	3767	3456	2877	3781	3240	3637	4645	47212
2013	2794	2595	4475	2719	2640	4009	2416	2811	3779	2440	3005	6107	39790
2014	2219	2602	2914	2263	2260	3489	3045	3501	2791	2746	3503	3001	34334
2015	2015	2642	3470	3648	3557	2523	2633	3400	2036	2249	3286	2999	34458
2016	2134	2437	1855	2042	2216	2067	2149	1453	1652	2243	2368	1972	24588
2017	2291	2038	1740	2538	1604	2076	2557	19:00	1748	2325	1980	1227	24024
2018	806	899	931	1733	1219	1215	1368	1398	1323	1386	913	1464	14655

9.4.2 Option 2 Results - Imputed daily footfall and DTW switched off

Based upon the option 2 fuzzy results, Figure 9.9 displays how the allocation of each of the medoids changes over time. Between 2011 and 2012, there appears to be a relatively sudden change in medoid allocation with this suggesting a phase shift of the lunchtime peak to an hour earlier. Figure 9.13 plots the intensity of territorialisation for Thursdays (non-market day) and the shift of the lunchtime peak from being between 13:00 to 14:00 minus 12:00 to 13:00 to an hour earlier after 2011 is apparent. Figure 9.13 therefore provides a useful view of how footfall changes hour to hour over the years for a particular day of the week. Figure 9.14 presents the results for a Tuesday (market day) but also shows the phase shift around 2011 although the morning period demonstrates a more intense period of territorialisation as was also picked out by the weekly cluster medoids in Figure 9.5.

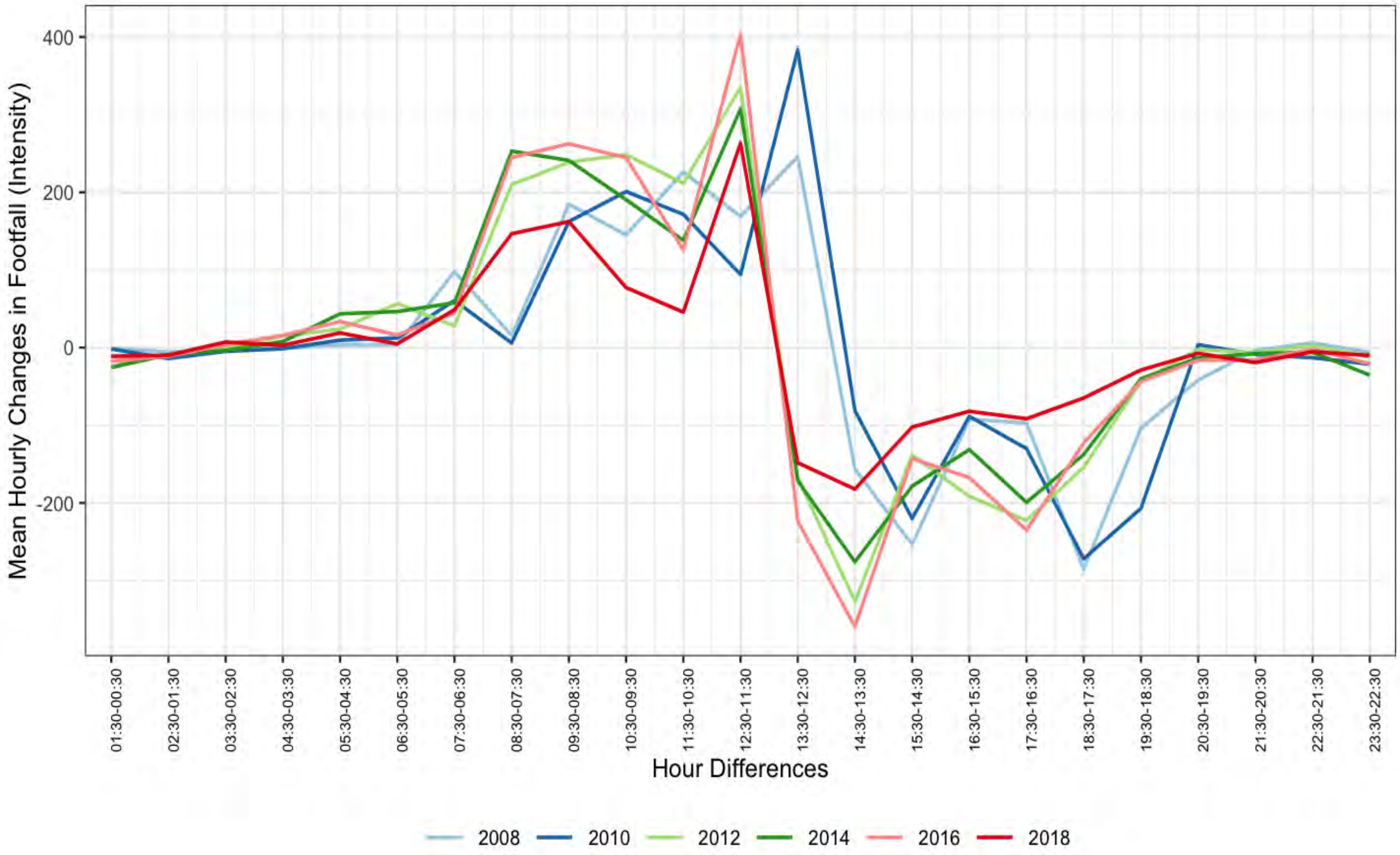


Figure 9.13. Intensity Plot showing mean changes in hourly differences for High Street on Thursdays

Figure 9.14. Intensity Plot showing mean changes in hourly differences for High Street on Tuesdays

9.5 Summary of Results

When processing the footfall sensors for Manchester, the data used, and fuzzy analysis parameterisations were the same as used for the annual analyses for the combined locations. In the case of Rotherham, where the differences between the sensors was much more subtle, the sensitivity of the decomposed daily and weekly footfall components and the fuzzy cluster parameters needed to be adjusted and made more discriminating. The options tested were:

- Option 1. For the footfall data, rather than use the decomposed daily and weekly values generated using the STL function, this option re-ran the analysis with the hourly footfall data (with missing data values imputed), both for the daily and weekly analysis periods.

- Option 2. Using the imputed footfall data as with option 1 but in addition, force the algorithm that matched each daily signature to use Euclidean distance, thus maximising the differences between each day and location.

The Option 1 analysis picked out changes in footfall for early Sunday mornings but otherwise no distinction between the medoids could be identified. The increased sensitivity of Option 2 though was able to pick out phase shifts in peak hours of lunchtime footfall with a shift from midday to an hour earlier. Note, the changes discussed above were based on the daily signatures as no significant changes could be identified for the weekly period over the whole of the period from 2007 to 2018. For the weekly analysis, it probably is the case that there is only one valid Medoid where k=1.

The results suggest that an ensemble approach (Lines and Bagnall, 2014; Bagnall et al., 2015) to the fuzzy cluster analysis might optimise the results. That is, assuming there are no computational constraints (as was the case for this study), performing the fuzzy cluster analysis with a range of parametrisations to explore the different sensitivity levels present in the data. The advantage of such an approach would then be to analyse and highlight different magnitudes of change within the data.

10 Discussion

To provide structure to the discussion of the research, the approach taken in this chapter is to address each of the study objectives and research questions in turn.

10.1 Objective 1 – Establishing a Theoretical Framework

> *To review and synthesise the existing literature within areas relating to place and place management (i.e., human geography, economics, marketing, retail, town management and urban planning), the everyday experience of place (i.e., phenomenology, lifeworlds and assemblage theory) and performance measurement and management (PMM).*

This study began with the provision of several years of footfall data made available to Manchester Metropolitan University (MMU) and the Institute of Place Management by Springboard (http://www.spring-board.info). As a starting point, with a background in meteorology and the verification of numerical weather prediction models (Bromley et al., 1994), the instinctive first step was to simply explore the data, to establish a ‘feel’ for what existed using graphical display techniques (Tukey, 1977). These initial investigations revealed a set of annual patterns in the footfall data that were further developed as a means of classifying places based upon their annual footfall signatures (Mumford et al., 2021). Yet, despite having the data, the theoretical approach to underpin this analysis was unclear, leading to the articulation of the first objective of this study.

Initially, the focus of reading was directed by the identification of the factors that have an influence upon the high street and those which the high street has influence over (see Parker and Ntounis, 2015), and a later, expanded list of factors (Parker et al., 2017), with the intention of finding a theoretical approach to attribute footfall to the influencing factors. However, the difficulty of attributing the specific influences of economics, politics, culture, technology etc back to the footfall data became quickly apparent; for example, how to account for the growth of internet retailing (Wrigley and Lambiri, 2015), economic recession (De Magalhães, 2012), local and national politics (Peck and Tickell, 1995), cultural changes (Shove and

Southerton, 2000) when these all operate at different scales of influence, from the micro to the macro (Parker et al., 2017) and, moreover, were unevenly distributed over space and time (Harvey, 1996). However, identifying a theory that could relate back to the footfall data was problematic.

What became apparent from the early explorations of the data (Parker et al., 2016) were the annual rhythms identified from monthly footfall totals. From plotting the hourly totals, it was evident that not only were daily rhythms identifiable, but so to were weekly rhythms. The notion of the existence of rhythms in the data lead to Lefebvre (2004) and rhythmanalysis which appeared to provide an approach with the emphasis on rhythms of different periodicities, acting through the body across space and time (Gregory, 2009). However, this was more of an analytical approach (Simpson, 2011) and Lefebvre (2004) provided little detail regarding the issue of method and how to operationalise rhythmanalysis (Simpson, 2012).

From the literature of everyday life (De Certeau, 1984; Stewart, 2007; Shove et al., 2009), came the ideas of patterns of social activity; of how the actions of individuals can coalesce into groups of common activity (Batty, 2002), where the individual at the micro-level (Relph, 1976; Tuan, 1977) can performance social practices alongside others and how these aggregated social practices can represent a meso-level of society (Seamon and Nordin, 1980; De Certeau, 1984). This cannot then be broken back down to the level of the individual (Schatzki, 2009), as the practice only becomes apparent as a body of people – for example, the social practices of commuting (O'Dell, 2009). Both Lefebvre (2004) and De Certeau (1984) point out the importance of distance from the social practices being observed, how the further away the observer becomes, only the collective meso-level patterns of social activates are identifiable and those at the micro-level of the individual, are obscured (as these are only apparent through detailed qualitative inquiry). From this thinking came the idea that the footfall patterns were also a meso-level performance measure of aggregated social activity (Duffy and Stojanovic, 2017). Finally, in considering social activity patterns, Cresswell (2015:53) provided the idea that places were 'ideal candidates' for Assemblage Theory (see DeLanda, 2006, 2016).

Assemblage theory (DeLanda, 2006, 2016) provided an ontology that fitted with a processual view of the footfall data, where the patterns apparent in the data could be considered as aggregated social activity (Dittmer, 2014a; Briassoulis, 2017a; Dovey et al., 2018). The ability for assemblages to emerge, to be real and become actual matched the idea that social practices can be switched on and off as a consequence of emergent events (Dovey et al., 2018), for example, the COVID-19 pandemic. In addition, DeLanda (2016) argues that any whole at a given scale is composed of smaller molecular parts. Thus at any level, assemblages exist as parts of populations, populations of persons, pluralities of communities, collectives of urban centres etc., and it is from the interactions within these populations that larger assemblages emerge as a *statistical result*, or as collective of unintended consequence of intentional action (DeLanda, 2016). This idea of collectives of persons matched the ideas already explored from the reading of everyday life literature (De Certeau, 1984; Stewart, 2007; Edensor, 2010). However, the Assemblage Theory literature appeared to provide little guidance regarding an analytical framework to understand the footfall patterns. This was provided by Territorology (Brighenti, 2010a; Brighenti and Kärrholm, 2018).

As the epistemological framework for analysing the footfall data, Territorology (Brighenti, 2010a; Brighenti and Kärrholm, 2018) was adopted. Territorology permits the rhythms apparent in the footfall data to be analysed as representing changes in territorial intensity over time – the degree of territorialisation. Combined with Assemblage Theory, this suggested that the intensity of processes within an assemblage (Brighenti and Kärrholm, 2018) is something that can be measured, and that the intensity of territorialisation processes as suggested by DeLanda (2016) can be inferred from the footfall data. Intensity is also noted by Brighenti (2014) as being required for territorialisation as an '*intensification of a shared (communal) environment'* (Brighenti, 2014:20). Hence, combining intensities with the processes of territorialisation, provided a means of conceptualising changes in footfall counts, across all timescales. From Gehl (2010) came the idea that these intensifications are social activities that can be considered necessary and/or optional resulting in the conceptual model presented in Figure 10.1 and intensity defined by Equation 10.1. Previous studies informed by notions of territorology (Kärrholm, 2008, 2016; Smith and Hall, 2018; Kärrholm and Wirdelöv, 2019) have taken a qualitative approach. By adapting the theory of territorialisation for use with the footfall data, this study shows that territorology can also be used as a theory to analyse the footfall data and that the footfall data facilitates a quantitative view of place.

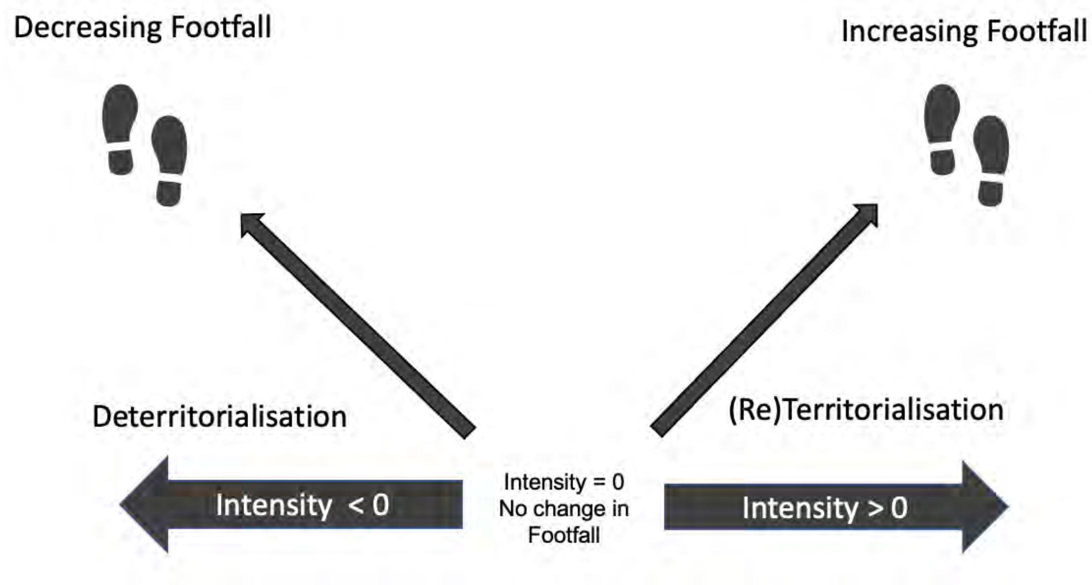


Figure 10.1. Territorialisation Intensity of Social Activity and Footfall

Equation 10.1. Intensity of Activity Types

$$Intensity_{ijk} = \sum_{i=0}^{n} necessary_i + \sum_{j=0}^{n} optional_j + \sum_{k=0}^{n} social_k$$

By considering the process of quantification that occurs with the footfall sensors with respect to each individual, all that identifies the person is reduced to a count of n=1, and thus anything qualitative is rendered invisible (Brighenti, 2019). Yet, by summing up the numbers of people, it is possible to identify the convergence of social activity territorialisation patterns (Brighenti and Kärrholm, 2018), and from these patterns, the common assemblages that exist between places (DeLanda, 2016). The assemblages represent the intensification of territorialisation (Brighenti and Kärrholm, 2018) that is occurring at each sensor location over time and space. This is a kind of movement space (Merriman, 2012), but one where the change in territorialisation intensity is measurable (i.e. the difference between hours) but the directionality of the flow of movement is unknown. There is no vector, no means to deduce the direction of pedestrian flow unlike for example, the pressure gradient force that exists in meteorology (Wallace and Hobbs, 1977). Thus, there is no means to determine if the footfall flow is focused towards a single direction or evenly distributed in all directions. Of course, this could be determined, but requires specific place knowledge. This is a weakness of the sensor data (available to date) as opposed to tracking pedestrian movements through Wi-Fi or mobile phone data (Lugomer and Longley, 2018; Sulis et al., 2018; Traunmueller et al., 2018; Philp et al., 2021). Footfall is viewed by this study to be a performance measure, not a key performance metric as defined by Melnyk et al. (2014) where targets and consequences for missing the targets are required. For this study, footfall is more an interactive measure (Melnyk et al., 2014), one that supports learning (Koufteros et al., 2014; Canonico et al., 2015), and something to indicate whether change is occurring.

The identification of the theoretical framework was an abductive process (Jagosh, 2020), where the initial data analysis helped inform thinking, in particular, the evidence of rhythms in the footfall data. Synthesis of the literature helped inform and develop the idea of conceptualising the footfall data within the framework of territorology (Brighenti, 2010a) and Assemblage Theory (DeLanda, 2016), the combination of which suggested that a quantitative approach could represent the collective meso-level rhythms of footfall (social) activity (Schatzki, 2009) in space and time. Finally, identifying the theoretical framework was a key objective for determining the approach of the research design and subsequent implementation. It is also one of the contributions made by this study by developing the theory of territorology (Brighenti, 2010a; Brighenti and Kärrholm, 2018) through taking a quantitative approach to the conceptualisation of collective social activities of pedestrians in towns and cities.

10.2 Objective 2 - Research Design

Create an analytical framework for analysing the hourly footfall data supplied by Springboard (www.spring-board.info<http://www.spring-board.info/>) at 500+ footfall remote sensor locations throughout the UK

This study brought together a set of skills developed over the years, one of which was experience of software development and use of database technology, both of which this study rejuvenated. The software languages Python and R were used for the analytical framework and are industry standards for data science (Wayner, 2017; Gallagher and Trendafilov, 2018). Both languages needed to be learnt and were used to create the following key components:

- Loading the original csv footfall files into a MySQL database (Python)
- Cleansing the data (Python)
- Imputation of Missing Results (R Studio)
- Decomposition into annual, daily, weekly, trend and residual components (R Studio)
- Fuzzy cluster analysis and output diagnostics (R Studio)
- Display and Interpretation of Results (R Studio, some Excel)

Originally, Python was the language of choice for the whole study but after various issues where problems were encountered with different versions of software, the switch to R was made. Hence why the initial parts of data processing are done using Python whereas the interpretation and results are all R based. Indeed, keeping the data storage and processing code and statistical analysis and display code separate is considered good practice (Wayner, 2017).

The analytical framework developed has some shortcomings. Firstly, the code for populating the database was never developed to permit continual ‘operational level’ updating of new footfall data. Secondly, the quality of the code developed is not of releasable standard, and therefore, cannot be shared for public use. R provides the option to package and release code through Github (https://github.com/r-lib) which is a repository for software code that allows code to be shared by other developers and application users of platforms such as R Studio. Both issues though are resolvable.

For the data analysis phases, R Studio (RStudio Team, 2018; R Core Team, 2019) proved to be easy to use, the documentation was excellent and clear, which was important as this detailed statistical function default parameterisations and what could be adjusted – a strength of R compared to Python (Gallagher and Trendafilov, 2018). Very useful indeed was the history R records of every command and function executed. Frequently during this study, there were gaps between reading and doing the data analysis work and being able to go back through the history of previous work saved a considerable amount of time avoiding the need to relearn the code. For generating graphics of the results, ggplot2 (Wickham, 2016) was used repeatedly and the ability to control all elements of the displays was one of the issues for switching from Python to R. In all, a lot of code was written through the iterative processes outlined in Chapter 4 – Research Design Operationalisation p134, although in the end, only a subset of the total code written was used to analyse the data and generate the graphical outputs.

To conclude, as an analytical framework, the software developed met the research requirements of this project. To be of use in a town management context, the building blocks are in place but further operationalisation and development of the codebase is needed, not least the delivery of the results through interactive dashboards as suggested by Kitchin et al. (2015).

A key choice for the framework was deciding how to analyse the footfall data. As noted already, one of the constraints for this study was the need to use pre-packaged statistical libraries to perform the analysis. As this research was not specifically a technological or statistical project, they were treated as tools to use; consequently, changes to underlying algorithms were considered out of scope for this study. Hence one of the decision factors in choosing the time-series cluster analysis package was the quality of the documentation. For this reason, the dtwclust R package (Sardá-Espinosa, 2019) was chosen, but another was the convenience of having the ability to perform the data analysis process in a single programme execution. That the documentation was well presented and useable was vital because by taking the data analysis down the path of fuzzy cluster analysis and using distance time warping, there was a lot of parameterisations to consider. Fuzzy cluster analysis was chosen, firstly because it was viewed as a form of analysis that could be used to model human activity patterns (D’Urso and Massari, 2013), but also because previous footfall pattern analysis research

(Monheim, 1998; Lugomer and Longley, 2018; Murcio et al., 2018) had not adopted this technique –presenting a potential methodological contribution .

However, fuzzy clustering and the required parametrisations make the method complex and prone to misplaced assumptions (Bezdek, 1981; Angstenberger, 2001). A source of 'worry' for this study was the subjective assessments of the parameterisation settings (Bezdek, 1981; Wang and Zhang, 2007) that are detailed in Chapter 4. Repeated tests based upon different parameter settings took a considerable amount of time and the only diagnostic to check the impact of the different settings was via the cluster validation indices plots (Wang and Zhang, 2007) and the Radviz diagrams (Sharko and Grinstein, 2009; Di Caro et al., 2010) – see Chapter 4 p160. In the end, a methodical process of working through the parameterisations was followed for the distance time warping, cluster algorithm and fuzzy analysis settings (Sardá-Espinosa, 2018). However, such a linear process though risks failing to fully appreciate the inter-related impacts of the parametrisations. What was never identified were routines in the R libraries that could help with deterministically deciding the correct settings – a reason to adopt an Ensemble approach, as suggested by Bagnall et al. (2016) and also implied by Lugomer and Longley (2018) and Murcio et al. (2018). If an ensemble of the parameterisations could be configured, then when reviewing the results, the best fitting results as determined by the cluster validation indices could be selected.

Hence one of the principles for this study was to acknowledge the parametrisations required and that the details of these parametrisations should be available via the Research Design Chapter and Appendix A - allowing the results to be reproducible and replicable Wolf et al. (2020). All the values are provided but there is always the danger that be some defaulted parameters that were not uncovered by this study. It is likely that there are refinements to be made, but from the results and by comparing these to other studies, there was enough similarity between the studies to suggest the research design was valid.

As a pre-processing step to the cluster analysis, the footfall data was decomposed into annual, daily, weekly, trend and residual components using the STL process of Cleveland et al. (1990). For the combined results, the decompositions provided useful insights for the different periods, especially the relationship between the daily and weekly footfall signatures. The one component of the data that was not examined in any detail, was the residuals and this is an area that should be followed up. For example, Zhu and Guo (2017) show how decomposed time-series of taxi journeys and analysis based on the residual component can pick out the unique and unusual events. From a footfall perceptive, this could constitute the impact of weather events, festivals, Black Friday, sports events, protests etc.

For the cluster analysis of all the combined footfall sensors, the results were extracted as individual years. Ideally, the dynamic fuzzy pattern recognition processes in Figure 10.2 suggested by Angstenberger (2001) would have been followed. By continually monitoring the next year iterations of the footfall data, this would have provided a means of continually assessing (Dolega et al., 2021) the footfall cluster patterns and the identification of any changes as clusters merge and split.

Instead, the approach taken by this study follows the static steps in Figure 10.2 which meant that though the results from one year to the next can be compared subjectively, there was no statistical mechanism to do this as Angstenberger (2001) suggests. This however, required a good knowledge of mathematics and statistics and appeared not to be available via the R packages. An attempt was made, but the results made very little sense, perhaps because the number of sensors was not a constant and by using medoids to represent the clusters, the medoids did not persist over the time period iterations. Consequently, this suggests that using c-mean centroids might be the better option for such an approach. What is suggested by Angstenberger (2001) is a blend of supervised and unsupervised learning techniques whereas for all the data analyses of this study, only unsupervised learning was used. However, whilst acknowledging weaknesses of the dependency upon the unsupervised approach, it should be noted that it still had the ability to discover results not previously identified in previous studies.

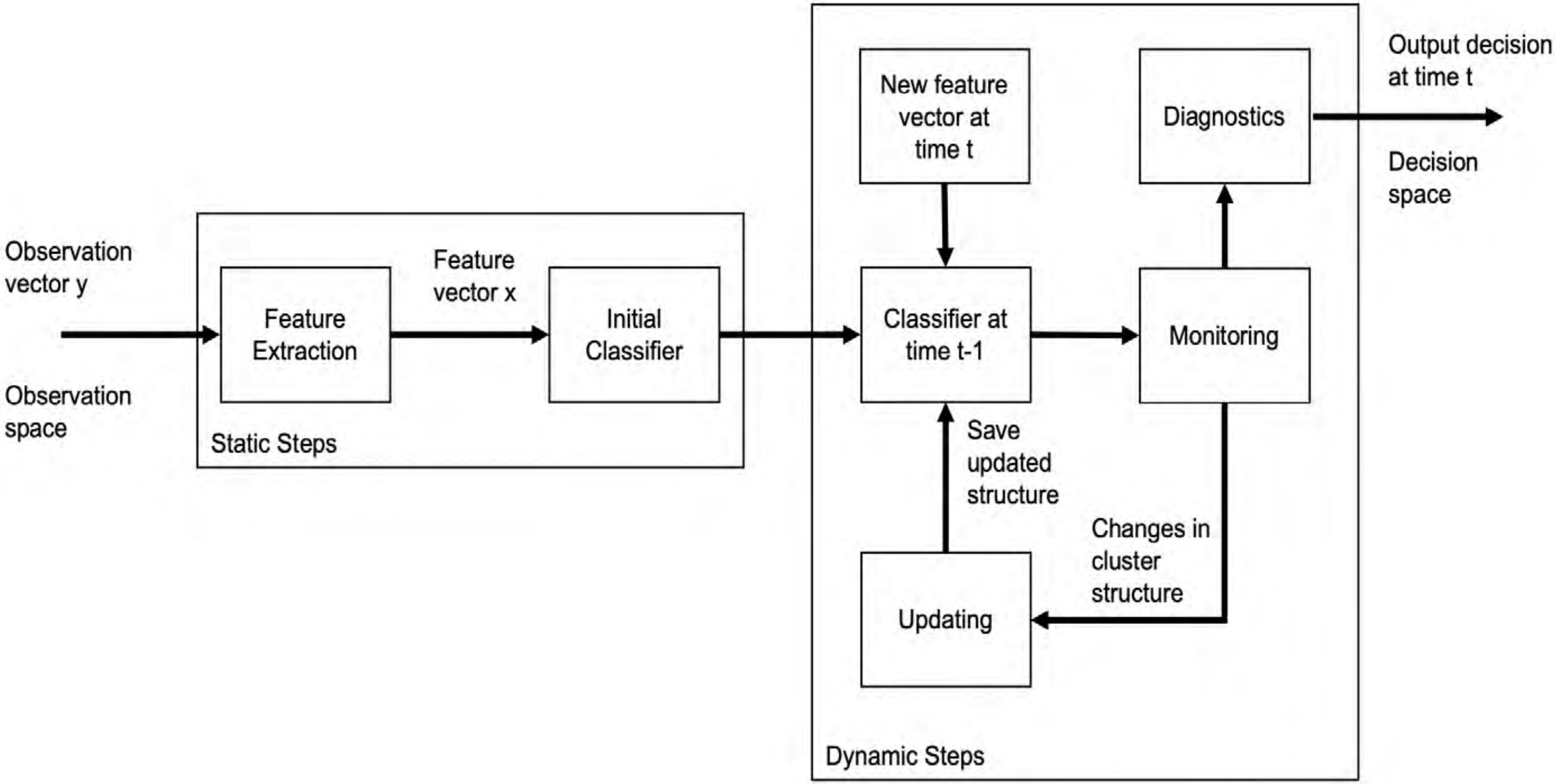


Figure 10.2 - The process of dynamic pattern recognition
(Source: Angstenberger, 2001:35)

The weakness in interpreting the changes to the fuzzy clusters over time for the combined results was not an issue for the exemplar cases. For these, the whole period of footfall data was processed, and the fuzzy results provided a very useful means of identifying how places change either gradually or suddenly as one cluster was replaced by another in the analysis. For this, run charts (Perla et al., 2011; Anhoej, 2015) proved a very useful insight tool. The exemplar results also necessitated an approach that changed the sensitivity of the algorithms used to detect differences between the footfall datasets and for this, the design of the analytical framework and the flexibility of dtwclust (Sardá-Espinosa, 2018, 2019) worked well. Parameterisations such as those used for distance time-warping could be switched off and the data being analysed would be switched from decomposed values produced via STL to the imputed values stored in the database. Overall, the analytical framework for the research has resulted in an extensive suite of software, from displaying the footfall data as simple plots for every sensor, to the fuzzy cluster analysis and the resulting outputs for validation and display of the results.

Apart from the cluster analysis, another aspect of the analysis was extracting and displaying the original footfall data to validate the cluster analysis findings. By storing the data in the MySQL database, extracting the data as required and then processing it into a form required for display via R was relatively straight forward. For example, as a validation check for all the data transitions and original data, the values were plotted out and saved in a library grouped by place and the associated sensors. As a result, it was always possible to check that nothing spurious was corrupting the data. Another example were the difference plots that display the hourly differences in footfall as a measure of intensity of territorialisation. In fact, these plots also suggest that the cluster analysis should maybe be performed again but instead of using the seasonally decomposed values, the hourly footfall differences should be investigated – a second order (rate of change) derivative analysis.

Finally, the UK planning authority centre designations of major city, regional centre, sub-regional centre, major town, and town (CLG, 2008, 2009; NPPF, 2019) provided useful insights for segmenting the footfall clusters. However, if the clustering process were to adopt a more dynamic learning process as suggested above by Angstenberger (2001), then merging the footfall clusters with the data-driven categories suggested by Dolega et al. (2021) might also support the ability to assess the dynamic nature of places and changes over time.

10.3 Objective 3 – Results

Identify the assemblages of everyday rhythms and periodic (annual, weekly, and daily) processes of territorialisation evident within the footfall data.

The third objective of this study concerns the discovery of assemblages and rhythms of social activities evident from the footfall data. The focus of the analysis was upon diagnosis of the social activity patterns apparent in the data. However, footfall data alone cannot determine the types of social activity and their causation. This might have been possible with additional qualitative data but was considered beyond the scope of the study. Thus, footfall is used as a quantitative diagnostic of meso-level aggregated social activity patterns though lacks the detail to determine the types of social activity and how they interrelate with each other and change over time. The objective is broken down into two research questions and the findings for each are discussed below.

10.3.1 Combined Footfall Sensor Results

The first research question is:

As a performance measure, what insights can footfall offer to identify how collectively, places change over time?

Combining the footfall sensor data for all locations provided an opportunity to assess collectively how places are changing and how they are similar. The first phase of the analysis was a validation step to ensure that the annual signatures decomposed via the STL algorithms (Cleveland et al., 1990) and then processed using the fuzzy clustering routines (Sardá-Espinosa, 2018) could produce results that mirrored those of Mumford et al. (2021). From the first results generated, it was evident that the results did correspond to the Mumford et al. (2021) monthly signatures despite there being differences in the time resolution of the data (hourly vs monthly). By using an hourly period resolution that was smoothed over 24 hours, this study was able to provide a more detailed view of the data.

Examples of these finer resolution features included the extent of the build-up to Christmas period, the identification of the end of summer holidays back-to-school shopping period, individual holiday weeks such as Spring half-term and also a drop in footfall outside of school or university term-times. These finer details could be picked up by the cluster algorithms but only because an appropriately fine enough data resolution was being used. At the same time, the general signatures identified by Mumford et al. (2021) were also evident and provided a means of classifying the results for each year to assess changes over time.

During the process of developing the software needed for the research design framework, the various iterations provided plenty of practice learning how to ‘read’ the fuzzy cluster outputs. Other forms of analysis outputs such as electronic cardiograms (Fent et al., 2016) and satellite imagery analysis (Voigt et al., 2007) highlight the need for interpretative experience. As experience grew, so did the appreciation of the less significant signals in the outputs, such as the examples above. Another important factor was the ability to continually compare the outputs from the cluster analyses to the original footfall data. This validation process not only provided confidence in the fuzzy cluster outputs but also helped identify the various display techniques used. For example, using hourly differences to plot changes in footfall intensity and the run charts for displaying the fuzzy cluster results for each individual location.

10.3.1.1 Annual Assemblages

Overall, in considering the annual territorialisation processes and the associated social activity rhythms (Brighenti and Kärrholm, 2018), the fuzzy cluster analysis identified the following assemblages. That is, the common collectives of day-to-day practices that emerge from the annual signature data as statistical results (DeLanda, 2016) through the fuzzy analysis process. The assemblages are:

- *Christmas period assemblage* - which has different levels of intensity and duration. In some locations, the signatures suggest a starting period in early

November whereas this can be later in other locations. As with the duration, the intensity of this assemblage also changes from place to place with the Major City locations being associated with the locations of most intensity. Reflecting that city locations have large catchment areas that are a result of having a greater range of workplaces, retail mix, entertainment, and leisure facilities (Coca-Stefaniak, 2013; De Nisco and Warnaby, 2014; Wrigley and Lambiri, 2015). The assumption is that this assemblage is dominated by optional and social activities (Gehl and Svarre, 2013) such as Christmas shopping and entertainment and therefore would be expected to have maximum duration and intensity in Major Cities. The Christmas period assemblage maps onto the Comparison signature of Mumford et al. (2021).

- *Holiday period assemblage* - linked to specific holiday periods associated with UK educational establishments (schools, universities etc.) and associated with a positive or negative intensification of territoriality. For example, there are peaks during Easter and Summer holidays (Richards, 2010; Newing et al., 2013), whilst in some locations, the periods outside school/university term-times are periods of de-territorialisation (Berry et al., 2016). The assumption is that this assemblage is dominated by optional and social activities when territorialisation intensifies (Gehl and Svarre, 2013:17) such as strolling, enjoying life, eating out etc. When there is deterritorialisation, this suggests the reduction of necessary activities such as going to a place of work or educational establishments. The Holiday period assemblage corresponds with the Holiday signature of Mumford et al. (2021) but is more granular and able to pick out specific holiday weeks such as half-term school holidays.

- *Seasonal assemblage* - suggests a rhythm more generally associated with the climatic seasons and daylight hours (Gehl, 2011), but the degree of intensity differs between locations. What distinguishes this assemblage from the holiday period rhythm is that there are no significant changes in intensification for the term time, non-term time periods. Probably, the seasonal assemblage and holiday event assemblage combine in many cases. The assumption is that this assemblage is dominated by optional and social activities (Gehl and Svarre, 2013) such as strolling, enjoying life, eating out etc. The seasonal assemblage is most closely associated with the Speciality signature of Mumford et al. (2021).

- *Balanced assemblage* - this is assumed to be a multi-functional assemblage where many factors combine to create an assemblage that changes little over time - a steady state rhythm where the territorialisation and de-territorialisation intensities all balance to form a constant footfall volume (Millington et al., 2015; Mumford et al., 2017). The assumption is that this assemblage is dominated by necessary activities (Gehl and Svarre, 2013) such as going to work, commuting, essential shopping etc. This maps to the Multifunctional annual type of Mumford et al. (2021).

- *Specific event assemblage* - such as the de-territorialisation associated with Christmas Day or for the 2008 medoids, the territorialisation of New Year's Eve. The assumption is that this assemblage is dominated by optional and social activities (Gehl and Svarre, 2013) such as sports events, festivals, etc (Hawkins and Lee-Anne, 2013). This is an example where the finer resolution of the data was able to pick out features from the cluster analysis that was not evident in the monthly data used by Mumford et al. (2021).

As a simplified representation, how these assemblages combine is illustrated in Figure 10.3. Over the study period, the fuzzy cluster results suggested that the prominence of the seasonal and holiday assemblage has reduced over time whereas the Christmas period, probably because of falling footfall amounts (Springboard, 2020), has become more significant. Results did show that for many places, the week of peak footfall totals varies interchangeably between the summer holiday or Christmas periods each year, although it should be noted the peak period was not limited to either with some locations indicating a peak period at times such as Halloween. That suggests that these are dynamic assemblages and that in using them to categorise places as used by Mumford et al. (2021), a dynamic categorisation process is needed that can adjust over time.

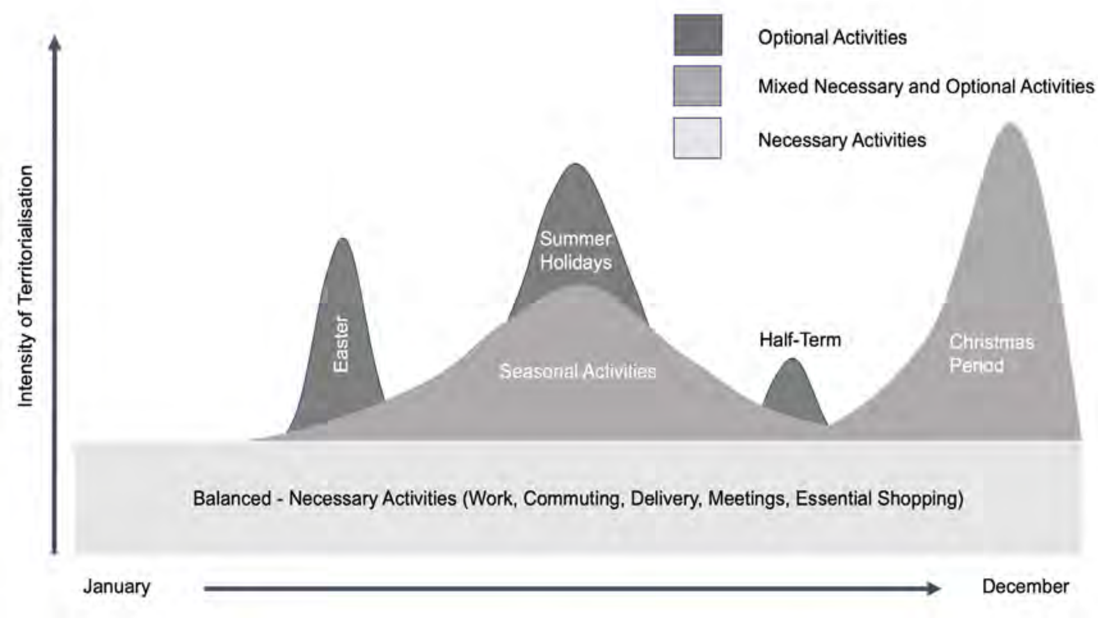


Figure 10.3 Showing the combinations of annual rhythms over period of a year

Figure 10.3 provides a conceptual view of the different assemblage types that can occur throughout the year. The assemblages displayed assume that territorialisation takes place for each period, but this need not be the case. In fact, the assemblage for the different holiday periods, seasonal and Christmas periods could all have zero intensity, leaving the annual signature to be represented by the balanced assemblage, or the Multifunctional signature of Mumford et al. (2021). Reflecting that footfall for each place is an aggregate of residents, workers as well as tourists etc and that each place has a unique 'dynamic catchment area' (Waddington et al., 2017). The annual assemblages identified match closely the signature types identified by Mumford et al. (2021) and also Monheim (1998). As this study used a higher data resolution, and a more detailed view of the annual signatures was possible, and this aided the discovery of additional rhythms of territorialisation and deterritorialisation during holiday periods. For example, during the summer holiday period, a period of deterritorialisation was identified for locations with strong links to educational organisations such as Universities and schools but also, the same effect occurred for some employment focused locations such as Fleet Street in London.

As discussed in Chapter 4 of the Research Design, the relative contribution of the annual component to the overall decomposed signature footfall totals is relatively small at around ten percent (see Figure 4.12 p149) In other words, the annual signatures are important, but they account for a small part of the footfall total variability. Far greater a contribution, about fifty-five percent, comes from the daily footfall signatures and these findings are discussed below.

10.3.1.2 Daily Assemblages

For the daily assemblages, by considering the territorialisation processes and the associated social activity rhythms (Brighenti and Kärrholm, 2018), the fuzzy cluster analysis identified the following:

- *Early Start-up assemblage* – the very start of the day with low levels of territorialisation intensification but detectable from 0500 onwards. The assumption is that this assemblage is dominated by necessary activities (Gehl and Svarre, 2013) such as deliveries, street cleaning, commuters etc.

- *Morning Commute assemblage* - the commuting period (O'Dell, 2009) linked to transportation systems (Timmermans et al., 1992) with sometimes a visible peak in morning footfall, another necessary activity. This assemblage was not identified for Towns or Major Towns and generally only for Regional and Sub-Regional Centres when footfall fall levels fell to a level that this assemblage became apparent.

- *Morning Visitors assemblage* - following the initial commute period, a period follows of early visitor activity, sometimes being the period of peak footfall for the day especially in Towns, and probably linked to market days (Hallsworth et al., 2015). This is probably a blend of necessary work and shopping activities and the optional meeting with friends etc.

- *Lunchtime assemblage* - the lunchtime period is a key daily assemblage and often the peak period of daily footfall. Again, a blend of necessary and optional activities. Note however that for Towns, the cluster Medoids suggest that the Morning assemblage is the period of peak footfall traffic, not lunchtime.

- *Afternoon Visitors assemblage* - depending upon place size and complexity, afternoon visitors can extend the footfall count beyond the lunchtime maximum. This assemblage is particularly associated with the Major City locations and for some, this period of social activity has reduced in intensity over the study period. The assumption is that these are mainly optional and social activities.

- *Evening Commute assemblage* - period of people leaving work and for some places an inflection point for total daily footfall to fall rapidly. Interestingly, the magnitude of the morning vs evening commute periods as displayed by the Medoids, rarely matched. This is assumed to be a necessary activity but can also become an evening and night-time visitor orientated activity – the experiential elements of places (Coca-Stefaniak and Carroll, 2015).

- *Evening Visitors assemblage* - for some places, this is associated with greater territorialisation intensity than the lunchtime period but mostly only for the Major City locations. Like the afternoon assemblage, for Major Cities, this was identified as a rhythm that has reduced its intensity over the period of the study period. The assumption is that these are mainly optional and social activities.

- *Night-time Visitors assemblage* - can extend into the early hours of the morning for specific City locations. The assumption is that these are mainly optional and social activities.

The daily assemblage identified follow quite closely the significant periods of the day theorised by Taylor and Parkes (1975), though there is more emphasis on optional and social activities throughout the day for this study. Also, the periods of each assemblage are not assumed to be fixed in time as the results show they vary by urban classification type as Table 6.10 illustrates with regard the periods of maximum (de)territorialisation. Table 6.10 also shows how stable these periods are over time, with the exceptions of Regional and Sub-Regional centres.

Table 10.1. Peak Intensity Hours of Territorialisation/De-territorialisation

Urban Classification Type	Morning Commute Peak	Time of Peak Territorialisation	Time of Peak De-territorialisation
Major City	Yes	1100 – 1200	1800 – 1900
Regional Centre	Yes (2014 +)	1000 – 1100 (2008) 1100 – 1200	1600 – 1700 (2008) 1700 - 1800
Sub-Regional Centre	Yes (2014 +)	1000 – 1100 0900 – 1200 (2014 +)	1600 – 1700 1700 – 1800 (2014 +)
Major Town	-	0900 – 1000	1600 – 1700
Town	-	0900 – 1000	1600 – 1700

Figure 10.4 provides a simple model view of how these assemblages interact over a 24-hour period. Of course, each assemblage can change in intensity and shape, nor would each form such encapsulated boundaries. For example, an evening commuter could also become an evening visitor, so the boundaries are much more fluid than the diagram suggests.

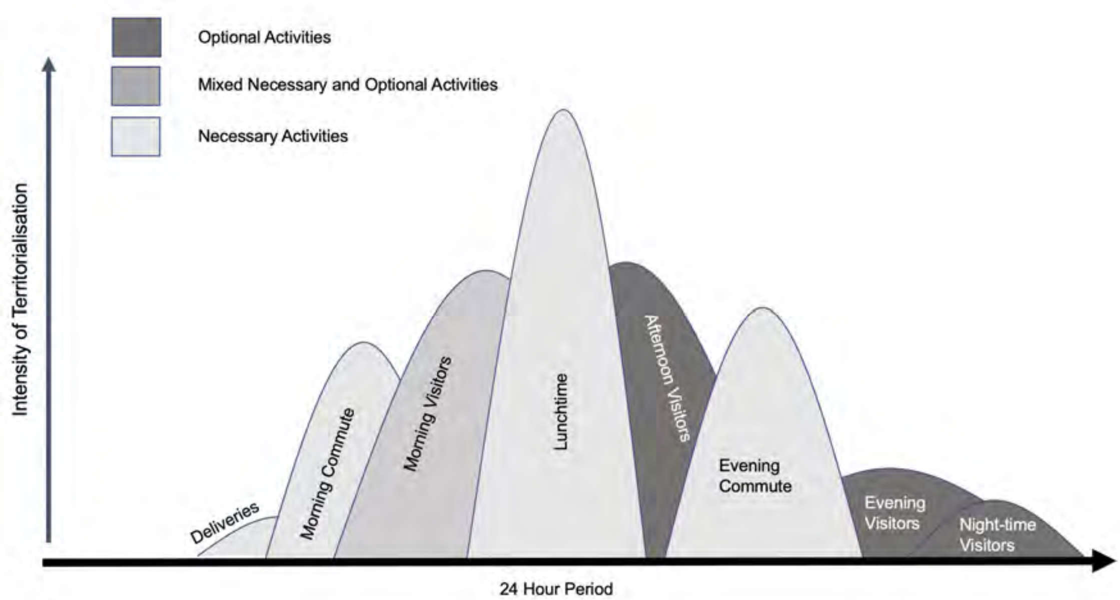


Figure 10.4. The combinations of daily assemblages

For example, Figure 10.5 provides a representation of the daily footfall for a Major City in the UK. Note how the example indicates the morning commute period intensification, a peak footfall period at lunchtime, and extension of territorialisation intensification into the afternoon until the period of the evening commute, which happens generally later for Major Cities than other urban types.

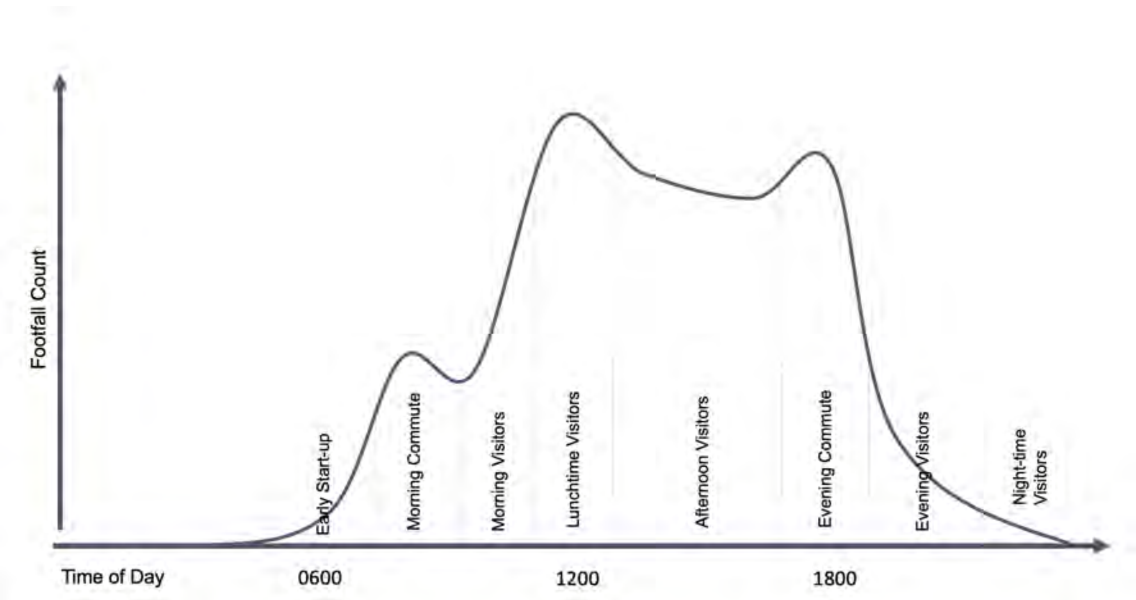


Figure 10.5. Model of Daily Footfall for a Major City location

In contrast, Figure 10.6 which is a representation of a Town location, territorialisation begins later, reaches a peak before midday, and then shows none of the territorialisation intensity of the afternoon displayed by the Major City representation in Figure 10.5. Overall, the daily territorialisation period for a Town is therefore shorter and more concentrated than that of a Major City.

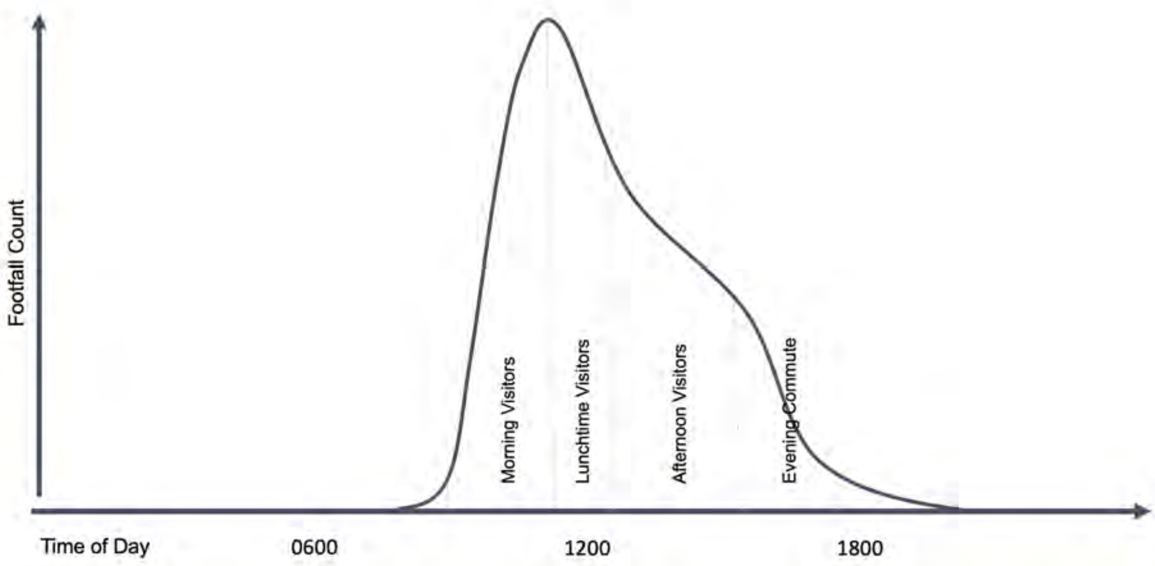


Figure 10.6. Model of Daily Footfall for a Town location

The daily clusters identified by this study match closely those identified by Lugomer and Longley (2018) and Traunmueller et al. (2018) and the daily signatures identified by Gehl (2011). Just as Lugomer and Longley (2018) find, in locations such as London, rather than the period of peak territorialisation being at lunchtime, this peak intensity occurs much later in the day, in a few cases, late evening and at night-time. City centres are complex locations and generally have a higher proportion of space accounted for by cafes and restaurants (Jones, 2020), providing work, retail, entertainment etc with an emphasis upon the provision of entertainments such as places to eat, cinemas, theatres etc (Coca-Stefaniak and Carroll, 2015; Millington et al., 2015). However what is not so clear in the findings of Lugomer and Longley (2018) is the presence of the late-morning peaks found in some of the towns by this study. Perhaps, this is due to the use Wi-Fi tracking and so maybe a population segment such as retired people are not accounted for in the totals (Mumford et al., 2021). It would be interesting to compare both the footfall sensor and Wi-Fi counts as differences identified might help distinguish patterns of social activity related to technology usage.

In considering the morning commute O'Dell (2009) describes it as characterised by people getting ready for work, reading papers, working on laptops, consuming coffee ready for the hours ahead, whereas the evening commute featured buttoned-down collars and loosened ties (O’Dell, 2009). The suggestion by O’Dell (2009) is that commuting is an important corridor for ritualised processes of identity transformation. As part of the footfall analysis, findings such as these might help infer differences in morning vs evening patterns. Whereas Lugomer and Longley (2018) describe the identified cluster shapes, for this study, the preference is to consider the individual shapes within these overall shapes thus the morning and evening commute periods are considered separate assemblages as suggested by O’Dell (2009). This is justified as the morning commute period (when identifiable) was found to be a more consistent rhythm, than the evening commute period which displayed much more variability, especially for the Major Cities. This suggests that the morning commute period could be more isorhythmic (Kärrholm, 2009), whereas, in the afternoon and evenings, the rhythms become more polyrhythmic (Kärrholm, 2012) as multiple types of social activities coincide.

The results are of course specific to the UK. Monheim (1998) mentions a traditional midday reduction in footfall traffic for locations in Germany and if the same study was to take place in Spain, like for example Martínez Plumé et al. (2019) and their study in Valencia using Bluetooth sensors, footfall would present very different diagnostics of patterns of social activities arising from different cultural and social practices (Escobar, 2001). However, the fuzzy cluster technique (D’Urso and Massari, 2013) appears very capable of 'discovering' these different patterns. Also, analysing the best and second-best fitting medoids, provides a picture of how each location is distributed between the different medoid clusters.

Generally, the daily assemblages show a close relationship between the urban classification type and assigned medoid signatures. For Town and Major Town locations in the urban hierarchy, the late morning and lunchtime period is identified as the most important period of territorialisation. As places increase in size and their complexity as places to work, retail offering and other services increases (Meserole, 1935; Wrigley and Lambiri, 2015; Delage et al., 2020), so too does the tendency for the periods of territorialisation to extend into the afternoons and evenings. Regarding how places change collectively over time, the results found no identifiable changes to the shapes of the daily signatures over the period of 12 years. The same signatures are evident across all the years although the levels of intensity of territorialisation have reduced. One consequence of the reducing intensity levels being the assumed increasing prominence of the more 'necessary' social activities such as the morning commute.

Another general observation would be that the period of 0700-0800 is consistently the period of greatest increase in footfall activity in the mornings for the Major Cities, Regional and Sub-regional centres. The same activities occur an hour later for Towns and Major Towns. Indeed, for the Towns and Major Towns, the period of maximum deterritorialisation during the week is just after lunch 1300-1400 and 1600-1700 whilst for the Major Cities is 1800-1900. For both Regional and Sub-Regional Centres, the same period was identified as 1300-1400 and 1700-1800. Thus, the larger the place, the sooner it is to territorialise and the later it de-territorialises – which is consistent with the Medoids identified and their fuzzy assignments based upon the urban classification types.

A benefit of using fuzzy clustering was the discovery that changes to the best fitting medoid allocations can be tracked over time (D'Urso et al., 2018). This allowed the fuzzy results for each year to be plotted against each urban classification type to provide a diagnostic of changes to the occurrence of the best fitting medoid allocations over each year. The results confirmed the general position that Towns and Major Towns are dominated by a peak territorialisation period either pre-lunch (1100-1200) or at lunchtime (1200-1300). However, the analysis also revealed that during the summer periods, there was an increased intensification in afternoon footfall territorialisation for Towns but not so much the Major Towns. Generally, this increase in the afternoons was evident for the other urban types whereas in the Winter period, the Major Cities, Regional and sub-regional centres indicated a reduction in visitors staying late. Thus, the fuzzy analysis reveals that there are seasonal changes each year in the daily rhythms across the urban classification types.

The final observation for the daily signature results is a reminder that they are for a generalised daily signature calculated not for each day but over the period of a week. So, the medoid signatures identify generalised daily signatures but it is the weekly signature that provides the delta (the daily differencing) to these daily signatures, and these are discussed in the next section.

10.3.1.3 Weekly Assemblages

The ability to differentiate places and their assemblages by urban classification also applied to the weekly medoid signatures. This is not surprising as the weekly signatures are the adjustment to the individual days of the week from the 'mean' daily signature. The main weekly assemblage identified were:

- *Saturday Territorialisation* - The increase in footfall associated with Saturdays and associated retail and entertainment activities (Monheim, 1998; Lugomer and Longley, 2018) . However, the adjustment is not constant throughout the year and has a seasonal component with less differentiation between weekdays and Saturdays in the Summer months. For some locations, especially those associated with work and employment, there is no increase and instead, deterritorialisation can occur.

- *Sunday (De)Territorialisation* – Generally, the reduction in footfall associated with Sundays. The scale of deterritorialisation is dependent upon urban classification type, with the maximum deterritorialisation being experienced by Towns. For some Major Cities, no deterritorialisation or even a degree of territorialisation was present.

- *Weekday Territorialisation* - The adjustments for weekdays can be positive and negative. The adjustments reflect changes in the Daily Assemblages and vary from day to day for the working week. The changes are much less evident than those of the weekend (apart from locations where Saturday has no peak territorialisation). Examples identified included market days (Hallsworth et al., 2015) where there was a distinct increase in territorialisation, although this was not consistent across all locations as market day in some locations failed to be significant enough to be recognised.

Overall, for Major Cities, Sundays are likely to be much less a period of de-territorialisation than for Towns and Major Towns. Reflecting the notion of synchronisation and opening hours of retail establishments for the different sizes of place (Kärrholm, 2012). The most obvious characteristics of the weekly signatures relate to Saturday and Sunday. For most locations, Saturday is the day of highest footfall and Sunday the lowest. The Saturday territorialisation period varies in intensity over the period of the year and for many locations, the differentiation between Saturdays and weekdays is at a minimum during the period of the summer holidays and similar reductions can also be identified for Easter and Half-term breaks. As the ratio of Saturday to Sundays and Saturdays to weekdays has reduced from 2007 to 2018, it is evident that the territorialisation impact of Saturdays for all locations has reduced over time.

There are however more subtle signals evident in the weekly medoid data with changes in the working week indicating a reducing deterritorialisation in the afternoons as the working week progresses. Presumably, as the week progresses people feel more and more like meeting with friends and going out after work hence as the week progresses, the footfall levels increase in the afternoons, evenings, and night-time. This makes the weekly medoids the most difficult to assess for collective locations but also suggests they are the most interesting. That represents an issue with the fuzzy cluster outputs in that, there are so many areas to explore in the data and that this study presents just some of those – the most obvious cases.

10.3.1.4 Summary

In combining the annual, weekly, and daily assemblages, the results suggest a reduction in the optional and social activities for the different urban classification types. For the annual assemblages, the most apparent change is the reduction in intensity of seasonal and holiday assemblages - or maybe better to say become less likely to be identified by the cluster analysis algorithms, as the rhythms are less distinguishable and therefore the inference made is that they reduce. The daily assemblages have remained relatively constant in their rhythm shapes but provide evidence that the periods from late morning to the evening have experienced a general reduction in territorialisation intensity. The daily assemblages also indicate seasonal impacts with afternoon territorialisation being greater during the Summer and holiday periods. The weekly signatures suggest a reduction in the territorialisation impact of Saturdays and there is also a seasonal element to this – with Saturdays displaying less of a difference with weekdays during the Summer and other holiday periods. Ideally, the assemblages identified would contain parametrisations of the different degrees of necessary vs optional and social activities but from the footfall data, this could only be assumed at best. Having highlighted the most represented assemblages and how they change over time for the combined sensor locations, the next section looks at specific exemplar places and how the identifiable assemblages shape social activity patterns.

10.3.2 Exemplar Findings

Where the previous section discusses the represented assemblages for all places, the next section considers the exemplar results to answer the research question:

> *What can footfall offer as a measurement of how change occurs over time in a particular place?*

The objective of looking at how individual places change over time inadvertently provided an additional research design benefit. By processing the results for footfall sensors in Manchester and Rotherham, a single fuzzy cluster analysis could be performed for all the available years of footfall data. Consequently, it was possible to evaluate how the cluster and fuzzy assignments evolved over the years without the added confusion of interpreting results with different numbers of clusters and medoids for each year. As the data volumes were sufficiently small, this was possible for all the exemplars without computer memory problems being encountered thus no sampling was necessary. Hence, this provided the opportunity to use different presentational tools to evaluate the results for each sensor. Of the presentational forms explored, the most useful was the run chart (Perla et al., 2011; Anhoej, 2015).

The run chart (Perla et al., 2011; Anhoej, 2015) provided a very useful technique for monitoring changes over time at each footfall sensor location. By plotting the fuzzy medoid assignment values, it was possible to track how the footfall patterns evolved over time, whether the transition from one medoid to another was gradual or sudden. This would not be possible with non-fuzzy clustering techniques, and this picked out a real benefit of using the run charts with the combination of fuzzy medoid assignment values. For the run charts, there was a small caveat to note, that because a smoothed line of the fuzzy allocations was added to each graph, it was possible to overlook the very specific changes in medoid allocation that can happen for very specific periods like Christmas.

However, the fuzzy analysis of annual signatures was not run for the exemplars partly because there was no means to compare periods such as Easter from one year to the next. Therefore, the annual signatures for each exemplar sensor were derived from the combined analysis. Thus, the limitations of the annual clustering approach still needed to be accounted for. Although when looking at individual sensor locations, the annual signature analysis was simpler.

10.3.2.1 Manchester

As an exemplar, Manchester was chosen for the contrast between the daily and weekly signatures. Using both the daily and weekly fuzzy cluster analyses, the different characteristics of the footfall sensor locations in Manchester could be analysed and these are summarised in Table 10.2. Reviewing the locations, the King Street footfall sensor picked out how afternoon and early evening shopping was important over the Christmas period and how over time, the territorialisation intensity of afternoon visitors has increased. Looking at the other sensors, the increase in afternoon territorialisation was also demonstrated by Market Street. Yet, King Street was also much more a weekday location whereas Market Street territorialises far more on Saturdays and to a degree, Sundays. So as a technique, the combined use of run charts and the fuzzy medoid assignments was excellent for identifying the types of place rhythms and periods of territorialisation that exist at any location but also for making connections between locations.

Table 10.2. Summary of Rhythm and Territorialisation Changes for Manchester 2007 - 2018

Street	Annual	Daily	Weekly	Changes
King Street	Multi-functional, with a Christmas peak. Initially a degree of seasonality which fades away	Working day rhythms (morning and evening commutes) dominate but at Christmas, also becomes territorialised in afternoons and evenings	Saturday peak footfall day but more exaggerated during Christmas. Note that between 2011 and 2015 period of peak weekly (not just Christmas) Saturday visits	Gradual transition period from 2011 to 2015 and after 2015 there was an increase in afternoon visitors.
Market Street	Mix of some Seasonal and mostly Multi-functional and Christmas rhythms	Peak at lunchtime and extending into afternoon and evening. Sudden increase of footfall in 2014 with further intensification of afternoon shopping period	Initially Saturday key day but becoming less so after 2014 as greater increase in workday week visitors.	Sudden shift in behaviour identified between 2014 and 2015 with large increase in footfall. Corresponds to increase in afternoon and early evening visitors.
New Cathedral Street	Multifunctional and Christmas rhythms with a degree of seasonality becoming more prominent in later years	Afternoon peak between 1400-1500 becoming more prolonged between 1200 to 1700 after 2011 with falling footfall.	Dominant Saturday peak but has become slightly less so after 2011 and working week signatures more apparent	Sudden change 2011 with slight loss of Saturday peak footfall and working day signatures become more apparent as footfall drops
Exchange Square (2014+)	Multifunctional and Christmas plus a degree of seasonality	Working Week and afternoon shopping	Saturday Peak dominates	Reduction in night-time activity during and after 2017

The run charts were particularly useful for picking out the rate of change from the assignment of one medoid to another. On some occasions, these changes were clearly seasonal. For example, King Street demonstrated a clear seasonal change in footfall rhythms before Christmas, becoming much more territorialised in the afternoons than at other times of year and highlights the value in combining the footfall rhythms with local knowledge. Again, looking at the King Street fuzzy assignments, there is a four-year transition period from 2011 to 2015 after which the afternoon periods is more territorialised. Whereas in 2011, New Cathedral Street demonstrates a very sudden change in medoid assignment. The fuzzy analysis therefore provides a useful tool to monitor the continuity of footfall rhythms and in conjunction with the run charts, provides a visual means of monitoring any changes.

Considering the assemblages identified for the combined results, these were apparent in the exemplar results but as with the combined results, only when they were the dominant signature. The rhythms of the morning (to a lesser degree) and evening commutes were not always identifiable from the cluster analyses. Yet from the plots of hourly footfall using the imputed values, these rhythms were clearly visible especially for New Cathedral Street. Hence it is important to combine the run charts with the summary plots of actual data to support any findings and to uncover the more subtle features.

The results from New Cathedral Street also benefited from having the rates of change in hourly intensity plots for each year. By looking at how footfall territorialisation intensifies throughout the day, the intensity plots were able to highlight that after 2010, the period of peak intensification of territorialisation had shifted from the period 1400-1500 to 1100-1200.

The daily and annual shapes of the footfall signatures identified by this study reflect those already identified by Monheim (1998), Lugomer and Longley (2018), Traunmueller et al. (2018) and Mumford et al. (2021). What this study adds are the weekly medoids and the capability to not just extract the annual, daily, and weekly shapes, but also to monitor how these change over time. The results from Manchester show how changes can be seasonal, can transition over several years or be much more sudden. This ability to track these changes though is only possible because fuzzy clustering techniques have been used.

10.3.2.2 Rotherham

Whereas Manchester provided an interesting diversity of signatures based upon the combined result analyses, Rotherham presented the opposite view of having no distinction between the sensors. Using the same parameterisations and data component signatures used for the Manchester analysis, the fuzzy cluster analysis was unable to discover sufficient distinction between the footfall sensors to produce valid results. This asked the question then of whether the sensors were just too similar for a contrast to be identified or the sensitivity of the analysis was not good enough. The analysis therefore became a test for the sensitivity of the fuzzy clustering technique and a test for the STL algorithm and the periodic signature decompositions.

To increase the sensitivity, hence differences between sensors, two different approaches were taken:

- Approach 1 – instead of including the decomposed signatures derived by the STL algorithm, the daily and weekly signatures were extracted directly from the imputed data instead.

- Approach 2 – in addition to using the imputed data as of Approach 1, the calculation of the distances that determined the similarities between the daily and weekly signatures was switched to using Euclidean distance. As a result, the distance time warping element was switched off and no attempt was made to align small time differences for signatures of the same shape.

Despite the two different approaches, in both cases, the weekly cluster analysis results could not identify a valid solution. The conclusion being that a cluster solution of k=1 was enough, or in other words, the average weekly signature was sufficient. However, the daily results for both approaches did achieve valid solutions that presented two unrelated findings. These were:

- Approach 1 – Of the seven daily clusters identified, only one displayed any change in medoid allocations and this related to a reduction in early hours footfall for each Sunday particularly during holiday periods on the High Street after 2015.

- Approach 2 – Again, for High Street, the analysis picks out market day on a Tuesday and a very distinct phase shift around 2011 where peak footfall shifted from lunchtime to late morning.

It should be noted that the cluster analysis for the annual signatures, based upon the combined results displayed much more variability for the Rotherham footfall sensors. For the annual signatures, Rotherham displayed a mix of a distinct seasonal rhythm and a Christmas period rhythm. As with the overall combined results, the dominance of the seasonal rhythm reduced over time but in nearly all years, was present. Only in 2017 did the seasonal component flatten out enough for the algorithms to consider the signatures a more multi-functional rhythm. Rotherham is an example that highlights the importance of plotting the basic time-series plots of yearly and monthly changes. The cluster analysis for both the daily and weekly signatures struggled to find a solution which suggests that either there is only one valid cluster solution, k= 1 or that more sensitive approaches are required. The Rotherham analysis highlights the need to 'tune' the fuzzy cluster algorithm so that the contrasts between sensors can be maximised. This again suggests that ensemble approaches (Lines and Bagnall, 2014; Bagnall et al., 2015) for the analysis could be considered assuming there is sufficient computing resource available. However, despite the need to adjust the analysis processes, the cluster analysis was still able to pick out changes over time for the annual and daily rhythms.

10.4 Objective 4 - Insights for Place Management

The final research objective to be answered is:

Evaluate how this information can provide insights for town centre managers for ongoing performance evaluation and assess the implications for strategic decision-making processes in a place context.

This also includes answering the third research question:

> *What use might place managers make of such footfall information to facilitate and improve decision making?*

Footfall has been identified as a key performance measure of place vitality and viability in the UK in virtually all iterations of planning policy guidance relating to town centres since 1993. During that time, several studies (Goodchild and Janelle, 1984; Monheim, 1998; Bromley et al., 2003; Lugomer and Longley, 2018; Sulis et al., 2018; Mumford et al., 2021) have identified the rhythm-based nature of footfall data. Limitations for these studies have been geographical coverage and the period of time that data is available, due to manual data collection methods (Goodchild and Janelle, 1984; Monheim, 1998; Wunderlich, 2014) and/or cost restraints (Traunmueller et al., 2018; Martínez Plumé et al., 2019; Nemeškal et al., 2020). With access to remote sensor data (Lugomer and Longley, 2018; Sulis and Manley, 2018; Sulis et al., 2018), the period of data and geographical coverage has increased to allow for a more generalised view of pedestrian movement rhythms. For example, with the study of annual footfall signatures by Mumford et al. (2021), longitudinal studies of changes to footfall patterns and rhythms over several years are now possible. This study builds on this previous research by repeating the annual signature investigations of Mumford et al. (2021), adding daily and weekly period analyses and also contributes using established data mining techniques to determine how the footfall rhythms change over time. A key component of the research design analytical framework was the use of the R package dtwclust (Sardá-Espinosa, 2019) which provided time-series fuzzy clustering functions as these were identified as useful means of understanding human activity (D'Urso and Massari, 2013).

The fuzzy analysis of the footfall data enabled the identification of the annual, weekly, and daily assemblages and the rhythms each represented. By separating the assemblages into their distinct rhythms, it is possible to consider (but not specifically identify) how they shift between those where an activity is considered necessary or optional (Gehl and Svarre, 2013). This was made possible by being able to view the temporal shapes of the footfall totals, how they changed across different locations at different hours of the day, days of the week and over the period of a year. The daily and weekly assemblages suggest that it is the optional activities of the afternoon and early evening that mostly differentiates one place from another. Essentially, the more diverse a place is, the larger it is, the more capable it is supporting afternoon, evening and night-time activities as identified by Delage et al. (2020) and Millington et al. (2015). The assemblages identified help conceptualise the different periods of footfall activity based upon the historic data of this study. However, they could also be used as a tool to conceptualise changes in town centre usage or aid considerations such as climate change.

For the place manager, being able to monitor the annual, weekly and daily footfall signatures provides an evidence-based diagnostic of how places are changing over time. Footfall is a real-time measure of place visitors and therefore is responsive to changes in real-time behaviour, rather than estimates of catchment or shopper populations (Mumford et al., 2021). The place manager is therefore better able to identify place specific interventions that correspond to the usage patterns of visitors and adapt these interventions as behaviours change. For example, the evidence of footfall patterns supports place managers to decide which prioritised interventions, as identified by Parker et al. (2017) to choose, such as recreational space, opening times or making the most of place-based anchors (not necessarily a retailer but maybe an employer or transport hub)

The exemplar results for Manchester show that the fuzzy cluster analysis provides an excellent tool for monitoring the continuity of the footfall assemblages. By displaying the fuzzy medoid assignment data using run charts, changes to the footfall rhythms can be identified either as seasonal, sudden, or more gradual transitions over time. The use of the fuzzy assignment values allows the town manager to view how a footfall sensor location transitions from one footfall signature to another, not as a binary membership between different clusters as non-fuzzy cluster techniques provide, but as a gradual, or not so gradual process. This ability is why D'Urso and Massari (2013) considered fuzzy cluster analysis a valid approach for investigating human activity. Hence, for the town manager, having sight of the run chart outputs provides a diagnostic of how social activity patterns for any location can change over time. However, based upon the knowledge gained during this study, there is a need to gain experience of interpretation (Voigt et al., 2007; Fent et al., 2016) and for this experience to be combined with town management practice and related academic disciplines, perhaps taking the approach of Engaged Scholarship (Van De Ven and Johnson, 2006; Ntounis and Parker, 2017) - an approach where the fuzzy outputs are viewed as a learning tool as suggested more generally for performance measurement and management by Koufteros et al. (2014) and Melnyk et al. (2014).

Furthermore, the fuzzy analysis outputs required additional supporting views of the footfall time-series. For example, this study made use of annual trends in footfall to provide an overall picture, weekly averaged time-series, monthly and annual plots of hourly footfall and so on. Of particular use was the use of the intensity plots, where the changes between hours were analysed and plotted. The intensity plots provided a tool to view where maximum changes in footfall territorialisation and deterritorialisation occurred in the day. In many of the different plot types, the decline in footfall levels seen across locations, could also associated with a fall in the footfall variability. Letting diversity diminish is to challenge one of the strengths of the urban landscape (Delage et al., 2020) – and footfall is a measure of this diversity and perfectly positioned to measure the variability and vitality of place. As this study shows, this variability has been decreasing over time as also found by Kärrholm and Wirdelöv (2019). Thus, footfall has the capability to be an environmental performance measure as identified by Melnyk et al. (2014) where what is measured is not just what is happening at an individual location, but also reflects influences external to a street, town, city, region or even country. For the town manager, increasing diversity and therefore aiming for greater footfall variability appears to be a good objective.

The next chapter summarises the findings discussed in this chapter and then highlights the study’s contribution, key limitations, implications, and avenues for future research.

11 Conclusion

The following chapter summarises the key findings detailed in the previous discussion chapter, and then provides the key contributions (theoretical and empirical), implications for academia and practice, a summary of limitations and areas for future research.

11.1 Key Findings

A combination of synthesis of the literature and exploratory data analysis helped inform and develop the idea of conceptualising the footfall data within the framework of territorology (Brighenti, 2010a) and Assemblage Theory (DeLanda, 2016), the combination of which suggested that a quantitative approach could represent the collective meso-level (street and town-centre) rhythms of footfall (social) activity (Schatzki, 2009) in space and time. This enabled a quantitative approach to the conceptualisation, and subsequent analysis, of collective social activities of pedestrians in towns and cities to achieve the research objectives, as outlined in the previous chapter.

To analyse the patterns of social activity, an analytical framework was developed using the software languages Python and R. Fuzzy cluster analysis was selected as the form of analysis as this had already been used to model human activity patterns (D'Urso and Massari, 2013), but also, previous footfall pattern analysis research had not adopted this technique – thus providing a methodological contribution. STL (seasonal trend decomposition using Loess) algorithms (Cleveland et al., 1990) were used to pick out the different periodic signatures (daily, weekly and annual) from the footfall data which then could be analysed through the fuzzy analysis package - dtwclust (Sardá-Espinosa, 2018, 2019). Although the implemented fuzzy cluster analysis required many parameterisations, with resulting assumptions, and used a subjective cluster validation process, this approach was found to be capable of detecting footfall patterns and how these patterns changed over time, especially, in the exemplar cases.

The next sections outline the key results based upon the footfall patterns and their evolution over time based upon the results from the fuzzy cluster analysis. What the findings illustrate is that footfall can be used as a diagnostic of periodic changes in collective social activity patterns, but cannot identify individual social activity types, and that footfall is much more than a descriptive statistical measure reporting daily, weekly, annual year-on-year changes in pedestrian counts.

11.1.1 Annual Footfall Patterns

The analytical framework was first tested against the annual signatures extracted from the footfall data using the STL algorithm (Cleveland et al., 1990). The objective being to ensure that the annual results previously identified by Mumford et al. (2021) using the same data source, could be replicated. As Table 11.1 identifies, the assemblages of social activity discovered in the data match those of Mumford et al. (2021) with the exception of specific events, a consequence of the study using hourly values instead of monthly averaged values. The annual results established that the analytical framework could reproduce previous results but also could resolve smaller scale patterns.

Table 11.1 - Comparison of Annual Signatures

This Study	Mumford et al. (2021) signatures
Christmas period assemblage	Comparison
Holiday period assemblage	Holiday
Seasonal assemblage	Speciality
Balanced assemblage	Multifunctional
Specific event assemblage	-

The annual analysis also found evidence of the annual footfall peaks of holiday period and seasonally based signatures reducing over time, whereas the footfall peaks at Christmas became more prominent, probably a consequence of the reduced prominence of the holiday and seasonally driven footfall social activities. It was also the case that in some locations, the annual peak of footfall counts - and therefore social activities of visitors - were interchangeable between the Christmas and holiday periods (such as the summer), suggesting that the annual signatures are not static for any location but potentially dynamic. By using a finer data resolution than used by Mumford et al. (2021), this dynamism becomes more apparent.

11.1.2 Daily Footfall Patterns

The daily signatures generated by STL are a generalised daily signature calculated not for each individual day of the week, but represent a rolling averaged period of a week. The resulting daily signature footfall patterns were found to closely resemble those identified by Lugomer and Longley (2018) and Traunmueller et al. (2018) and the daily signatures identified by Gehl (2011). Just as Lugomer and Longley (2018) find, in city locations, rather than the period of daily peak territorialisation being at lunchtime (as was the case for regional and sub-regional centres), the peak intensity often occurs much later in the day - in a few cases, late evening and at night-time. Generally, the daily assemblages show a close relationship between the urban classification type and daily signatures. For Town and Major Town locations in the urban hierarchy, the late morning and lunchtime period is identified as the most important period of territorialisation. As places increase in size and their complexity as places to work, the retail offering and other services increases, as does the tendency for the periods of territorialisation to extend into the afternoons and evenings. Another general observation would be that the larger the place, the earlier in the day it territorialises, and the later it de-territorialises – which is consistent with the footfall daily patterns identified and their fuzzy assignments based upon the urban classification types.

For those locations (generally the larger centres) where a morning peak of commuter activity was evident, the period of activity was found to be a consistent, (rather than the evening commute) period, which displayed much more variability (O’Dell, 2009), especially for the Major Cities. This suggests that the morning commute period is more isorhythmic; whereas, in the afternoon and evenings, the social activity rhythms become more polyrhythmic as multiple types of social activities coincide, as suggested by Kärrholm (2012).

Regarding how places change collectively over time, the results found no identifiable changes to the shapes of the daily social activity patterns over the period of 12 years. The same patterns are evident across all the years although the levels of intensity of territorialisation have reduced. Additionally, during the summer period, there was an increased intensification in afternoon footfall territorialisation for Towns, but not so much the Major Towns.

Generally, this increase in the afternoons was evident for the other urban types, whereas in the Winter period, the Major Cities, Regional and sub-regional centres indicated a reduction in visitors staying late. Thus, the fuzzy analysis reveals that there are seasonal changes each year in the daily rhythms across the urban classification types. The weekly signature provides the delta (the daily differencing) to the daily signatures, and these are discussed below.

11.1.3 Weekly Footfall Patterns

Regarding the weekly footfall patterns of social activity, for Major Cities, Sundays are likely to be much less a period of de-territorialisation than for Towns and Major Towns. The most obvious characteristics of the weekly signatures relate to Saturday and Sunday. For most locations, Saturday is the day of highest footfall and Sunday the lowest. Over time, the weekly signatures suggest a reduction in the territorialisation impact of Saturdays and there is also a seasonal element to this – with Saturdays displaying less of a difference with weekdays during the summer and other holiday periods. There are also more subtle signals evident in the weekly data with changes in the working week indicating increasing social activity in the afternoons as the working week progresses.

11.1.4 Exemplar Findings

In Manchester and Rotherham, using run charts to plot the fuzzy medoid assignment values, it was possible to track how footfall patterns change over many years, and view transitions of social activity from one pattern to another, and whether these changes were gradual or sudden. For example, in Manchester, the King Street footfall sensor picked out how afternoon and early evening shopping was important over the Christmas period and how over time, the territorialisation intensity of afternoon visitors has increased. The results for Manchester show how changes in social activity patterns can be seasonal, and can transition over several years or be much more sudden. As a technique therefore, the combined use of run charts and the fuzzy medoid assignments was excellent for identifying the types of place rhythms and periods of territorialisation that exist at any location, but also for making connections between locations.

Finally, the footfall patterns identified would ideally contain parametrisations of the different degrees of necessary vs optional and social activities but from the footfall data, this could only be assumed at best. The daily and annual shapes of the footfall signatures identified by this study reflect those already identified by Monheim (1998), Lugomer and Longley (2018), Traunmueller et al. (2018) and Mumford et al. (2021). What this study adds are the weekly footfall patterns and the capability to not just extract the annual, daily, and weekly shapes, but also to monitor how these change over time.

11.2 Contribution

Through these findings, this study makes theoretical, methodological, and practice-based contributions to place management, as follows:

11.2.1 Theoretical Contribution

Although this study sought to analyse already existing footfall data, no *a priori* theoretical position existed as to how footfall should be conceptualised. Thus, the process of theory discovery followed a retroductive process, combining a data-driven epistemological approach (Kitchin, 2014a) with a more traditional review of existing theory relating to the understanding and conceptualisation of urban places. Initial investigations of the data revealed the existence of annual rhythms and so the idea of rhythm helped focus the search for theory. After consideration of macro and micro theoretical perspectives, the study chose to conceptualise the meso-level social activities of pedestrians in towns and cities drawing on and developing the theory of territorology (Brighenti, 2010a; Brighenti and Kärrholm, 2018) in this context.

Using the territorology concept, previous research such as Kärrholm (2016) and Kärrholm and Wirdelöv (2019), focused upon the micro-level and the individual, and therefore their investigations were qualitatively based and phenomenologically orientated. For this study, the concept of territorology is developed so that the processes of territorialisation and the changes to territorialisation intensification provide a framework for analysing the footfall data via quantitatively detectable rhythms of collective social activity. Thus, rather than focusing on the individual and micro-level, the concept of territorology is applied at the meso-level of statistically represented collective social activities. Consequently, the concept of territorology is demonstrated to be applicable across different dimensions of urban social activity, where both the quantitative (meso-level and statistically represented social activities) and qualitative (micro-level and individual/collective activities) territorialisation processes can potentially be identified and analysed concurrently.

Whereas territorology provided a framework for the analysis of the footfall data through the understanding of place rhythms within bounded space and time, the resulting combination of social activity rhythms from the footfall data were conceptualised as assemblages, as supported by assemblage theory (DeLanda, 2006, 2016). Thus, the identified assemblages embody the periodic rhythms of each footfall sensor and indicate a measure of place complexity. For example, the diverse rhythms identified for the footfall sensors within the Manchester BID area suggest variation in social activities and a place that is more polyrhythmic where multiple social processes coexist. In contrast, Rotherham presented very little rhythmic diversity for the different footfall sensors, suggesting a place that is more isorhythmic and driven by singular social processes.

In summary, the theoretical contribution of the study can be articulated as follows:

- Footfall is a meso-scale performance measure of collective social activities in urban places.
- Territorology and changes in territorialisation intensities can provide an analytical framework to assess the evolving periodic rhythms of urban social activity.
- The combination of different social activity rhythms can be considered as

assemblages and the diversity of rhythms suggests a means to understand place complexity.

11.2.2 Methodological Contribution

Methodologically, the study uses open-source data analysis software (MySQL, Python and R) to find new ways of analysing and presenting the footfall data without the need for in-depth statistical or mathematical knowledge. With over ten years of data, the study had to select data mining techniques that could process the volume of data within the constraints of the available IT platform capabilities. Despite implementation complications, fuzzy cluster analysis of the time-series footfall data was adopted as a method to analyse human activity patterns, as suggested by D'Urso and Massari (2013). Thus, the study was able to identify a comprehensive range of different annual, weekly, and daily place rhythms. For individual locations, the fuzzy cluster analysis was able to provide a means of detecting seasonal, short-term, and long-term changes in the rhythms of footfall activity – contributing a novel way of monitoring changes in urban social activity. However, it should be noted that footfall data, although able to demonstrate changes in social activity patterns, was unable to identify the individual social activity types that make up the aggregated footfall hourly totals. Validation of the research design was accomplished by comparing results from previous research (Lugomer and Longley, 2018; Mumford et al., 2021), however, the fuzzy cluster process required several parameterisations, each of which influenced the results.

In summary, the methodological contribution of the study can be summarised as follows:

- The analysis is performed using fuzzy cluster analysis of the time-series footfall data.
- The changes in fuzzy cluster allocations for individual places provides a novel means to detect change in urban social activity patterns.

11.2.3 Practice-based Contribution

For the practice of place management, this study has shown that footfall has the capacity to detect and differentiate the dominant patterns of aggregated social activities of town and city users in the UK, through the identification and monitoring of annual, daily, and weekly assemblages and associated rhythms. Across these different time periods, the research method adopted was able to comprehensively show how collective social activity varies for different urban types and how places, both individually and collectively change over time with respect to the social activity rhythms identified.

With over ten years of data, the study also provided a robust means of analysing changes to social activity patterns for individual towns and cities using run charts (time-series of the fuzzy cluster allocation scores). These run charts inform place managers of periodic social activity patterns; for example, the seasonality of weekly rhythms, and any changes to these that might be occurring. The run charts pick out gradual changes over time, where social activity is transitioning from one rhythm shape to another, as well as sudden changes. Consequently, footfall is identified as a learning performance measure (Canonico et al., 2015) that can monitor changes in the territorialisation of collective social activity but not necessarily provide diagnosis. Where further investigation is thought necessary, this will require a blend of quantitative and qualitative approaches (Philp et al., 2021; Sun, 2021) to understand the specific social processes (territorialisations) that are contributing to the changes in the collective social activities.

In summary, the practice-based contribution of the study can be summarised as follows:

1. With over ten years data, the results are robust and provide insights of how annual, weekly, and daily footfall activity rhythms change between and within places.
2. Footfall is demonstrated to be a performance measure of meso-scale changes in collective social activity.
3. The changes in social activity patterns provide a diagnostic for place managers that changes in visitor behaviour are occurring, although not why.

11.3 Implications

Conceptualising footfall through Territorology (Brighenti, 2010a; Brighenti and Kärrholm, 2018) and Assemblage theory (DeLanda, 2006, 2016), provided a framework to analyse quantitatively, the rhythms apparent in the footfall data. However, since footfall is a reductive measure, the social activities that footfall helps diagnose cannot be explicitly identified. Hence, although this study presents a conceptual model, to validate the model, more qualitative measures are needed for the analysis to identify the specific social activities.

Footfall is viewed by this study to be a high-level diagnostic performance measure, not a key performance metric as defined by Melnyk et al. (2014) where targets and consequences for missing the targets are required. Hence for the place manager, footfall can diagnose that some aspect of visitor activity is changing, but not necessarily why. Thus, for the place manager, being able to monitor the annual, weekly and daily footfall signatures provides an evidence-based diagnostic of how places are changing over time. The place manager is therefore better able to identify place specific interventions that correspond to the usage patterns of visitors and adapt these interventions as behaviours change.

11.4 Summary of Limitations

The key limitations of this study are:

- The footfall data used for this study precedes the COVID-19 pandemic period. Therefore the analysis focuses on longer term systematic changes in social activity rather than the sudden reductions in footfall numbers caused by COVID-19 (High Street Task Force, 2021).

- The study focuses upon time rather than spatial dimensions apparent in the footfall data. Thus the findings highlight individual place changes over time, not how places and their relationships have changed.

- From 2007 to 2018, the number of footfall sensors increased from 74 to

538. These increases meant that the representation of the data changed each year as the proportion of cities, regional centres and towns altered over time. This change in representation was partly accounted for by using yearly results but what was not done was the selection of a control set of sensors against which these annual changes could be compared. In fairness, deciding which sensors should be in the control set was itself a sampling problem as most sensors in 2006 were based in city locations. However, this is still a limitation of the analysis framework in that changes in sensor representation vs actual changes in the data is not accounted for explicitly.

- To perform the data analysis, missing data needed to be resolved. As most missing values were for very short periods, the Stineman impute algorithm was used to fill in the missing values. However, what was not established was the spatial distribution of the missing data values, nor was the missing data checked to see if the spatial distributions were random. This consequently reflects a limitation of the study in that the process of imputation was primarily used to prepare the data for the cluster analysis using reasonably fitting values, rather than establishing an understanding of the distribution and causes of missing data.

- With the footfall data, the analytical approach considered by this study was to use fuzzy cluster analysis (i.e., unsupervised learning). However, on reflection, more time could have been given to experimenting with other classification and clustering techniques, for example, k-nearest neighbour.

- The objective of this study was not to build statistically valid predictive models of footfall patterns (a limitation in part due to a lack of statistical and mathematical specialism), but instead aimed to perform a diagnosis of historic data. For this reason, although the algorithms used by this study can be applied to generate statistically valid machine learning models this was not done. Hence, there is no attempt at cross-validation of the footfall data, where data is split into training and testing data sets and used to statistically validate algorithm generated models. Such an approach might have been used to differentiate between changes in the sensor representativeness versus actual changes in the footfall data.

- To perform the fuzzy cluster analysis, the dtwclust R package (Sardá-Espinosa, 2019) was used. A key reason for choosing this package was the clarity of the documentation and the ability to perform the data analysis process in a single programme execution. This highlights a limitation of the study in that the analysis was very dependent upon pre-packaged functions that required no mathematical software programming and reconfiguration.

- The analysis does not include the residual values. The focus of the study is on the representative and regular patterns extracted from the data rather than the exceptions. This though is not to dismiss the value of the data - it was simply a matter of research scope. One of the suggestions of this study is that the residual values need to be investigated more.

11.5 Future Research Avenues

To progress the research, the following are possible next steps:

1. The conceptual framework and the data analysis methods chosen for this study provide a foundation for assessing place complexity by identifying the diversity of social activity rhythms and discovering how these social activity patterns evolve over time and space. An option for future research is to further validate the model using more qualitative measures needed to identify the specific social activity types. Hence, the fuzzy analysis could be redone to focus on the diversity of place rhythms based upon changes in territorialisation intensification to identify for each place, the degree of complexity and whether the place rhythms are isorhythmic and/or polyrhythmic. From such an analysis, it should be possible to identify changes and differences in the resilience and adaptability of places, for example, how places recover from COVID-19. In addition, to support the development of the theoretical framework and to provide further insights, additional quantitative and qualitative information sources could be

combined that include both meso-scale and micro-scale insights such as suggested by Philp et al. (2021), Sun (2021) and Kärrholm (2016). The aim of the study being to validate the conceptual model and use it to discover why places differ and to identify what can be done to support those places that are struggling.

2. With a focus on the research design and the mathematical/statistical elements, review the process of analysing the footfall data to determine if there are better and/or more refined means of assessing the footfall rhythms. For example, using ensemble techniques (Lines and Bagnall, 2014; Bagnall et al., 2015) to continually test parameterisation settings, continual fuzzy analysis assessments (blending supervised and unsupervised processes) or maybe using discrete wave analysis methods to discover regular and irregular periodicities in the footfall data other than those that are daily, weekly, and annual.

3. Continue the analysis of the existing data, in particular the residual values and see if these can be tied back to market days, weather, sports, events etc. The output from such a study would then help inform how the weather, sports events etc impact footfall (or not) in town centres.

4. Assuming that the insights from this study would be used by place managers, employ an engaged scholarship approach (Ntounis and Parker, 2017) and develop appropriate ways to share the results with place management stakeholders to trigger meaningful outcomes and actions. Through co-creation with place managers, identify learnings and common patterns that can be shared much as medical practitioners use for electronic cardiograms (Fent et al., 2016). This could be by creating a guide plus provision of the outputs through, for example, a suitable interactive user interface, thus putting in place a software toolkit that can analyse and disseminate the footfall diagnostics in a manner required by place managers to support evidence-based decision making.

12 Appendix A - Research Design Considerations

The sections in this Appendix provide specific details of the setup of the research design, in particular technological considerations, and statistical parameterisations. The sections are:

- The system configuration details of the computer used to perform the footfall analysis
- R vs Python summary
- Additional information regarding the data sources used
- Database setup including the schema and table specifications
- Pre-processing additional details
- Missing Data imputation details
- Transformation - STL components
- Data mining - the fuzzy cluster analysis components provided by dtwclust R package
- Interpretation and evaluation details

12.1 System Configuration

The database and software processing were all performed using an Apple MacBook Pro (15-inch, 2017). The operating system was macOS Mojave with:

- Processor: 3.1 GHz Intel Core i7
- Memory: 16GB 2133 MHz LPDDR3
- Graphics: Radeon Pro 560 4 GB & Intel HD Graphics 630 1536 MB
- Disk: 1TB solid state hard drive

The version of MySQL used was 8.0.12 Community Edition and MySQL Workbench 8.0 was used to manage the database performance, database schemas and programme and test stored procedures, functions, and SQL scripts as required. PyCharm 2018.1 IDE (https://www.jetbrains.com/pycharm/) was used for developing and running the Python programmes which included:

- Python 3.6
- MySQL Python Connector modules
- Pandas
- Numpy

RStudio was the R IDE used (final version used was 1.3.959 - the software was continually updated throughout the study).

12.2 Python vs R

Information Week India (2019) indicates that Python was found to be the top choice amongst data scientists and analysts. Mainly since data modelling ideas can be put into production more easily than with R but also because Python is being taught more.

Both Python (McKinney, 2012; Haslwanter, 2016) and R (R Core Team, 2019) languages are used in this study. Initially, Python was used to perform the extraction, processing and loading from the CSV files into the database. R was then used to perform analysis and further processing on this data. Whereas Python is a full-service language (Wayner, 2017) that emphasises productivity and readability, and targets developers, R generally caters to data analysis, statistics, and graphical models. The syntax of Python makes coding and debugging easier, but the statistical power of R can be harnessed with a few lines of code (Gallagher and Trendafilov, 2018).

Python makes pre-processing easy although there is no reason to use R for the same purposes. In fact, it’s structurally unsound to mix up data purification routines with data analysis routines. R was built for statistical analysis - so that is what it is for (Wayner, 2017). Wayner (2017) states:

> *Why not make the best of both worlds, as many data scientists already do? The first stage of data aggregation can be accomplished with Python. Then the data is fed into R, which applies the well-tested, optimized statistical analysis routines built into the language. It's as if R is a library for Python. Or*

maybe Python is a pre-processing library for R (Wayner, 2017).

For the Python development work, PyCharm 2018.1 (https://www.jetbrains.com/pycharm/) was the Integrated Development Environment (IDE) of choice and for R, RStudio (RStudio Team, 2018) (https://rstudio.com) was used. As suggested by Wayner (2017), the initial pre-processing development was developed in Python whereas the subsequent data analysis was performed using R. This though was a result of frustration with Python and issues of library compatibilities as initially, Python was thought to be the platform to be used for this research. As this was a research project, no consideration was given to operationalising the code.

12.3 Data Sources

Table of Places and their Planning Categorisation used for this study was based upon (Mumford et al., 2021).

Table 12.1. Place Planning Categorisation and the number of footfall sensors

Place	Major City	Major Town	Regional Centre	Sub-Regional Centre	Town	Undefined	Grand Total
Aberdeen City Centre			11				11
Aberystwyth Town Centre					1		1
Altrincham High Street					2		2
Ammanford		1					1
Antrim Town Centre					2		2
Arbroath					1		1
Armagh					1		1
Ashford Borough Council		1					1

Ayr				2			2
Ballymena					3		3
Banbridge Town Centre					1		1
Barnsley Town Centre		3					3
Barnstaple High Street				1			1
Barry Town					2		2
Basingstoke Town Centre				2			2
Bath City Centre				5			5
Bedford			2				2
Beeston					1		1
Belfast			5				5
Bexleyheath				3			3
Bird Street, NWEC						1	1
Birmingham City Centre	1						1
Blackburn BID				2			2
Blackpool				3			3
Bognor Regis Town Centre				1			1
Bournemouth				3			3
Bournemouth Coastal BID				3			3
Brentford High Street		2					2
Bridgend Originals				2			2
Brierley Hill					1		1
Brighton BID			1				1
Bristol			1				1

Brixton				3			3
Bromley			1				1
Burnham on Sea					2		2
Bury St Edmunds				1			1
Cambridge			5				5
Camden				5			5
Canterbury City Centre				1			1
Cardiff			7				7
Carmarthen		1					1
Carnoustie					1		1
Carrickfergus Town Centre		3					3
Cheltenham Town Centre				1			1
Chester				5			5
Chichester				1			1
Clacton On Sea Originals					2		2
Cleethorpes-Historic		1					1
Coleraine					2		2
Congleton (Innovate Project)					1		1
Cosham					1		1
Covent Garden External				11			11
Croydon			3				3
Dartford Town Centre				1			1
Dartmouth Town Centre					1		1

Derby				5			5
Derry City Centre			2				2
Douglas, Isle of Man				3			3
Dover Town Centre					1		1
Dudley		1					1
Dundee Town Centre			1				1
Durham				5			5
Ealing			1				1
Ealing Road Town Centre			1				1
Eastleigh BID				2			2
Edinburgh	1						1
Eltham Town Centre				1			1
Exeter			5				5
Fitzrovia BID				7			7
Glasgow	6						6
Gloucester		1					1
Gravesend				1			1
Great Yarmouth					3		3
Greenwich Town Centre		1					1
Grimsby				1			1
Guildford			4				4
Guisborough					1		1
H & M Oxford Street East	1						1
Halesowen					1		1
Halifax Town Centre				1			1

Hammersmith				1			1
Harlesden						2	2
Harrow BID			3				3
Hastings Town Centre				1			1
Havering - Colliers Row						1	1
Havering - Elm Park						1	1
Havering - Harold Hill						1	1
Havering - Rainham						1	1
Heart of London	5						5
Holmfirth Town Centre					1		1
Hornchurch						1	1
Horsham Town Centre					1		1
Huddersfield				1			1
Hull				7			7
Huntingdon Originals					1		1
Ilford			1				1
Ipswich			1				1
Irvine			1				1
Kendal Town Centre					1		1
Kenilworth					3		3
Kensington				6			6
Lancaster BID				2			2
Largs		1					1
Leamington Spa - Originals				3			3

Leeds	8						8
Leicester Square	1						1
Lichfield BID		4					4
Lisburn				2			2
Liverpool	5						5
Llanelli		3					3
London New West End	35						35
Loughborough BID				5			5
Lurgan Town Centre				1			1
Luton			4				4
Maidenhead				1			1
Maidstone			1				1
Manchester	4						4
Manchester City Centre - Cheetham Hill					1		1
Manchester City Centre - Rusholme					1		1
Manchester City Council - Fallowfield					1		1
Manchester City Council - Gorton					1		1
Manchester City Council - Harpurhey					1		1
Manchester City Council - Victoria Avenue					1		1

Manchester City Council - Withington					1		1
Manchester City Council - Wythenshawe					1		1
Mansfield				2			2
Market Harborough					1		1
Melton Mowbray		1					1
Morley (Innovate Project)					1		1
Neath					1		1
Newbury BID		1					1
Newcastle	2						2
Newport City Centre		2					2
Newry BID				3			3
Northampton			4				4
Northbank BID			9				9
Norwich			2				2
Nottingham	8						8
Oldham				1			1
Ormskirk Town Centre		1					1
Oxford			3				3
Perth High Street				2			2
Plymouth			4				4
Poole		2					2
Portadown Town Centre					1		1
Porthcawl Originals					2		2

Portsmouth				1			1
Preston City Centre				1			1
Reading BID			2				2
Redcar		2					2
Regent Street Association	2						2
Rhyl		1					1
Richmond Town Centre						1	1
Rochdale Town Centre		1					1
Romford						2	2
Rotherham		6					6
Rugby				2			2
Salisbury BID				3			3
Saltburn - Redcar					2		2
Saltcoats		1					1
Scarborough				3			3
Scunthorpe				1			1
Sedgley					1		1
Sheffield				3			3
Shepherds Bush			1				1
Shrewsbury BID		2					2
Skipton		2					2
Sleaford					3		3
Sloane Street				14			14
Slough Town Centre				1			1
Southport		1					1
Southsea		1					1
Spennymoor		1					1

St Andrews Town Centre						1	1
St Helier				1			1
St Jamess and Piccadilly				4			4
Stafford				1			1
Stirling			2				2
Stockton-on-Tees				1			1
Stoke-on-Trent				4			4
Stratford Upon Avon		1					1
Sunderland City Centre			6				6
Sutton BID- Old			2				2
Swansea City Centre				4			4
Swindon				3			3
Taunton				3			3
Transport for London	36			1			37
Treaty Centre, Hounslow-High Street			4				4
Truro City Centre				1			1
Upminster						1	1
Wakefield- Old				1			1
Walsall Town Centre					1		1
Walthamstow				1			1
Warwick					1		1
Waterloo Quarter BID				3			3
Watford			5				5

Wellingborough BID					1		1
Wembley						1	1
Weston Super Mare		2					2
Weymouth BID				4			4
WHSmith - Aylesbury Flow						1	1
WHSmith - Berkhamsted Flow						1	1
WHSmith - Colchester Flow						1	1
WHSmith - Harpenden Flow						1	1
WHSmith - Petersfield Flow						1	1
WHSmith - Southampton Flow						1	1
Willesden Green Town Centre						2	2
Wimbledon				1			1
Windsor Town Centre External				1			1
Wolverhampton BID				2			2
Woolwich				2			2
Worcester		1					1
Worthing		1					1
Wrexham Town Centre		2					2

York Originals			4				4

12.4 Database Details

As well as using MySQL, a visual development tool, MySQL Workbench (https://www.mysql.com/products/workbench/) was also required for monitoring the database processes, creating and running SQL programme scripts, stored procedures and functions (Harrison and Feuerstein, 2009) needed for the data load and query processes. Crucially, the database drivers for connecting the database engine with Python (https://www.mysql.com/products/connector/) and R (https://CRAN.R-project.org/package=RMariaDB) were available as open-source packages. By adding indexes to the tables as required, this ensured that data extraction was a rapid as possible.

12.4.1 Table 1. Dim_Region

Table used to store the different regions assigned to each footfall sensor location

Field Name	Description	Notes
regionID	Region identifier	Primary Key
region_Desc	The region name	For example, Greater London

12.4.2 Table 2. Dim_Place

Table used to store the different cities and towns where each footfall sensor is located

Field Name	Description	Notes
placeID	Place identifier	Primary Key
place_Desc	The city/town name	e.g., Chester

12.4.3 Table 3. Dim_Camera

Table used to store details for each sensor including metrics for missing data and quality checks

Field Name	Description	Notes
cameraLocationID	Camera identifier	Primary Key
location_Desc	The street location	e.g., High Street
Latitude	Latitude of camera	
Longitude	Longitude of camera	
placeID	Place identifier	Town or City where camera located
Postcode	Postcode	Where known.
countNA	Number of missing data footfall counts	Total count for all the period of data available
percentNA	Percentage of missing footfall data	Missing data percentage
LongestGapNA	Longest consecutive gap in the footfall data	Longest gap of consecutive missing data values
mostFrequentNA	The most frequent number of consecutive missing data	Most frequent missing data gap
mostOverallNA	Identified the most ferequent missing data count	The Median missing data gap
Acc24	Identifies if the footfall data has a 24-hourly auto correlation signature	Used as a quality filter to determine whether decomposing the data into daily, weekly signatures was meaningful

12.4.4 Table 4. LocationData

Table used to provide a single location identifier for the footfall data that defines the region, place and sensor details.

Field Name	Description	Notes
locationID	Location identifier	Primary Key (PK)
regionID	The region identifier	Foreign Key for Dim_Region table PK
placeID	The place identifier	Foreign Key for Dim_Place table PK
cameraLocationID	The camera identifier	Foreign Key for Dim_Camera table PK

12.4.5 Table 5. FootfallData

Table that stored the original hourly footfall data, imputed and decomposed footfall data.

Field Name	Description	Notes
recordID	Record identifier	Primary Key
eventDateTime	The hour over which footfall data was counted	So, a time of 09:00 means that the data was collected from 08:00 to 09:00
locationID	The location identifier	Region, place and camera location
Count	The footfall hourly count	This is the original data
dailySignature	The decomposed daily signature	
weeklySignature	The decomposed weekly signature	
annualSignature	The annual decomposed signature	
residual	The residuals after decomposition	
trendSignature	The decomposed trend	
imputedCount	The footfall count after missing data values were provided	

12.5 Time-series Clustering - A Review

Clustering is a data mining technique used during exploratory data analysis (Brunsdon, 2016) to identify structure in a data set by objectively organising data into homogeneous groups where the within-group-object similarity is minimised and the between-group-object dissimilarity is maximised (Warren Liao, 2005; Aghabozorgi et al., 2015). Pattern recognition can be performed using training data otherwise known as labelled data (*a priori* known information). This is known as *supervised pattern recognition* or in the terms of machine learning, *supervised learning* (Theodoridis and Koutroumbas, 2009:7). Where training data is not available, the goal of pattern recognition is to identify underlying *similarities* and *cluster* (group) similar vectors together. This is known as *unsupervised pattern recognition* or *unsupervised learning* or *clustering* (Theodoridis and Koutroumbas, 2009:7) where the data is un-labelled. Thus, cluster analysis (unsupervised learning) is essentially about discovering groups in data that are not known *a priori*, unlike supervised learning where the aim of the analysis is to assess membership of an existing classification (Everitt et al., 2011). With no *a priori* data available, the approach taken by this study was to use cluster analysis and unsupervised learning.

A time-series is essentially classified as dynamic data (Antunes and Olivera, 2001) because its feature values change as a function of time, which means that the value of each point is an observation made chronologically (Aghabozorgi et al., 2015). A univariate time-series is the simplest form of temporal data being a collection of observations collected regularly in time, where each observation represents a value that is numeric (Wang et al., 2004; Aghabozorgi et al., 2015). The footfall data is therefore a series of univariate time-series for each sensor location.

Time-series clustering (Warren Liao, 2005; Fu, 2011; Aghabozorgi et al., 2015) is mostly utilised to discover patterns that appear frequently (Verbesselt et al., 2010b; Copeland, 2012; Chanda et al., 2015), or, to discover patterns that happen surprisingly (D’Urso and Massari, 2013; Rasheed and Alhajj, 2014; Zhu and Guo, 2017). The objective of the clustering is to recognise dynamic changes in time-series; provide the ability to predict and recommend; or to discover patterns in the data (Aghabozorgi et al., 2015). However, time-series classification/clustering problems are differentiated from traditional classification/clustering problems because the attributes are ordered (Bagnall et al., 2016). The approach taken by this study, whole time-series clustering (Aghabozorgi et al., 2015), is focused on clustering a set of individual time-series with respect to their similarity. Other approaches exist although Keogh and Lin (2004) suggest that the results of these can be meaningless as patterns can be found in even in randomly generated data.

The following sections outline four components identified by Aghabozorgi et al. (2015) (see Figure 12.1) required for time-series clustering:

- Dimension reduction / representation method
- Distance Measurement
- Clustering Algorithm
- Prototype definition and evaluation

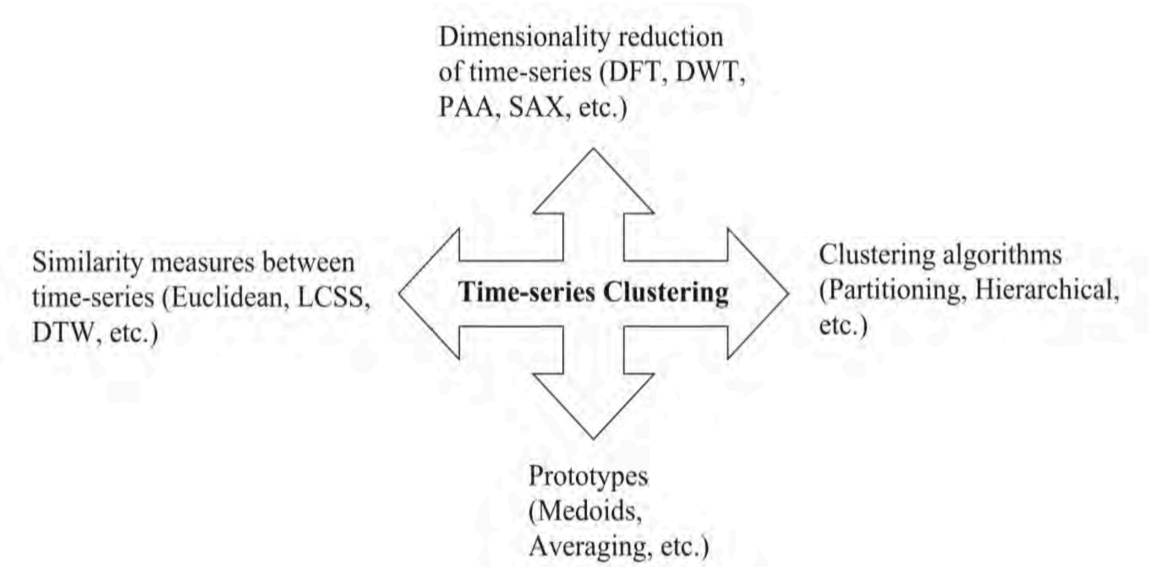


Figure 12.1 - The four aspects of time-series clustering
(Source: Aghabozorgi et al., 2015:33)

12.5.1.1 Representation Methods for Time-Series Clustering

High dimensionality and noise are characteristics of most time-series data (Keogh and Kasetty, 2003); thus dimensionality reduction methods are normally used in whole time-series clustering to address these issues and improve performance (Aghabozorgi et al., 2015). Aghabozorgi et al. (2015) find that most of the research in this area, has focused on representation and dimensionality reduction (Lin et al., 2007; Fulcher and Jones, 2014). With respect to this study, the features of interest in the data were periodic vectors (annual, weekly and daily) and therefore these components were extracted from the data.

12.5.1.2 Distance Measurement - Similarity and Dissimilarity

A common group of techniques for data-mining time-series is distance-based clustering based upon time-series similarity/dissimilarity (Agrawal et al., 1993; Fu, 2011; Aghabozorgi et al., 2015). There are many different measures and whereas in traditional clustering, distance between static objects is exactly match based, in time-series clustering, distance is calculated approximately. Euclidean distance (Mumford et al., 2021), Dynamic Time Warping (Berndt and Clifford, 1994; Izakian et al., 2015; Kate, 2015) and Longest Common Sub-Sequence (LCSS) are some of the most popular measurement methods used for specifying similarity between time-series data (Aghabozorgi et al., 2015).

For whole series time series, as used by this study, two series are compared either as a vector or by distance measures. Most research effort has been directed at finding techniques that can compensate for small misalignments between series using elastic distance measures (Jeong et al., 2011; Izakian et al., 2015). For example, in Figure 12.2, two time series are displayed with two measurement points at *t* and *t-1.* If Euclidean distance is used, the distance between the two series is that shown as a sum of the distance between the two series. However, if a distance time warping approach is taken, the distance can be considered zero if the time-period between the two series is considered irrelevant as the shape of both is identical. As the footfall data has a resolution of an hour, allowing a degree of flexibility with the hourly alignment was considered beneficial in discovering similarities, rather than differences between sensors.

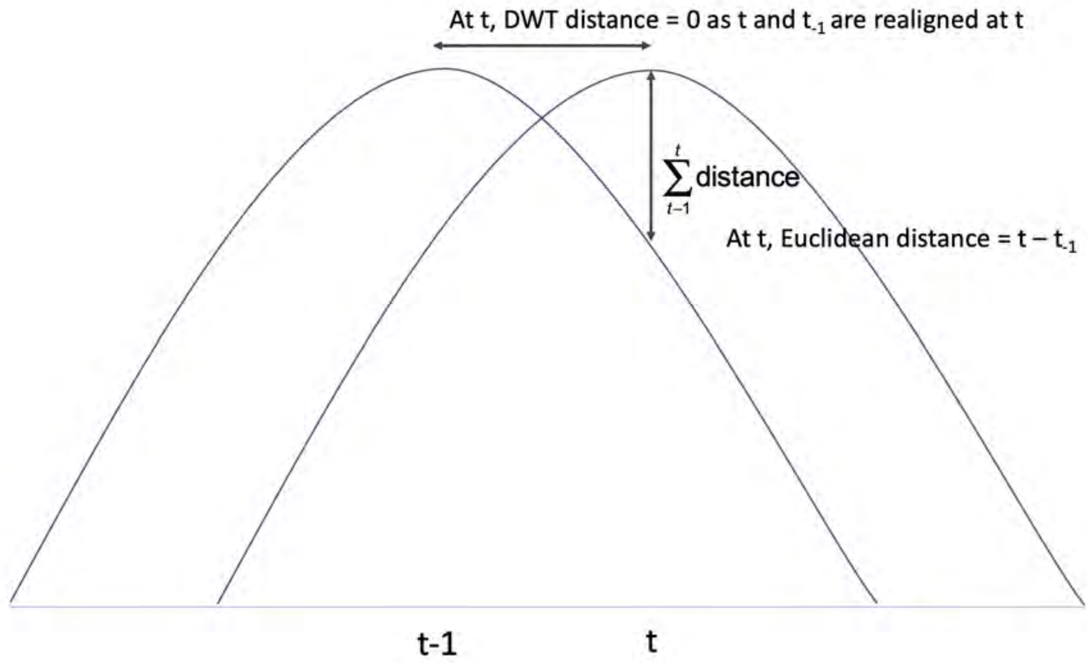


Figure 12.2 - Euclidean vs DTW Distance

Therefore, for this study, distance time warping (DTW) is adopted to allow these slight misalignments in time to be matched. Other techniques look for intervals (Deng et al., 2013; Lines and Bagnall, 2014), short pattern shapelets (Ye and Keogh, 2010; Hills et al., 2013), dictionary based sub-series (frequency of repetition based) (Lin et al., 2012), combinations of types (Bagnall et al., 2015; Kate, 2015) or are model based by fitting a generative model to each time-series and comparing the similarities (Bagnall et al., 2015).

Of the distance measures identified in the literature, both Aghabozorgi et al. (2015) and Fu (2011) find that Euclidean distance and Distance Time Warping (DTW) (Kruskal and Liberman, 1983; Kate, 2015; Łuczak, 2016) are the most common methods for similarity measure in time-series clustering. In terms of time-series classification accuracy, the Euclidean distance was identified as competitive but not always the most suitable, whereas Dynamic time warping (DTW) was viewed as popular and field-tested. DTW was detailed as a technique by Kruskal and Liberman (1983) and is recognised as being computationally expensive (Fu, 2011). Different methods have been proposed to refine the DTW algorithm to improve speed (Rakthanmanon et al., 2013), although for this study, this was not found to be an issue.

In a test, Bagnall et al. (2016) employed different similarity measures between time-series that quantity distance between two series. The standard benchmark was DTW but that found an Elastic ensemble technique (Lines and Bagnall, 2014) was more accurate where the ensemble was a combination of 11 nearest neighbour classifiers (Lines and Bagnall, 2014). However, Elastic ensemble techniques require considerable computing resources, so for this study, DTW and in a specific case, Euclidean distances are used.

12.5.1.3 Time-series Cluster Prototypes

Finding the cluster prototype or the cluster representative time-series is an essential subroutine in time-series clustering approaches (Aghabozorgi et al., 2015; Sardá-Espinosa, 2018). It is expected that all series within a cluster are similar to each other and finding the series that summarises the most important characteristics of a cluster is of great interest. Generally these are called the time-series centroids (Sardá-Espinosa, 2018). Prototyping is particularly important for the quality of clusters generated by partitioning algorithms such as k-Means, k-Medoids and Fuzzy C-Means (FCM) (Aghabozorgi et al., 2015). In the medoid approach, as used by this study, the centre of the cluster is defined as a sequence which minimises the sum of squared distances to other objects in the cluster. Given the distance between time-series pairs is calculated using a distance measure such as DTW or Euclidean, then, one of the time-series in the cluster with the lower sum of square-error is defined as the medoid of the cluster (Aghabozorgi et al., 2015).

12.5.1.4 Time-series Clustering Algorithms

The algorithms used for clustering time-series data can broadly be grouped into: partitioning, hierarchical, grid-based, model-based and density-based (Aghabozorgi et al., 2015). Of these types, the partitioning and hierarchical algorithms were considered for this study and are discussed below.

In a hierarchical cluster, the data is not partitioned into a particular number of clusters at a single step. Instead, the classification is performed as a series of partitions, that is initiated from a cluster containing all the data to *n* clusters containing a single individual (Everitt et al., 2011). In general, hierarchical algorithms are weak in terms of their quality because they cannot adjust the clusters (Kaufman and Rousseeuw, 2005) after splitting a cluster in divisive methods or merge in agglomerative methods (Aghabozorgi et al., 2015). As a result, Aghabozorgi et al. (2015) found that usually, hierarchical clustering algorithms are combined with another algorithm to create a hybrid clustering approach to remedy this issue. However, one of the strengths of the technique is not needing to define the number of clusters as an input parameter, which is a well-known and outstanding feature of the algorithm as it is hard to define the number of clusters in real world problems (Aghabozorgi et al., 2015).

A partitioning clustering method creates *k* groups from *n* un-labelled objects in the way that each group contains at least one object. One of the most used algorithms is k-means (MacQueen, 1967) where each cluster has a prototype which is the mean of its objects - see Mumford et al. (2021) for example. The main idea of behind k-means clustering is the minimisation (usually) of the total distance (typically Euclidean distance) between all objects in a cluster from their cluster centre (Warren Liao, 2005; Aghabozorgi et al., 2015). The solution relies upon an iterative scheme that is initiated using an arbitrarily chosen cluster membership. The distribution of objects among the clusters and the updating of cluster centres are the two main steps of the k-means algorithm (Warren Liao, 2005).

Another algorithm of the partitioning family is k-Medoids known as partitioning around medoids (PAM) (Kaufman and Rousseeuw, 2005) - for an example see Dolega et al. (2021) where the prototype for each cluster is one of the nearest objects to the centre of the cluster (Aghabozorgi et al., 2015). Using K-medoids is considered to be more robust to the presence of outliers and noise and, the possibility of obtaining non-fictitious representative sequences in the clusters is very appealing and useful in human activity pattern analysis (D’Urso and Massari, 2013). Computationally, k-means and k-Medoids are very fast compared to hierarchical clustering making them very suitable for time-series clustering despite the handicap of needing to determine the number of clusters before clustering (Aghabozorgi et al., 2015).

The k-means and k-Medoids algorithms make clusters that are ‘hard’ or ‘crispy’ meaning an object is a member of a cluster or not (Aghabozorgi et al., 2015). Alternatively, fuzzy clustering is another clustering technique, where, instead of assigning data to individual clusters, the Boolean-like nature of assignment is relaxed by assigning strength of membership grades to each individual cluster (Everitt et al., 2011; Aghabozorgi et al., 2015). Fuzzy C-Means (FCM) (Bezdek, 1981) and Fuzzy C-Medoids (FCMdd) (Krishnapuram et al., 2001) are two well-known and representative fuzzy clustering techniques. FCMdd selects the cluster centres using some of the existing data points (medoids), whereas FCM generates a set of cluster centres using a weighted average of data. In both cases, the intent is to minimise a weighted sum of distance between data points and cluster centres (Izakian et al., 2015).

Fuzzy clustering has two main advantages over crisp methods. Firstly, membership can be combined with other information - for example using Bayes’ theorem where the memberships are probabilities. Secondly, the memberships of any given object indicate whether a second best cluster is almost as good a fit as the first, a phenomenon that crisp membership techniques hide (Everitt et al., 2011). This ability to compare degrees of membership and how these vary over time, proved to be a very useful analysis tool for the footfall data.

12.5.1.5 Time-series Clustering Evaluation Measures

To evaluate the clusters generated by time-series cluster algorithms, different methods can be used. Visualisation and scalar measurements are the major techniques for evaluation of clustering quality which also is known as clustering validity in some articles (Hathaway and Bezdek, 2003). Numerical measures that are applied to judge various aspects of cluster validity can be classified using two types (Aghabozorgi et al., 2015):

- External Index: this index is used to measure the similarity of formed clusters to the externally supplied class labels or ground truth, and is the most popular clustering evaluation method (Halkidi et al., 2001). In the literature, this index is known also as supervised methods because the ground truth is available (Aghabozorgi et al., 2015).

- Internal Index: this index is used to measure the goodness of a clustering structure without respect to external information. In the literature, this index is known also as unsupervised methods (Aghabozorgi et al., 2015). For this study, these are the validation indices that are used.

The objective of validation functions in clustering is to formalize the goal of attaining high intra-cluster similarity (objects within a cluster are similar) and low inter-cluster similarity (objects from different clusters are dissimilar). Internal validation compares solutions based on the goodness of fit between each cluster and the data (Aghabozorgi et al., 2015). There are many cluster validation indices such as Sum of Squared Error, Silhouette index (Rousseeuw, 1987), Soft Mutual Information (Lei et al., 2017) and the Dunn Index. It should be noted that (Bezdek, 1981:98) viewed the cluster validity problem as 'one where the mathematics were exceedingly difficult to formulate', and that therefore, the validation indices are heuristic in nature.

12.6 Pre-Processing

The transform processes focused on the quality of the data, resolving character forms that caused database errors (ñ and í) and, every location was checked to ensure that no hour period was missing from the data record, motivated by the fact that sorting this out at the data loading stage, removed the need for extra processing and logic once analysis of the data took place.

Once the data loading processes were completed, three quality checks were carried out on the data:

- A duplicate record check
- Verification that no hourly data was missing
- Checking camera and place locations were correct

12.6.1 Duplicate record check

The first check ensured there were no duplicate records. The reason for duplicate records existing was that each annual CSV file included the whole of the initial week and final week of each year which meant the data from the previous year and following year was included in the data. Initially, the Python code was programmed to remove such duplicates but the load rates into the database caused by adding this check were so slow (between 5 and 20 records a second) that the code was first altered to allow pooled database connections (which increased the load rate to 30 to 50 records a second) and finally, the check was removed (increasing the load rate to 500 records a second). Making these changes meant that instead of taking 3 days to load a single CSV file into the database, the loads then took a couple of hours. To remove the duplicates, a SQL statement was then run against the database.

12.6.2 Verify that all hourly values present

A test looped over every camera to ensure that the number of records stored matched the number of hours expected for the start and end dates of the data.

12.6.3 Checking Camera and Place Locations

In one location, a problem during loading was encounter when data from the same camera was split between two different places. As it happened, the footfall data for one of the duplicated locations was all missing and therefore was excluded from the load.

For other locations, a place identifier was defined more than once with different cameras assigned to each place identifier. This arose because in one town or city, a BID scheme might pay for one set of footfall cameras and the Council for another. For the purposes of this study, where these splits were identified, the cameras were remapped to identify with a single place identifier. In total, the cameras for 9 towns/cities were manually remapped running SQL update statements.

12.7 Missing Data - Imputation

Although imputeTS was the chosen package for processing the missing data values, there are other R packages identified by Moritz et al. (2015) such as the forecast package (Hyndman et al., 2019b). As most missing values were for very short periods, the Stineman impute function was used to fill in the missing values. For most of the cameras, this produced very good results. On the other hand, values for Kenilworth (see Figure 12.3), where the missing values covered a longer period, this confused the impute function and the imputed values are clearly not correct. In this case, the Kalman filter option was tested but found to produce very similar values.

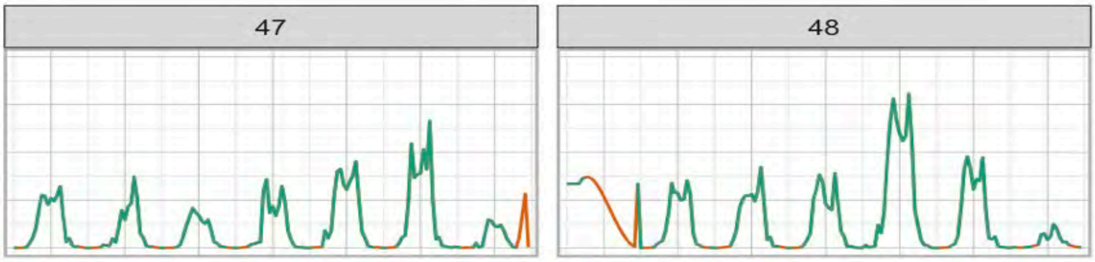


Figure 12.3 - Imputed footfall values (red)

Where no data existed for a period, no attempt was made to impute the values as was the case for one of the cameras in York Figure 12.4. In such cases, the data was excluded.

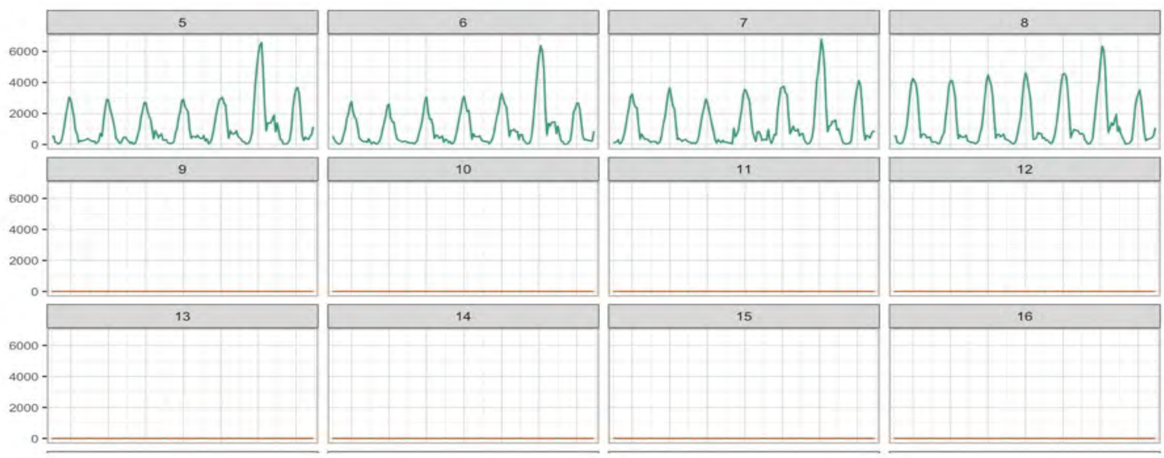


Figure 12.4 - Imputed footfall values and missing data

For every camera (see Figure 12.5 below), imputeTS produces a summary table of results which indicate how many missing values were found, the frequency of consecutive missing values and where in the time-series missing values occurred.

Summary Data

```
## [1] "Length of time series:"
## [1] 8760
## [1] "-------------------------"
## [1] "Number of Missing Values:"
## [1] 2695
## [1] "-------------------------"
## [1] "Percentage of Missing Values:"
## [1] "30.8%"
## [1] "-------------------------"
## [1] "Stats for Bins"
## [1] "  Bin 1 (2190 values from 1 to 2190) :      658 NAs (30%)"
## [1] "  Bin 2 (2190 values from 2191 to 4380) :      688 NAs (31.4%)"
## [1] "  Bin 3 (2190 values from 4381 to 6570) :      666 NAs (30.4%)"
## [1] "  Bin 4 (2190 values from 6571 to 8760) :      683 NAs (31.2%)"
## [1] "-------------------------"
## [1] "Longest NA gap (series of consecutive NAs)"
## [1] "21 in a row"
## [1] "-------------------------"
## [1] "Most frequent gap size (series of consecutive NA series)"
## [1] "1 NA in a row (occuring 252 times)"
## [1] "-------------------------"
## [1] "Gap size accounting for most NAs"
## [1] "6 NA in a row (occuring 131 times, making up for overall 786 NAs)"
## [1] "-------------------------"
## [1] "Overview NA series"
## [1] "  1 NA in a row: 252 times"
## [1] "  2 NA in a row: 30 times"
## [1] "  3 NA in a row: 75 times"
## [1] "  5 NA in a row: 140 times"
## [1] "  6 NA in a row: 131 times"
## [1] "  7 NA in a row: 93 times"
## [1] "  21 NA in a row: 1 times"
## NULL
```

Figure 12.5 - Tabulated summary statistics generated by ImputeTS

Finally as a starting point for viewing the data, the time-series imputed values for each camera was plotted using R ggplot2 (Wickham, 2016) and R Markdown (Xie et al., 2018; Xie, 2019) for every year and week. As remarked by Tukey (1977:141), simply plotting a time-series might not show much but in this case, the objective was to check that the imputed values generated by the R package imputeTS (Moritz and Bartz-Beielstein, 2017) were realistic. An example of this output is shown in Figure 12.6. In this example, although there has been missing data identified for each day, as it occurs at night, the imputed values look reasonable.

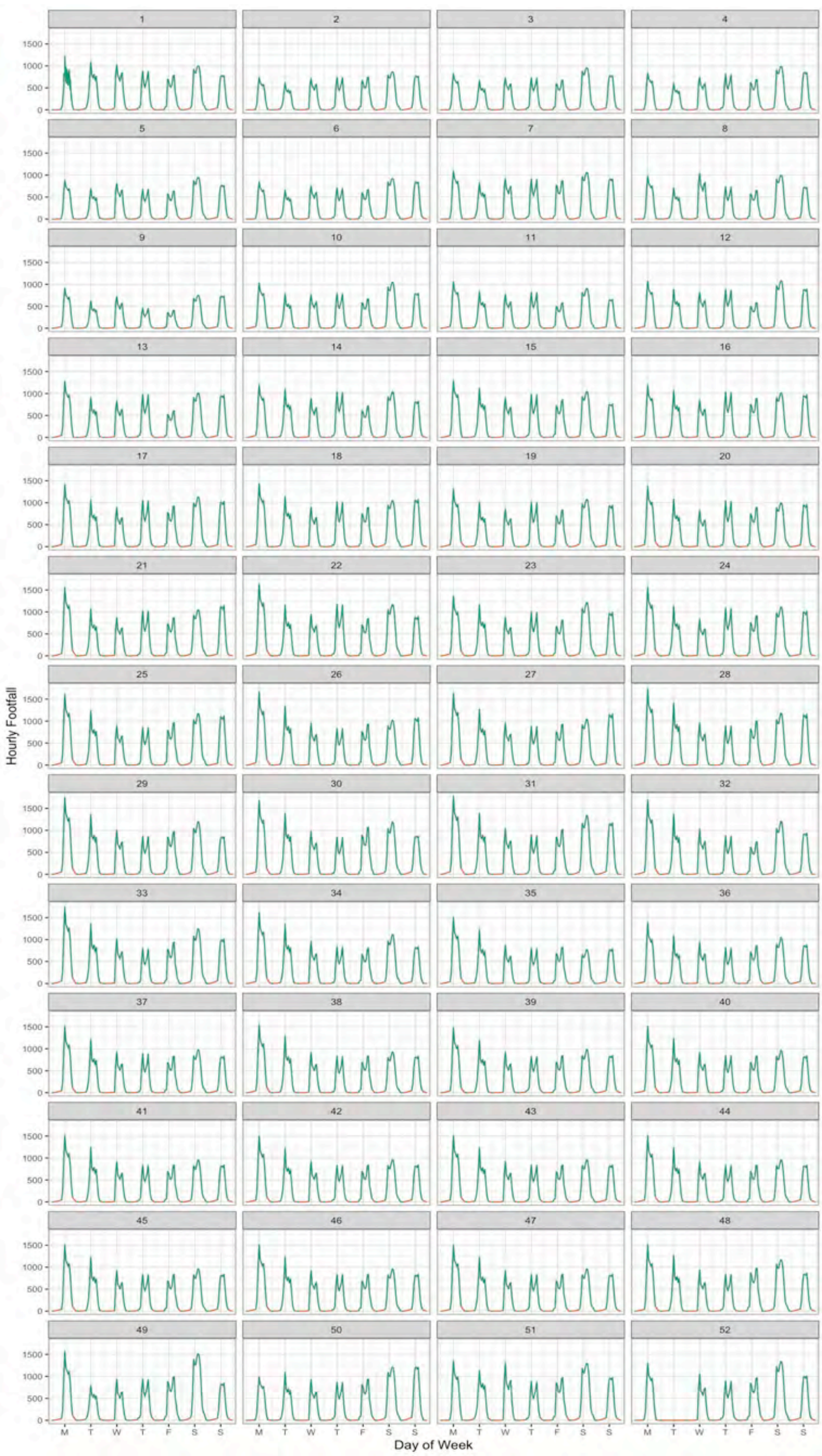


Figure 12.6 - Displaying the imputed and original footfall values for a year

12.7.1 Removing Leading Zero Values

The summary statistics from ImputeTS were particularly useful for identifying camera data where the initial values were all zero and at time, it could be several weeks before the camera data was returning none zero values. In all these cases, the data was removed. In all, 21 cameras required removal of this data. Where cameras were found to have too much missing data, they were flagged as unsuitable for further processing. In all, this excluded only 13 cameras.

12.8 Transformation

12.8.1 Decomposition Approach Autocorrelation Validation

A sample of cameras were checked to determine if there were seasonal and periodic fluctuations in the data. For each, an autocorrelation (ACF) was run against the data to determine the levels of periodicity in the data. From the ACF diagram below, Figure 12.7, a strong 24- and 168-hour cycle can be identified in the data.

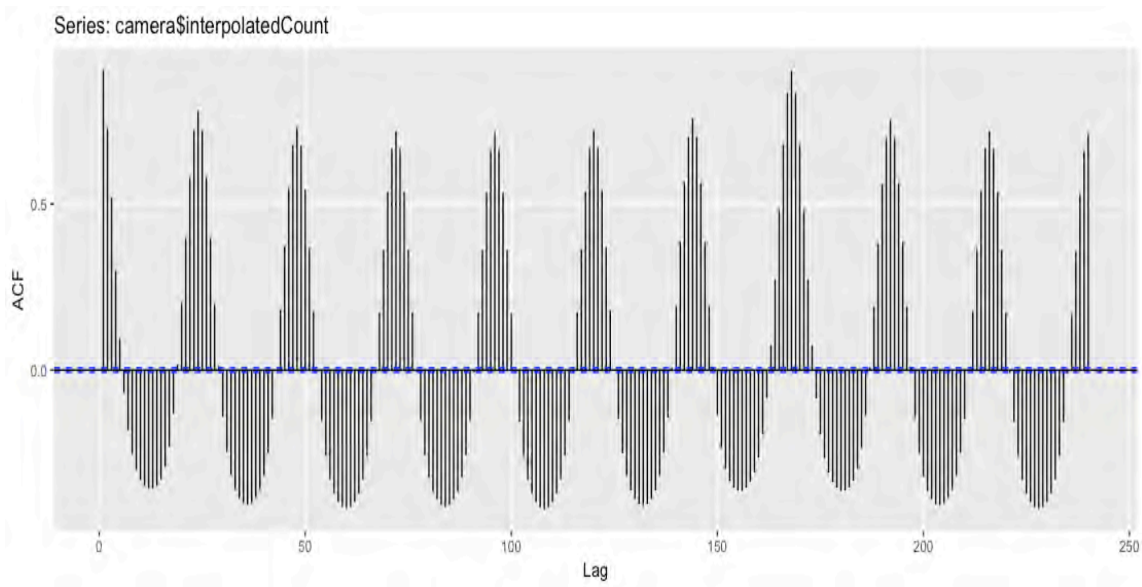


Figure 12.7 - Autocorrelation lags for the imputed footfall data.

12.8.2 Decomposition Process and Parameterisations

The MTSL function (Hyndman et al., 2019b) provides default values for the processing of the data, and these are discussed below. However, Cleveland et al. (1990) was clear that the defaulted parameters should be chosen carefully by the analyst. In the most basic form of the STL equation (Cleveland et al., 1990:3) only one component of seasonality is assumed however the strength of the STL function and the reason why it is used for this study is the ability to process multiple seasonal components using Loess.

STL consists of two recursive procedures. An inner loop nested inside an outer loop. In each pass of the inner loop, the seasonal and trend components are updated once. Includes option for post smoothing of components if thought necessary. STL produces a well-behaved component apart from local roughness so this can be smoothed using loess. (Cleveland et al., 1990). In order to set the required parameters Cleveland et al. (1990) suggests that the parameters used to smooth for seasonal components need to be tailored for each application.

Cleveland et al. (1990) suggests that for STL, robust estimation is needed when known non-Gaussian behaviour in the time-series leads to extreme transient variation. This controls the outer loop over STL and by default this is set to a value of 2 by MSTL which happens to be the value recommended by Cleveland et al. (1990) in order provide near certainty of convergence. However, because of the size of each sensor time-series and the level of noise, a more cautious approach was taken and a value of 10 was viewed as giving better certainty convergence. Upon testing, it was found to have little impact upon computational time. The other MSTL parameter was the s.window parameter. The choice of s.window determines the variation in the data that makes up the seasonal component and the choice depends upon the characteristics of the data series (Cleveland et al., 1990). An intrinsic ambiguity exists in the definition of seasonal variation and the data analyst defines the seasonal variation in choosing the smoothing parameter. It should be noted that this ambiguity is true of all seasonal decompositions, not just STL (Carlin and Dempster, 1989; Cleveland et al., 1990). Cleveland et al.

(1990) recommended that the s.window value should always be odd and at least a value of 7.

In terms of coefficients, since the MSTL trend parameters are set by default (Wang et al., 2007), only the s.window and time periods can be tuned. The view was taken that it was more important to reduce the residual than reduce the noise in the seasonality component since this could be resolved using further Loess filtering when doing the cluster analysis to remove outliers etc - as suggested by (Cleveland et al., 1990).

The emphasis for this study was for the MSTL function to extract as much as possible into the seasonality components, and so the s.window parameter value is set to minimise the residual elements and a value of 13 was used - which happened to be the default value. At the same time, convergence of the outer loop weightings was required and a value of 10 was chosen rather than 2.
Using the formula below (Equation 12.1) suggested by (Cleveland et al., 1990:14), outer loop iteration convergence of weighting values were check to see how many iterations were required.

$$\frac{\max_v |U_v^{(k)} - U_v^{(K+1)}|}{\max_v U_v^{(k)} - \max_v U_v^{(k)}} < 0.01$$

Equation 12.1 - STL outer loop parameterisation validation (Source: Cleveland et al., 1990:14)

Where $U_v^{(k)}$ and $U_v^{(k+1)}$ are successful iterations of a seasonal component

Results of the outer iteration convergence tests are provided in the tables below.

Table 12.2 - Outer iteration convergence tests for Great Yarnouth camera data

Great Yarmouth (King Street) No Iterations	Daily	Weekly	Annual
2 vs 3	0.004	0.004	0.026

3 vs 4	0.002	0.002	0.015
4 vs 5	0.002	0.001	0.009

Table 12.3 - Outer iteration convergence tests for London Northwest End (Heddon Street at Piccolino) camera data

London Northwest End (Heddon Street at Piccolino) No Iterations	Daily	Weekly	Annual
2 vs 3	0.006	0.006	0.016
3 vs 4	0.004	0.004	0.008

Table 12.4 - Outer iteration convergence tests for Blackpool (Promenade at Coral Island) camera data.

Blackpool (Promenade at Coral Island) No Iterations	Daily	Weekly	Annual
2 vs 3	0.010	0.008	0.023
3 vs 4	0.006	0.005	0.013
4 vs 5	0.005	0.004	0.009

Table 12.5 - Outer iteration convergence tests for Chester (The Cross) camera data.

Chester (The Cross) No Iterations	Daily	Weekly	Annual

2 vs 3	0.005	0.011	0.016
3 vs 4	0.003	0.008	0.010
4 vs 5	0.002	0.006	0.008

In all above cases, convergence was reached by the 4th or 5th iteration but as the computational overhead was minimal, a default of 10 was used for all decompositions.

The MSTL function was therefore programmed as:

decomposeff <- mstl(footfall, lambda = NULL, s.window = 13, iterate = 10)

Where lambda was set to NULL so that no Box-Cox transformation was performed on the data (Hyndman et al., 2019b). This was done to help with visualisation of the output and enabling the results of the decomposition to be related back to the original footfall count data. For each camera where decomposition was performed, the hourly decomposed results were written back to the database so that no further processing of this type would be required for the data cluster phase of analysis.

12.9 Data Mining

The sections below detail the components used to perform the cluster analysis using R package dtwclust (Sardá-Espinosa, 2018, 2019).

12.9.1 Random Start Seeding

Technically, fuzzy clustering can be repeated several times using different random starts. However, comparing the results is difficult as the medoids allocated can be different. However, the overall fuzzy grouping remains the same, or almost the same, once the algorithms converge (Sardá-Espinosa, 2018). For this reason, a constant seed value of 1 has been used therefore ensuring that repeated runs of the clustering software can generate the same results each time.

12.9.2 Code Example for dtwclust

Below, is an example of the code used to parameterise dtwclust. In this case, the configuration settings are specific to processing daily results. See dtwclust for more details (Sardá-Espinosa, 2019).

```
  cfgsDaily <- compare_clusterings_configs(
    types = c("f"),                      [performance fuzzy cluster analysis]
    k =  c(2L:20L),                      [analyse using 2 to 20 clusters]
    controls = list(
      fuzzy = fuzzy_control(
        iter.max = 30L,                  [fuzziness parameter – maximum iterations
allowed]
        fuzziness = 1.5,                 [fuzziness parameter – the assigned crispiness]
        delta = 0.001                    [fuzziness parameter – convergence criterion]
      )
    ),
    preprocs = pdc_configs(
      type = "preproc", none = list()
    ),
    distances = pdc_configs(
      type = "distance",
      fuzzy = list(
        dtw_basic = list(
          window.size = c(1L),           [dtw parameter – window of -1,0,+1 between
points]
          norm = c("L2")                 [dtw parameter – Euclidean distance between
points]
        )                                [dtw parameter – step.pattern symmetric2 as
default]
      )
```

```
  ),
  centroids = pdc_configs(
    type = "centroid",
    fuzzy = list(
      fcmdd = list()                    [fuzziness algorithm – use fcmdd - medoids]
    )
  )
)
```

12.10 Interpretation and Analysis

Other R packages used to help generate the results as combinations of graphs or in HTML output were:

- gridExtra (Auguie, 2017) - used to combine various plots together
- htmltools (RStudio and Inc, 2017) - needed to generate specific HTML
- knitr (Xie, 2019) - needed whilst constructing HTML displays
- RMarkdown (Xie et al., 2018) - used for HTML generation

12.10.1 Plotting Fuzzy Cluster Results

Apart from Radial Coordinate Visualisation (Radviz) diagrams, another technique is to use parallel coordinate plots (PCPs – see Figure 12.8) which are a well-known visualisation technique for viewing multivariate data (Holten and Van Wijk, 2010). Holten and Van Wijk (2010) performed a user study using PCPs to evaluate cluster identification performance. This was a visualisation tool tested by this study and was found to be of some use for the checking of the fuzziness parameter tuning. However, as a visualisation technique, as noted by Holten and Van Wijk (2010), the technique suffers from visual clutter. One option that Holten and Van Wijk (2010) suggest is to animate the output, although this was not attempted.

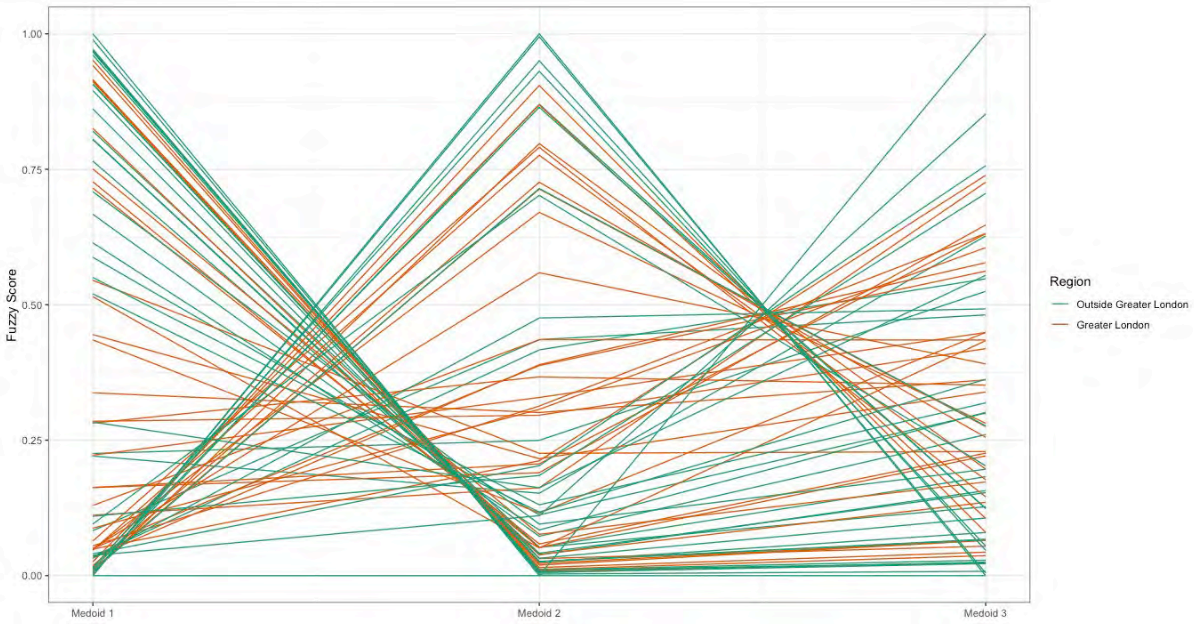


Figure 12.8 - Example of a PCP showing the fuzzy scores for Annual Medoids in 2007

Zhao et al. (2018) evaluated four presentational techniques used to analyse fuzzy cluster results. These were radial coordinate visualisation (Radviz), parallel coordinate plots (PCPs), principal component analysis (PCA) and scatterplot matrix (SPM). The techniques found to be most useful were Radviz and PCP and the least was PCA due to the insufficiency of the presentation of cluster information. Zhao et al. (2018) note however, that other techniques such as heatmaps were not considered as part of their research.

The Radviz package created by Abraham (2016) provides the basic display options. Various displays of Radviz have been experimented with to enhance the visualisation of fuzzy clustering (Zhou et al., 2017; Zhou et al., 2019), these are not however available through the R Radviz package used.

One aspect of the graphical output generation that was considered was the use of colours and which combinations should be used. To help ensure that suitable colours were used (Zeileis et al., 2009), the colour palettes detailed by Frazier (2020) were used.

13 Appendix B – Combined Sensor Annual Results

13.1 Fuzzy Cluster Outputs

Below, are listed in order of year, all the CVI, Radviz, Boxplot and Medoid plots for the annual signatures.

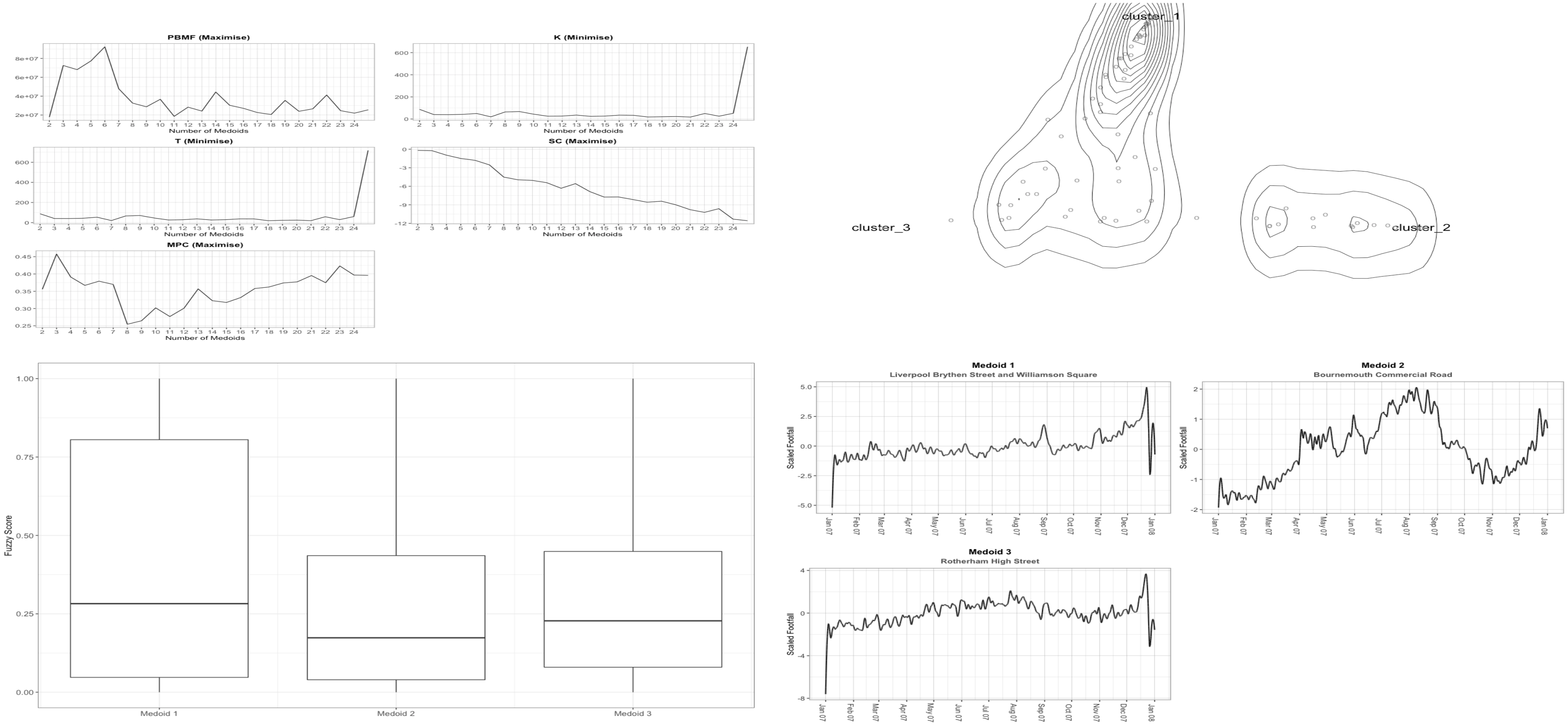
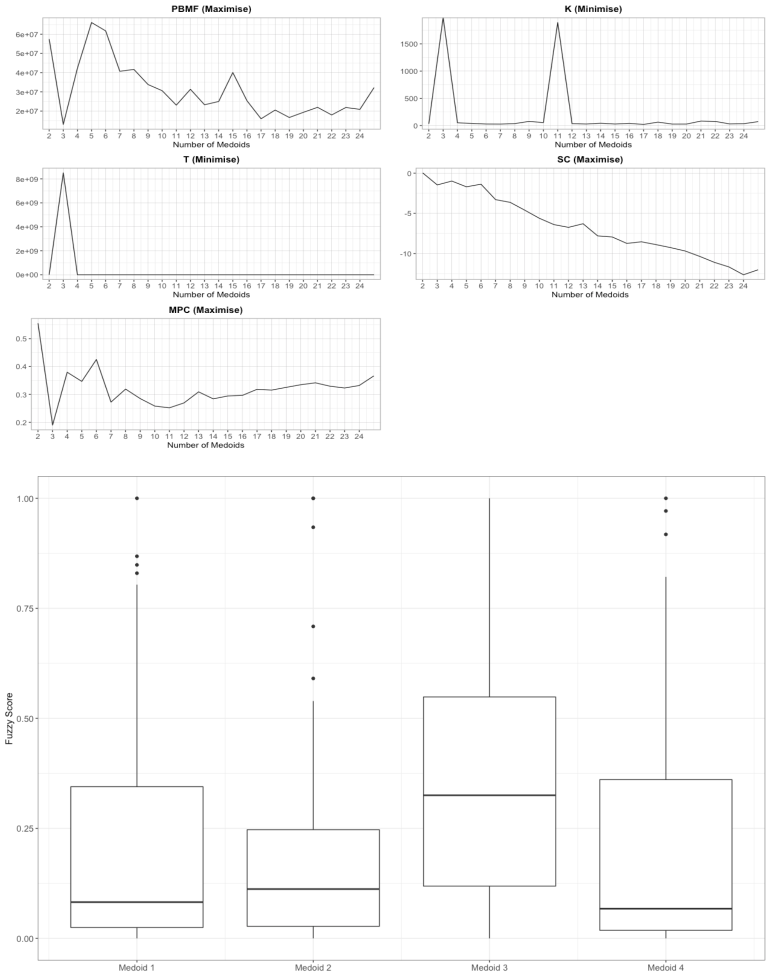


Figure 13.1 - Results for 2007 Annual Fuzzy Analysis k=3



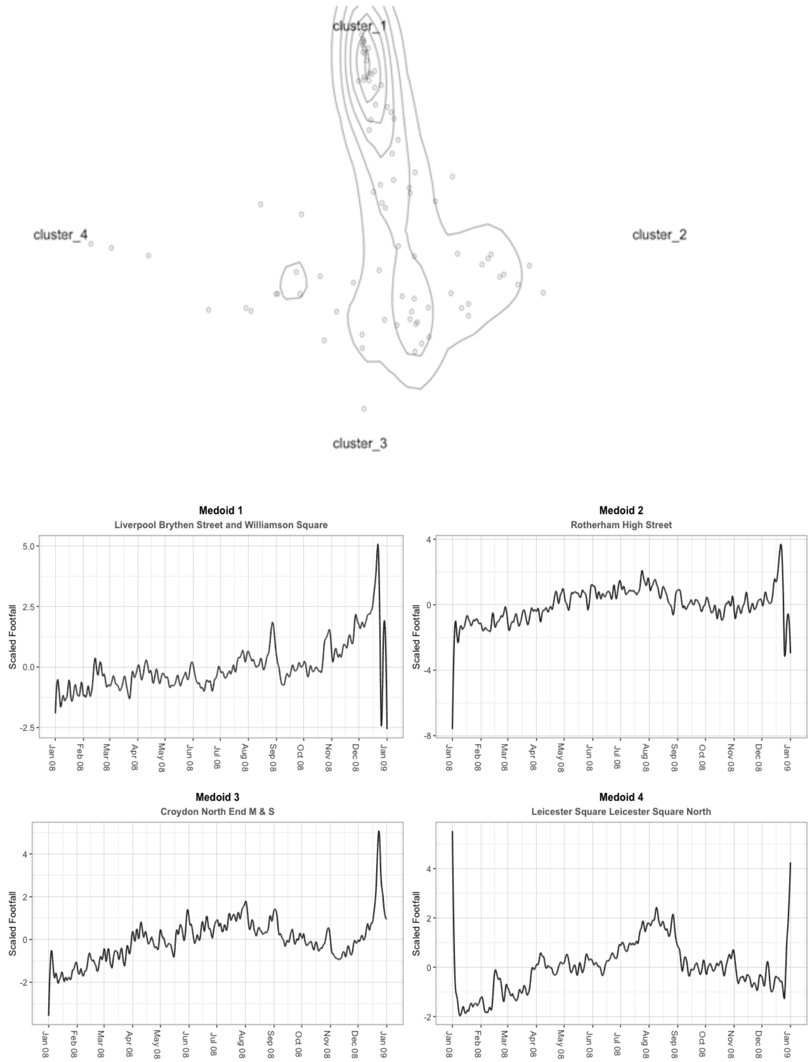


Figure 13.2 - Results for 2008 Annual Fuzzy Analysis k=4

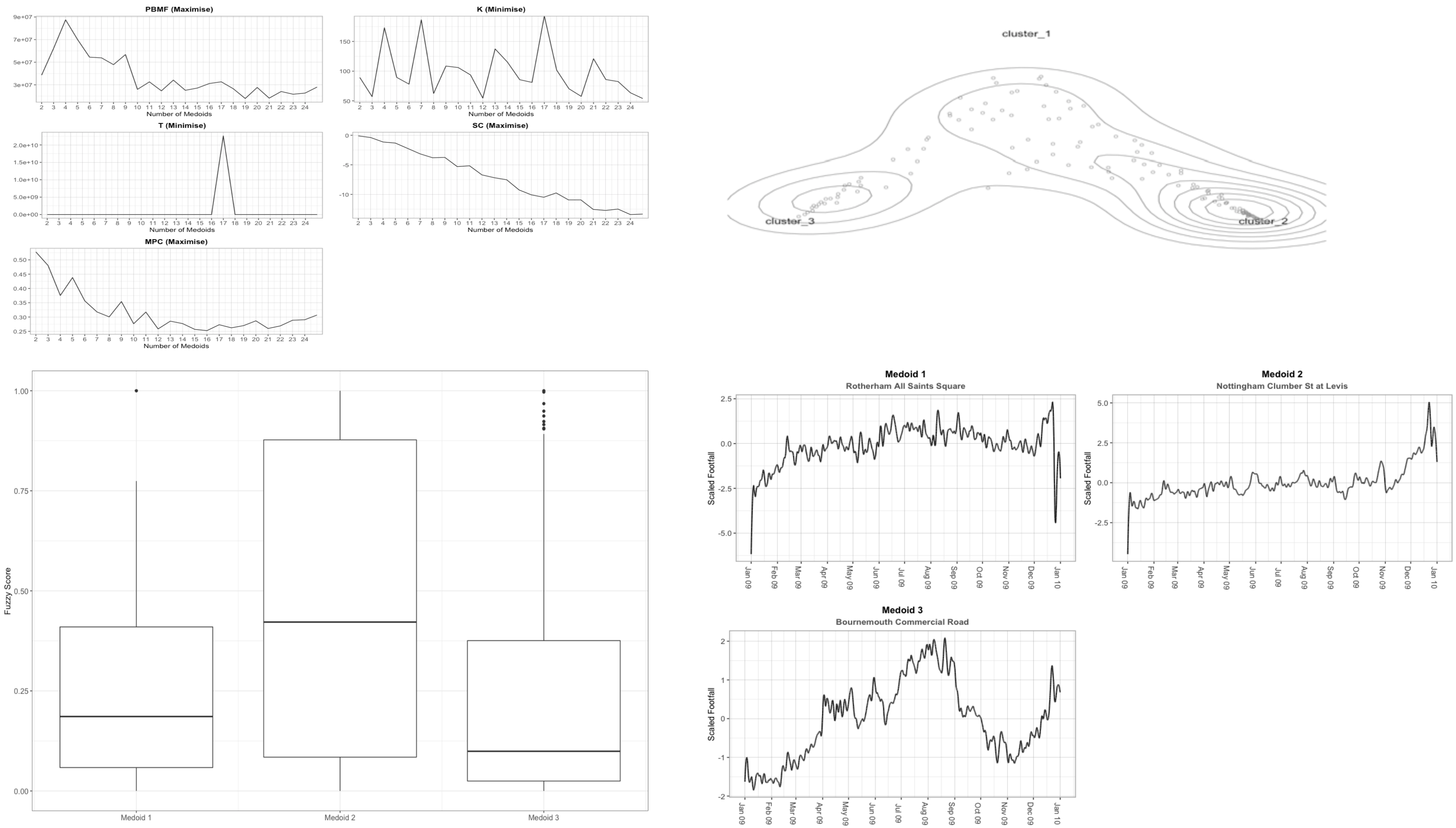


Figure 13.3 - Results for 2009 Annual Fuzzy Analysis k=3

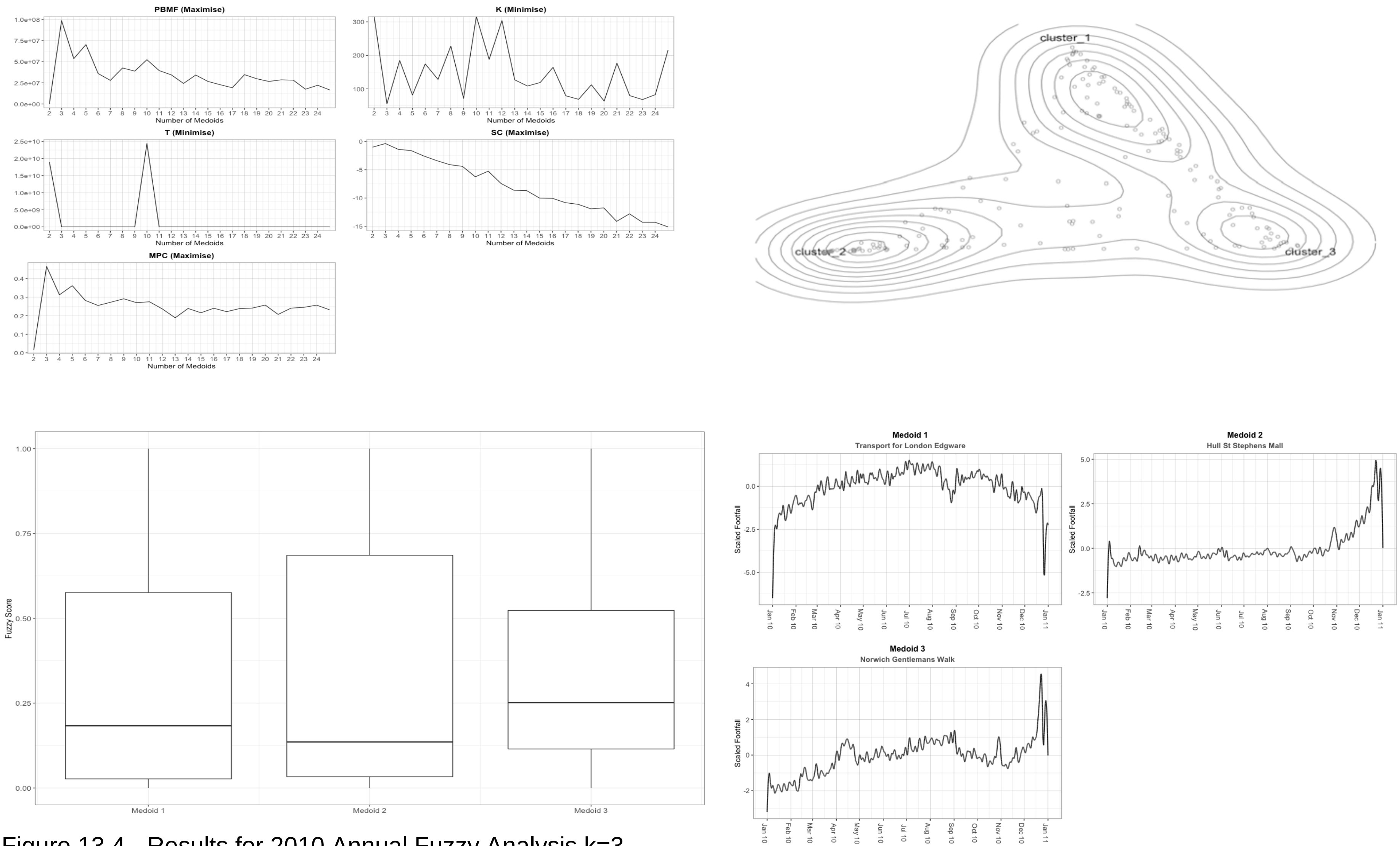


Figure 13.4 - Results for 2010 Annual Fuzzy Analysis k=3

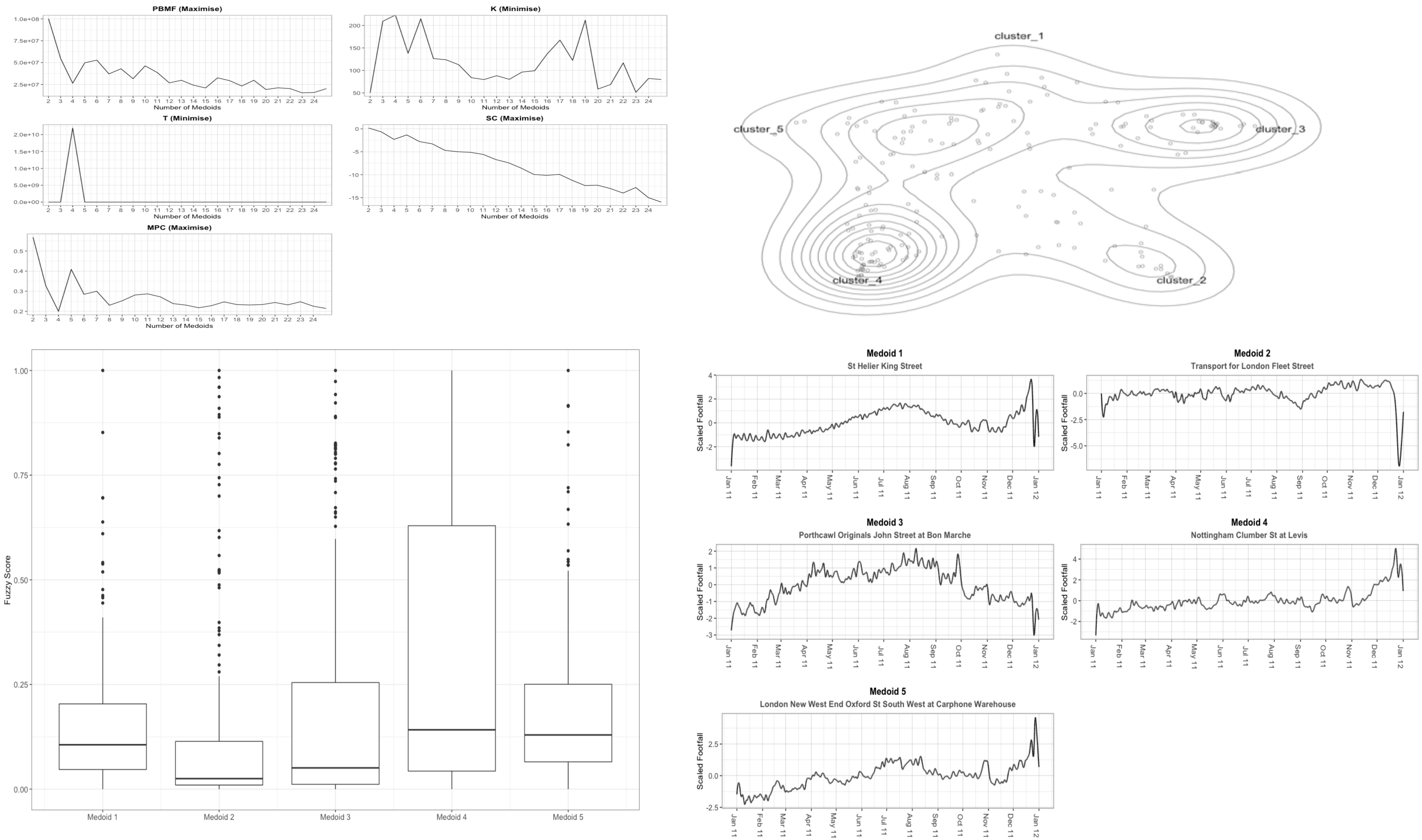


Figure 13.5 - Results for 2011 Annual Fuzzy Analysis k=5

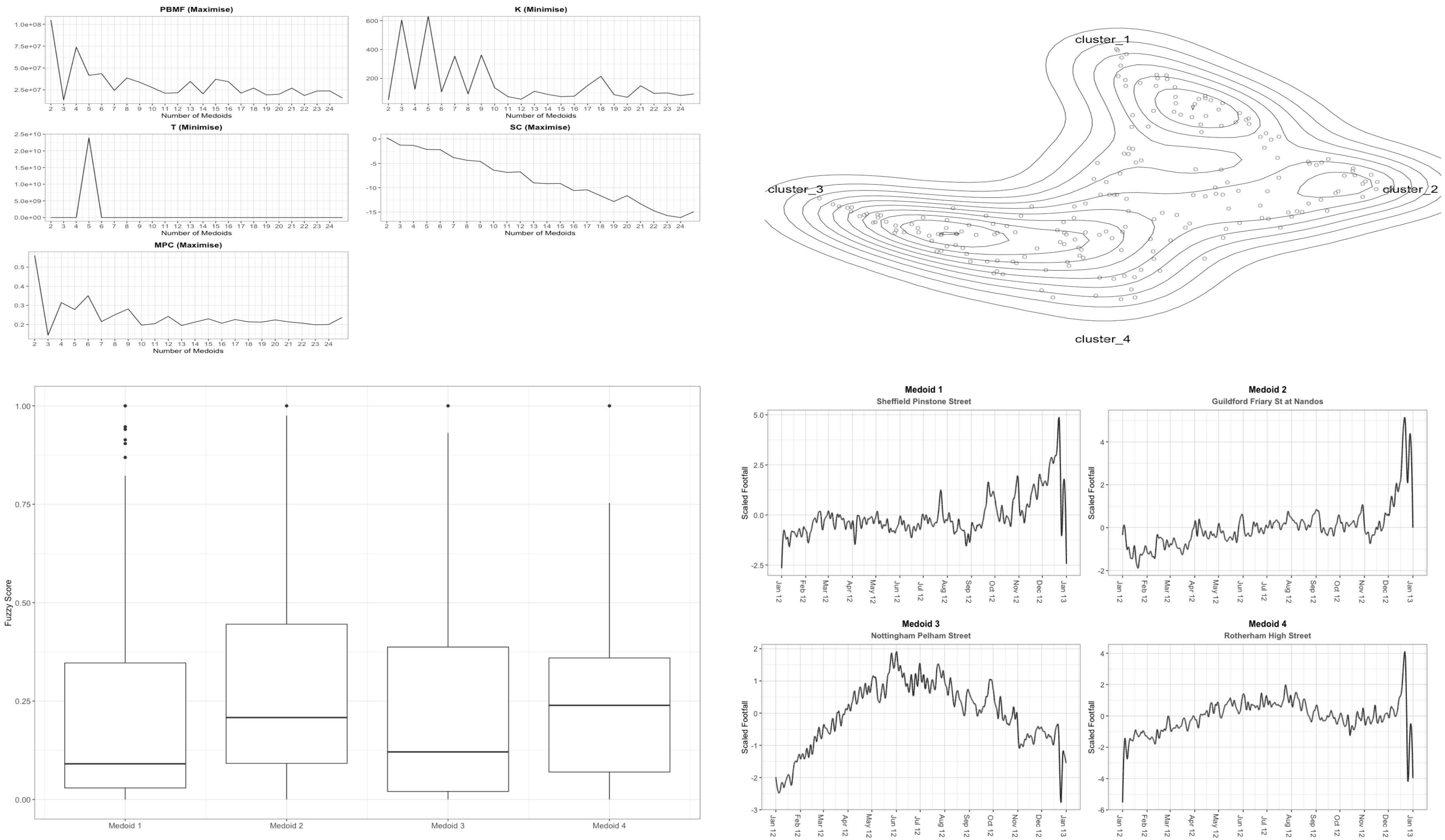
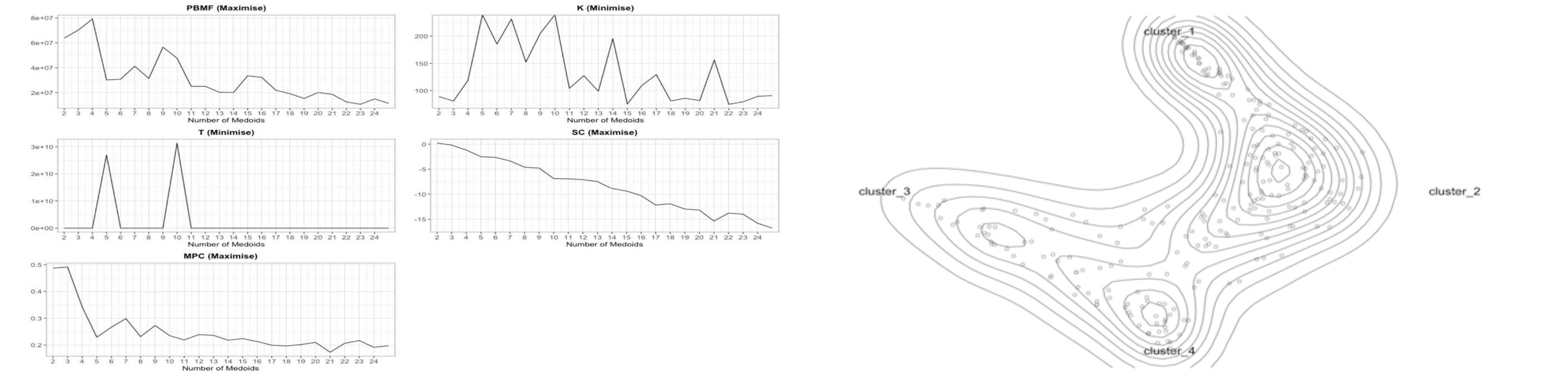
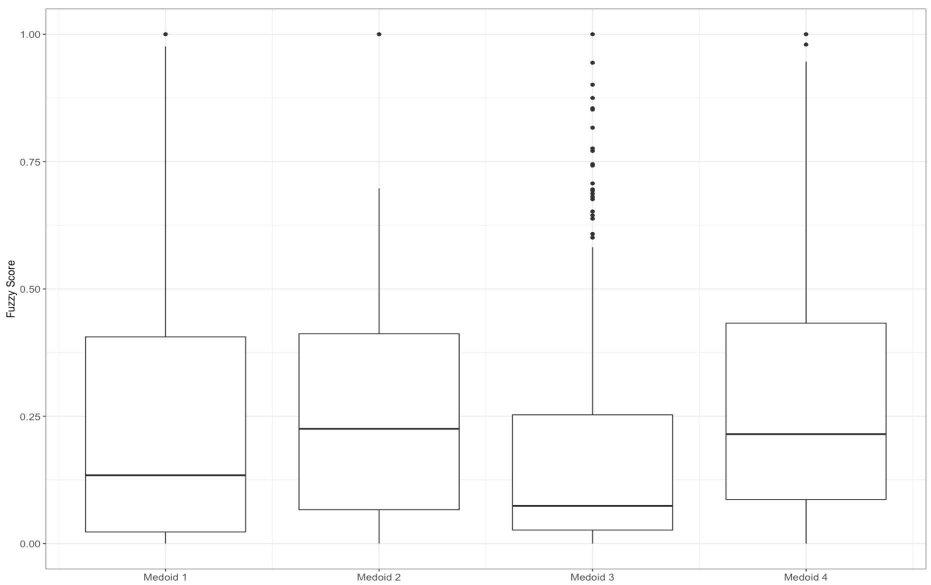


Figure 13.6 - Results for 2012 Annual Fuzzy Analysis k=4





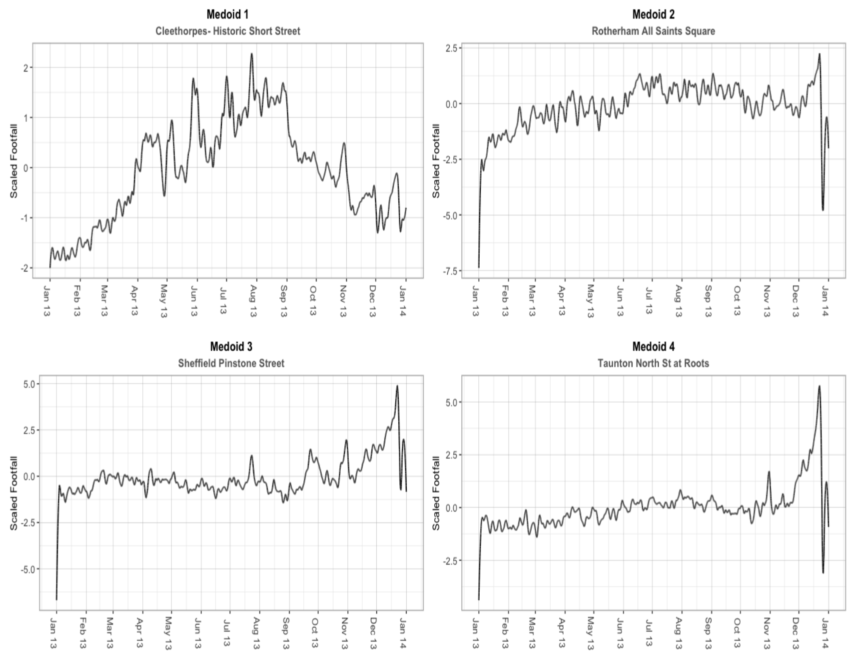
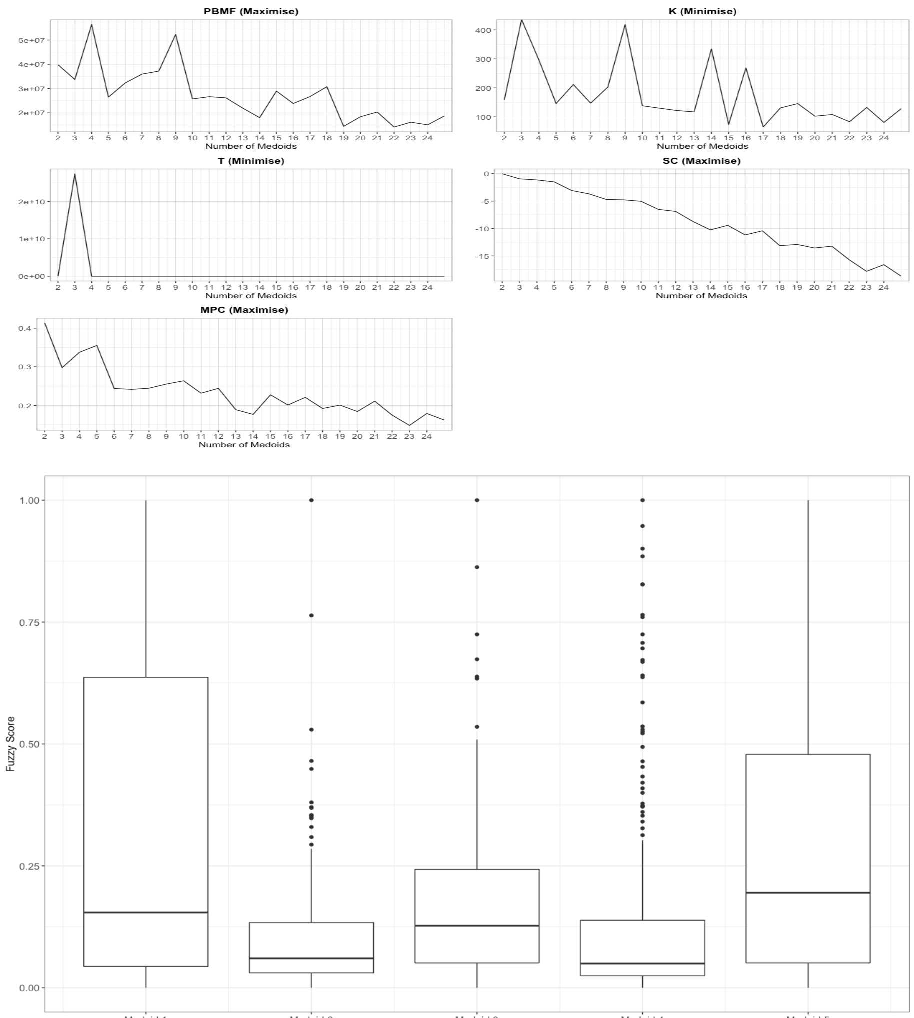


Figure 13.7 - Results for 2013 Annual Fuzzy Analysis k=4



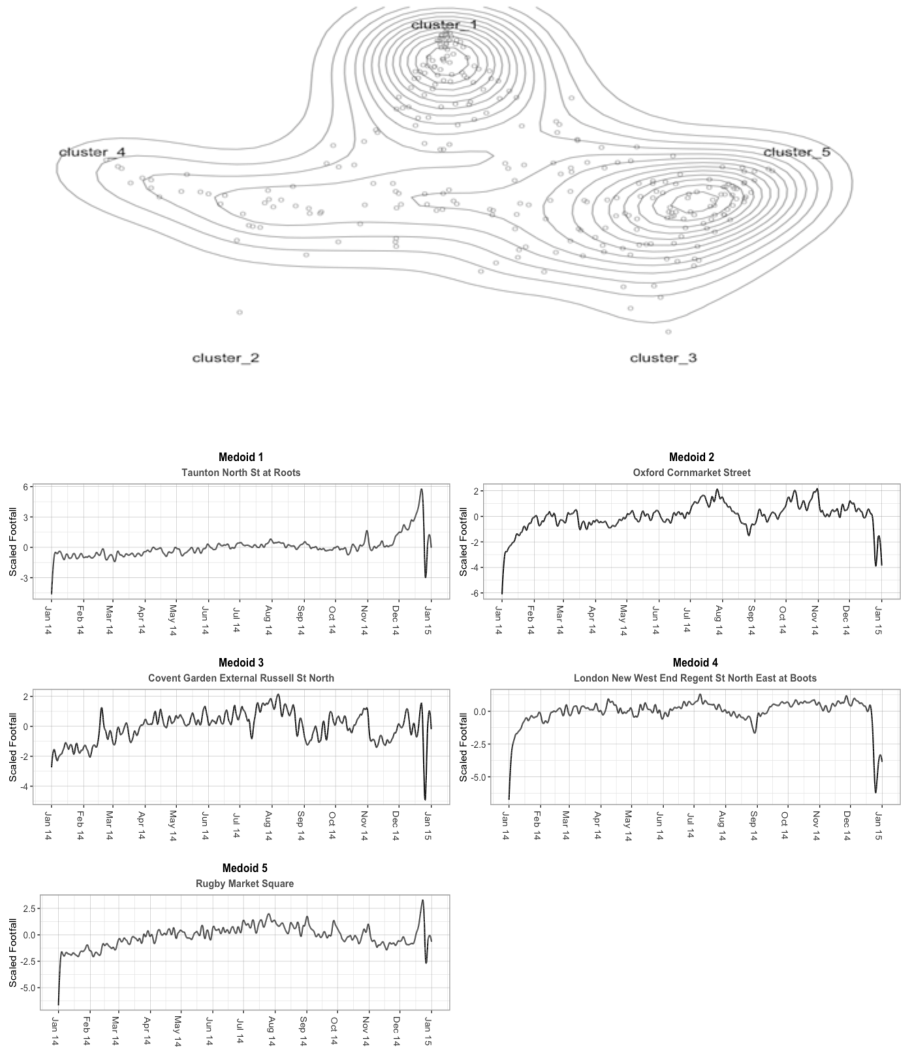
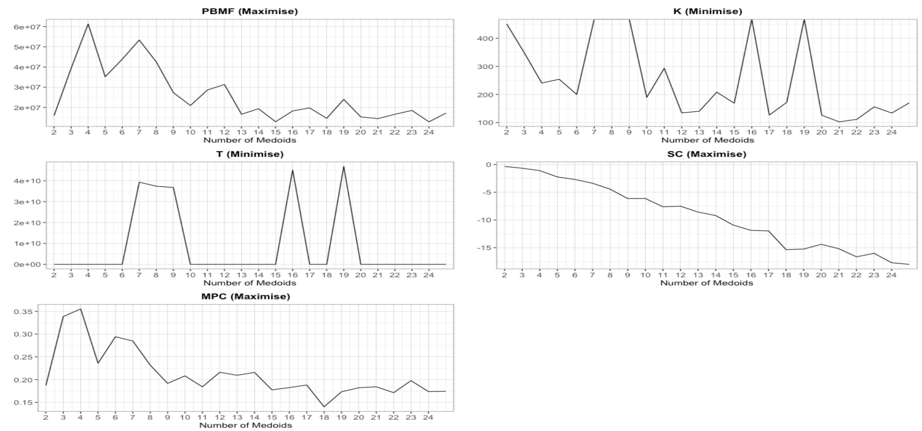
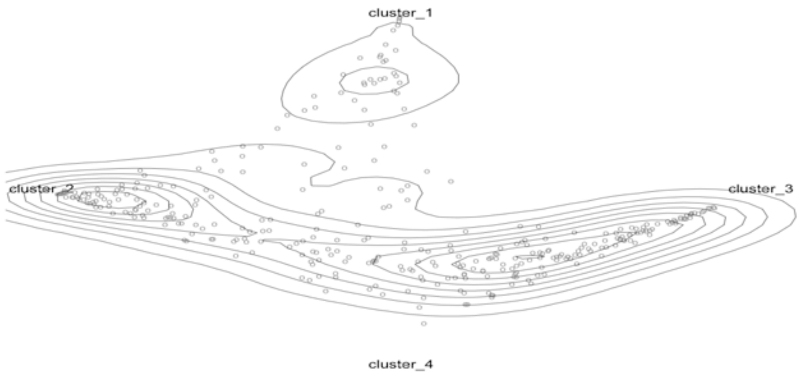
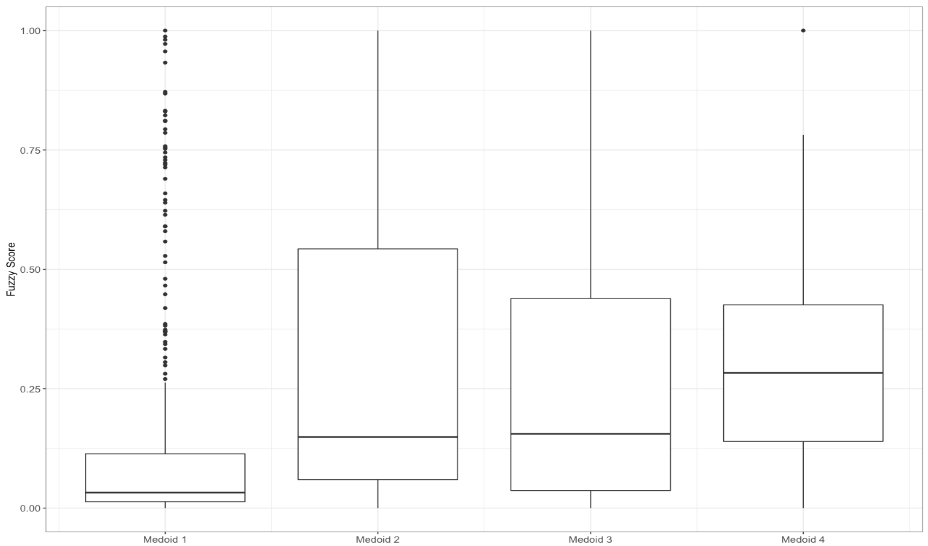


Figure 13.8 - Results for 2014 Annual Fuzzy Analysis k=5







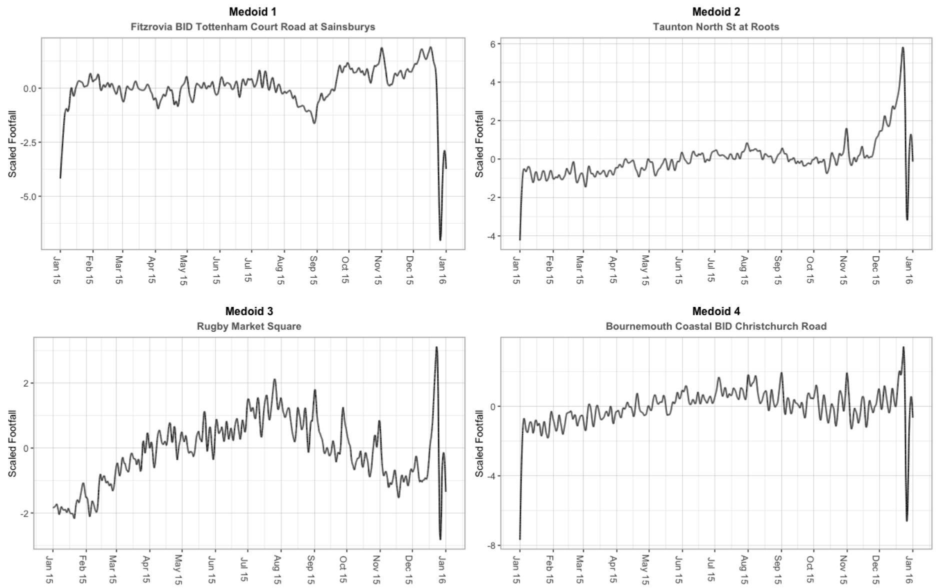


Figure 13.9 - Results for 2015 Annual Fuzzy Analysis k=4

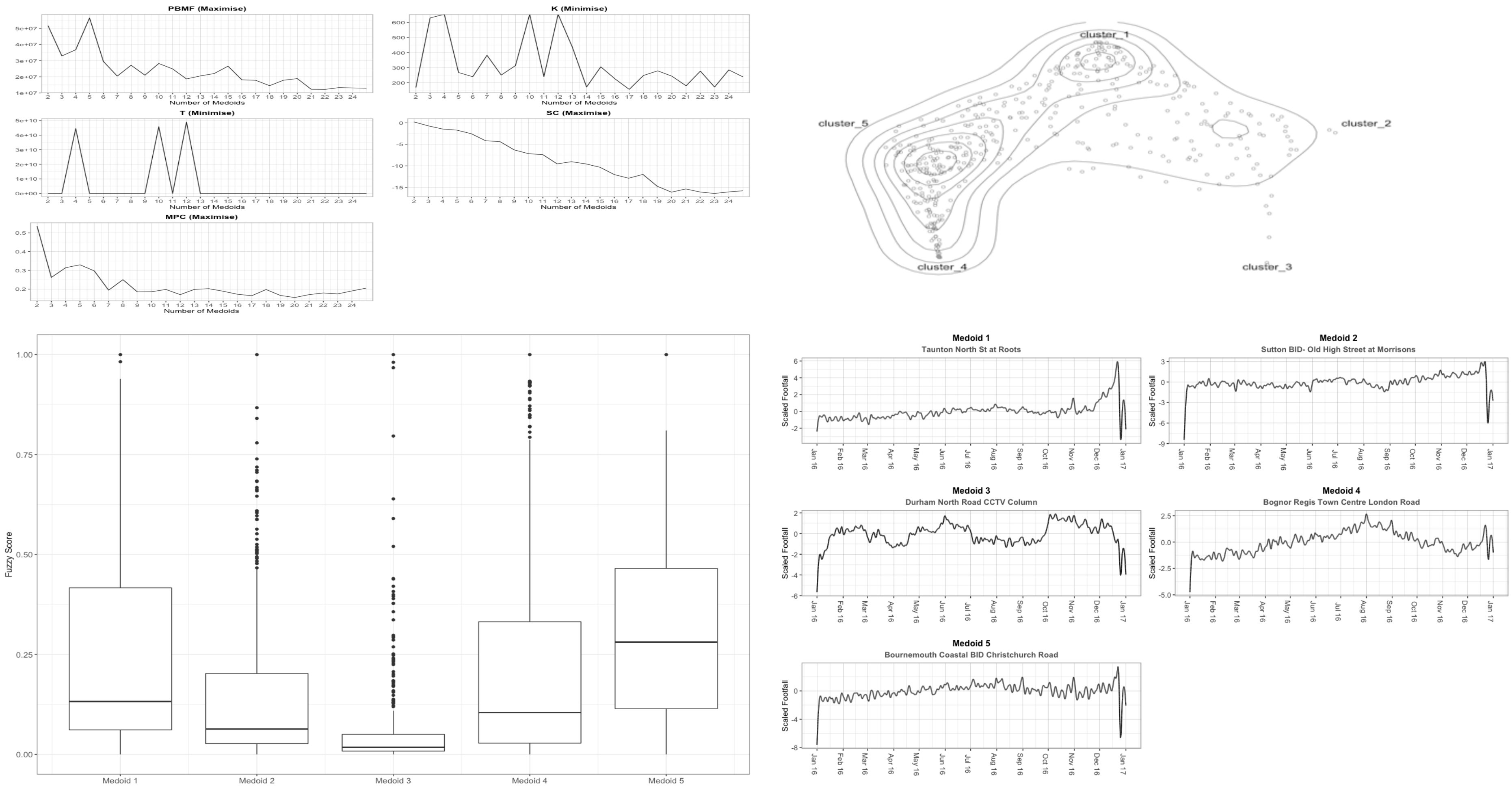


Figure 13.10 - Results for 2016 Annual Fuzzy Analysis k=5

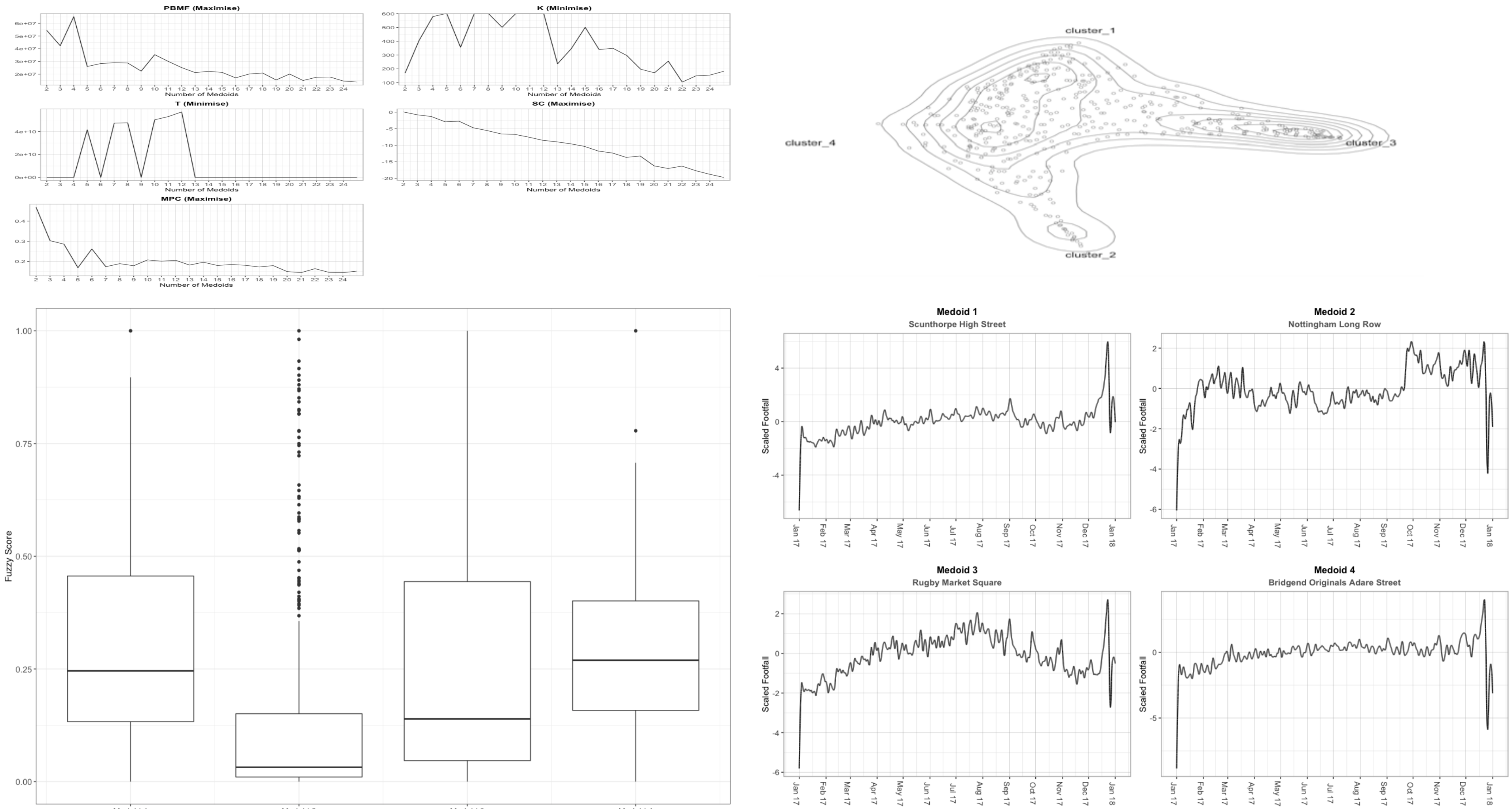


Figure 13.11 - Results for 2017 Annual Fuzzy Analysis k=4

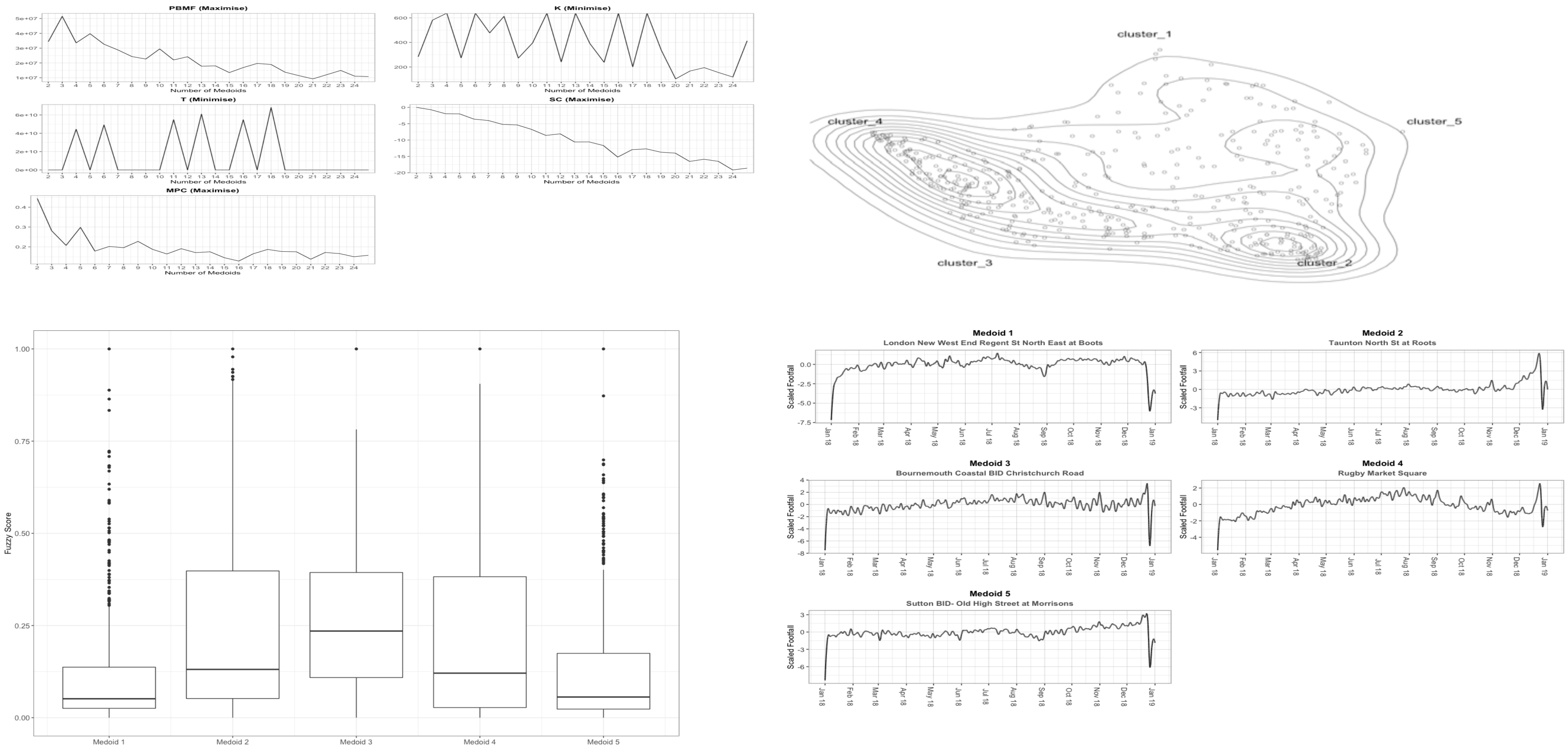


Figure 13.12 - Results for 2018 Annual Fuzzy Analysis k=5

13.2 Fuzzy Cluster Descriptive Analyses

13.2.1 Annual Results for 2008

Figure 13.2 displays the medoids identified to represent 2008. Note, that for all the individual years, there is no prescribed order to medoid allocation so even though the same medoid might appear across different years, it will not necessarily be assigned the same medoid position. In the case of medoid 4, the medoid assigned included a very significant footfall intensification not at Christmas but for the period of New Year's Eve. To reflect this, the analysis type was labelled seasonal plus new year. However, this signature pattern only appeared as a medoid in the 2008 analysis. It identifies the importance of events though as individual processes of territorialisation. Both medoids 2 and 3 display similar signatures and are both are referred to as mixed in the analysis. As with 2007, the medoids pick out the Christmas Day drop in footfall.

13.2.2 Annual Results for 2009

Figure 13.3 displays the medoids identified to represent 2009. Medoid 1 presents a common signature pattern where the Christmas period intensity exceeds that of the summer season period, but only slightly. As will be seen in the analysis later, the representative medoids suggest that the seasonal and mixed signatures interchange frequently.

13.2.3 Annual Results for 2017

Figure 13.11 displays the medoids identified to represent 2017. Medoid 2 in Figure 13.11 is an example of a footfall signature influenced by term times. Medoid 4 is identified as a Christmas type since the Christmas peak is more significant than it initially appears due to the very significant New Year fall in footfall.

Table 13.1. Annual Results Territorialisation Type Summary for 2017

	Territorialisation Intensity Type				
Medoid	Christmas Peak	Seasonal Territorialisation	Seasonal De-territorialisation	Multi-functional	Analysis Type
1	High	Low	Low	Medium	MF-Xmas
2	Medium	Low	High	Medium	Term-Time
3	Medium	High	Low	Low	Mixed
4	High	Low	Low	Medium	MF-Xmas

13.2.4 Annual Results for 2018

Figure 13.12 below displays the medoids identified to represent 2018. Medoid 5 in Table 13.2 is identified as a Christmas type since the Christmas peak is more significant than it initially appears due to the very significant New Year fall in footfall.

Table 13.2. Annual Results Territorialisation Type Summary for 2018

	Territorialisation Type and Intensity				
Medoid	Christmas Peak	Seasonal Territorialisation	Seasonal De-territorialisation	Multi-functional	Analysis Type
1	Low	Low	Medium	Medium	Term-Time
2	High	Low	Low	High	MF-Xmas
3	Medium	Medium	Low	Low	Mixed
4	Medium	Medium	Low	Low	Mixed
5	Medium	Low	Medium	Medium	MF-Xmas

13.3 Other Supporting Materials

The tables and figures that follow are additional supporting materials used to generate the results.

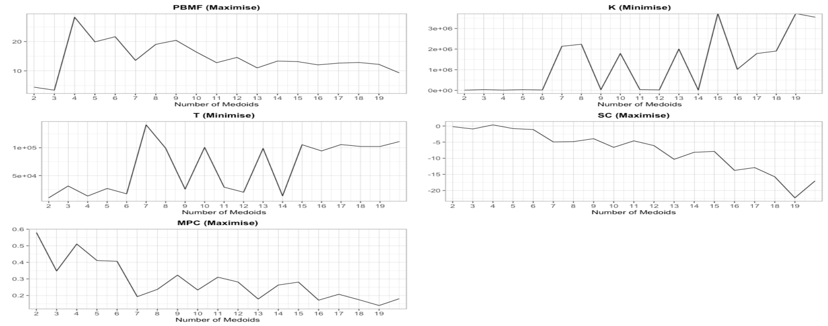
Table 13.3. Percentage of peak footfall by week for each year.

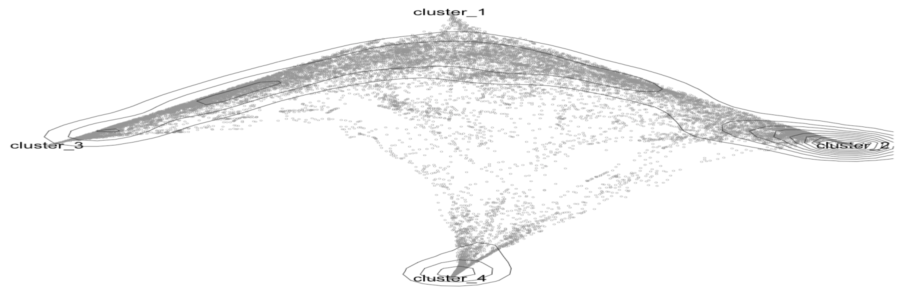
Week No.	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Total
1	1.27%	3.23%	5.41%	0.00%	0.50%	0.00%	1.56%	1.05%	3.75%	0.23%	0.21%	0.37%	1.16%
2	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.35%	0.00%	0.46%	0.00%	0.37%	0.15%
3	2.53%	1.08%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.27%	0.23%	0.86%	0.56%	0.37%
4	0.00%	2.15%	0.00%	0.54%	0.50%	0.90%	0.00%	0.35%	0.00%	0.23%	0.00%	0.19%	0.27%
5	0.00%	0.00%	0.68%	0.00%	0.00%	0.00%	0.39%	0.35%	0.27%	0.23%	0.00%	0.19%	0.18%
6	0.00%	0.00%	0.00%	0.00%	0.00%	0.45%	0.39%	1.05%	0.00%	0.69%	0.00%	0.00%	0.24%
7	2.53%	2.15%	0.68%	1.08%	0.00%	0.90%	0.39%	0.00%	0.27%	0.92%	1.07%	2.23%	0.97%
8	0.00%	0.00%	3.38%	0.00%	0.99%	0.45%	1.17%	0.70%	0.80%	0.92%	0.21%	0.56%	0.73%
9	0.00%	0.00%	2.03%	3.76%	0.50%	0.90%	0.39%	0.00%	0.00%	0.00%	0.00%	0.00%	0.43%
10	0.00%	0.00%	0.00%	0.00%	0.50%	0.45%	0.00%	0.70%	1.07%	0.00%	0.21%	0.00%	0.27%
11	1.27%	0.00%	0.00%	0.00%	0.00%	1.35%	0.39%	2.09%	0.27%	0.23%	0.43%	0.56%	0.55%
12	0.00%	1.08%	6.08%	1.61%	0.50%	1.79%	0.00%	0.00%	0.00%	0.23%	0.86%	0.00%	0.70%
13	0.00%	0.00%	0.68%	0.00%	0.50%	2.69%	1.17%	0.35%	0.00%	1.62%	0.00%	0.00%	0.58%
14	3.80%	0.00%	0.00%	2.69%	4.46%	2.24%	1.95%	0.00%	0.54%	0.69%	4.93%	0.37%	1.74%
15	1.27%	0.00%	0.00%	2.15%	0.00%	0.00%	0.00%	0.35%	4.56%	0.46%	1.71%	0.19%	1.04%
16	1.27%	0.00%	0.00%	2.69%	8.42%	0.00%	0.00%	4.53%	0.80%	0.92%	0.21%	4.66%	2.10%
17	0.00%	0.00%	4.73%	1.61%	5.45%	0.00%	0.00%	0.00%	2.14%	0.46%	0.21%	0.37%	1.04%
18	3.80%	0.00%	1.35%	0.00%	1.49%	0.00%	4.28%	4.88%	0.27%	2.31%	1.07%	1.30%	1.70%
19	0.00%	3.23%	0.68%	0.00%	0.00%	0.45%	1.56%	0.00%	0.27%	1.15%	0.43%	0.74%	0.64%
20	0.00%	1.08%	0.00%	2.15%	0.99%	0.00%	0.00%	1.39%	0.80%	0.46%	0.00%	2.79%	0.94%
21	1.27%	1.08%	1.35%	2.15%	0.50%	9.42%	1.17%	0.70%	1.61%	1.39%	5.57%	2.05%	2.56%
22	2.53%	0.00%	4.05%	2.15%	1.98%	0.45%	0.78%	1.05%	0.54%	1.39%	1.71%	0.74%	1.28%
23	0.00%	0.00%	0.00%	0.00%	0.00%	1.35%	3.50%	0.35%	1.61%	0.92%	0.64%	2.05%	1.13%
24	0.00%	1.08%	0.68%	3.23%	0.50%	0.00%	0.78%	1.39%	0.54%	0.69%	1.07%	0.19%	0.79%
25	0.00%	1.08%	0.68%	2.69%	0.00%	0.00%	0.78%	2.79%	1.61%	0.23%	0.64%	2.23%	1.19%
26	1.27%	3.23%	1.35%	1.08%	4.95%	1.79%	1.56%	1.39%	0.54%	0.69%	2.14%	5.21%	2.22%
27	0.00%	5.38%	2.70%	4.30%	2.48%	0.00%	1.17%	2.44%	4.02%	2.77%	4.50%	3.91%	3.07%
28	0.00%	0.00%	2.03%	2.69%	1.49%	0.45%	7.78%	1.05%	3.49%	0.92%	0.64%	1.68%	1.95%
29	0.00%	0.00%	0.68%	1.61%	1.98%	0.45%	3.89%	1.39%	0.80%	5.77%	0.43%	1.49%	1.86%
30	2.53%	8.60%	1.35%	4.30%	2.48%	3.59%	1.17%	6.62%	0.27%	5.77%	2.14%	0.37%	2.83%
31	6.33%	4.30%	3.38%	1.08%	0.99%	1.79%	2.72%	3.83%	5.63%	2.77%	1.71%	4.28%	3.17%
32	7.59%	0.00%	4.73%	1.08%	0.50%	4.48%	5.45%	1.05%	4.29%	2.77%	2.14%	1.86%	2.77%
33	2.53%	4.30%	2.70%	0.54%	2.97%	0.45%	1.17%	2.09%	1.88%	2.31%	1.50%	2.23%	1.92%
34	1.27%	2.15%	3.38%	2.15%	0.00%	1.35%	1.95%	2.09%	1.07%	1.85%	4.71%	1.12%	2.01%
35	0.00%	0.00%	2.03%	1.08%	0.50%	0.90%	3.11%	0.35%	2.41%	0.69%	1.28%	1.49%	1.31%
36	0.00%	0.00%	0.00%	0.00%	0.50%	4.04%	0.39%	0.35%	0.00%	0.46%	0.43%	0.00%	0.49%
37	0.00%	0.00%	2.70%	0.00%	0.99%	1.35%	0.00%	0.35%	0.27%	1.62%	0.43%	0.19%	0.64%
38	0.00%	2.15%	0.00%	2.15%	0.50%	0.00%	0.78%	1.05%	0.54%	1.15%	1.93%	0.19%	0.88%
39	0.00%	0.00%	2.03%	1.08%	4.95%	1.79%	2.33%	1.74%	2.14%	2.77%	1.71%	8.01%	3.07%
40	0.00%	0.00%	0.00%	0.54%	0.50%	2.24%	0.78%	2.44%	8.04%	3.46%	2.78%	0.74%	2.37%
41	0.00%	0.00%	0.00%	1.08%	0.50%	1.35%	0.78%	0.00%	0.80%	0.69%	0.86%	0.56%	0.64%
42	0.00%	0.00%	0.68%	1.08%	1.98%	0.45%	0.39%	0.70%	0.54%	0.69%	0.00%	0.93%	0.64%
43	1.27%	0.00%	0.68%	15.59%	2.48%	0.45%	0.00%	0.35%	0.27%	3.46%	2.57%	1.30%	2.22%
44	0.00%	1.08%	1.35%	1.08%	0.50%	8.97%	2.33%	4.88%	5.36%	0.46%	0.64%	1.12%	2.34%
45	0.00%	0.00%	0.00%	0.00%	0.50%	0.00%	0.00%	0.35%	0.54%	0.69%	0.43%	0.19%	0.30%
46	0.00%	0.00%	0.68%	1.08%	0.50%	0.45%	1.56%	0.00%	0.80%	0.69%	1.07%	0.56%	0.70%
47	0.00%	0.00%	0.68%	2.15%	0.99%	0.90%	1.17%	0.70%	0.80%	2.08%	1.28%	0.74%	1.10%
48	0.00%	1.08%	0.00%	0.00%	5.45%	0.45%	4.67%	5.23%	1.34%	3.00%	1.93%	0.56%	2.13%
49	3.80%	0.00%	3.38%	5.91%	2.97%	1.79%	3.89%	3.14%	1.88%	5.08%	4.28%	4.84%	3.74%
50	12.66%	1.08%	12.16%	7.53%	3.47%	0.45%	2.33%	2.44%	2.68%	14.32%	2.78%	2.79%	4.99%
51	34.18%	40.86%	12.16%	2.69%	19.31%	34.08%	27.24%	29.27%	26.27%	12.70%	33.19%	29.98%	25.14%
52	5.06%	8.60%	4.05%	9.68%	7.92%	2.24%	0.78%	0.35%	1.07%	3.23%	0.43%	0.93%	2.59%
53	0.00%	0.00%	2.70%	0.00%	0.00%	0.00%	0.00%	0.00%	0.27%	0.00%	0.00%	0.00%	0.15%

14 Appendix C – Combined Sensor Daily Results

14.1 Fuzzy Cluster Outputs

Below, are listed in order of year, all the CVI, Radviz, Boxplot and Medoid plots for the daily signatures.





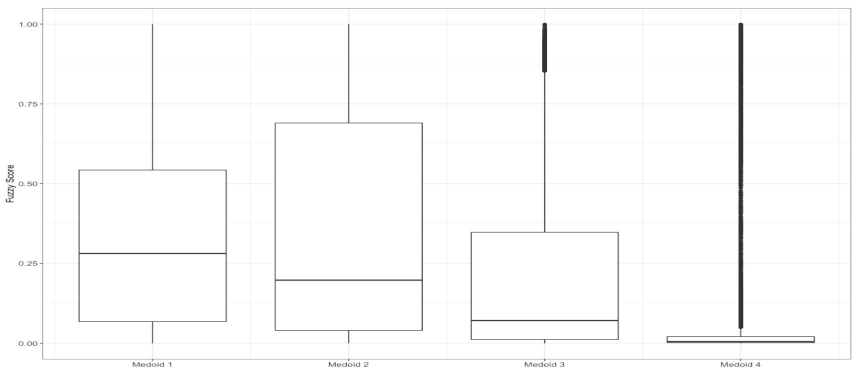
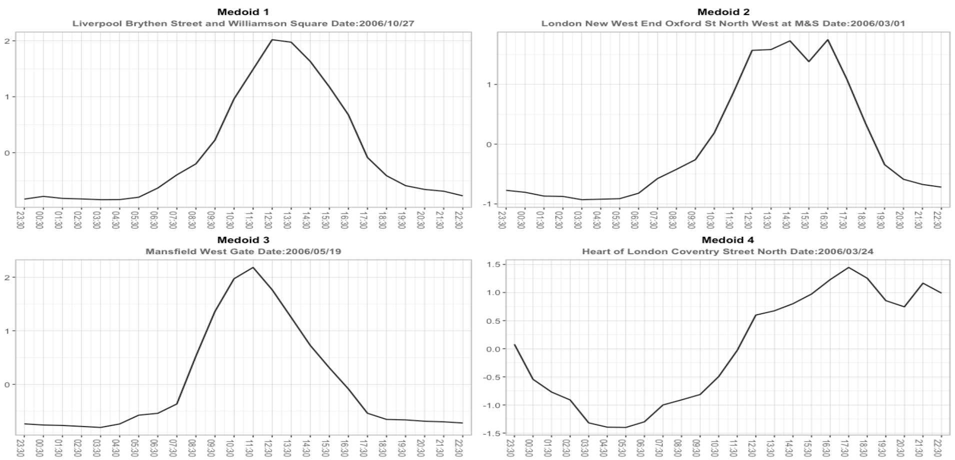
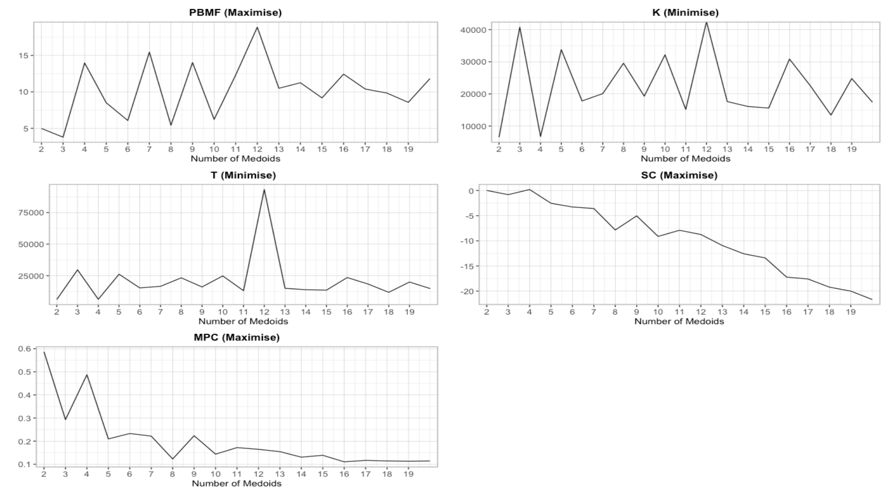
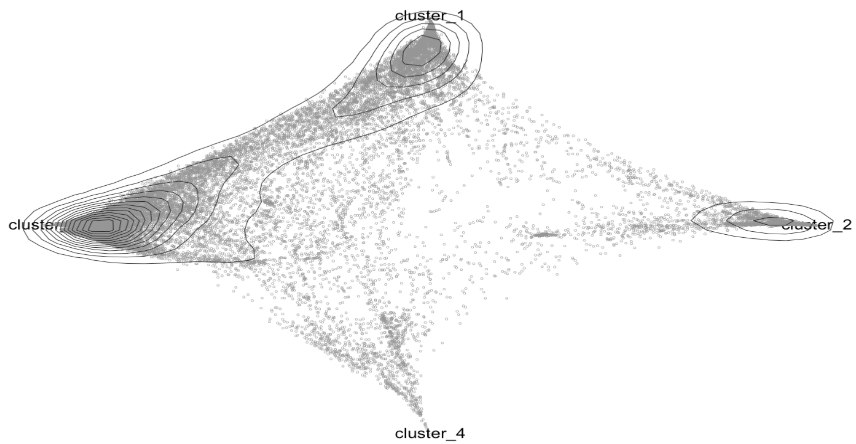
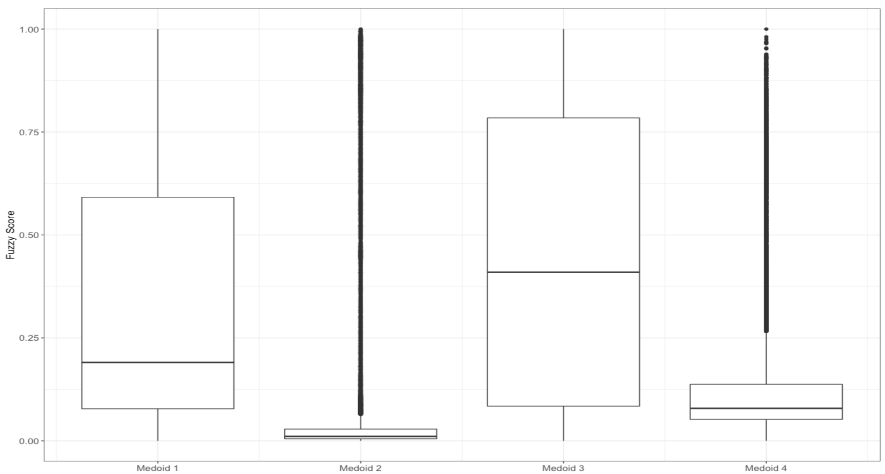


Figure 14.1 - Results for 2006 Daily Fuzzy Analysis k=4









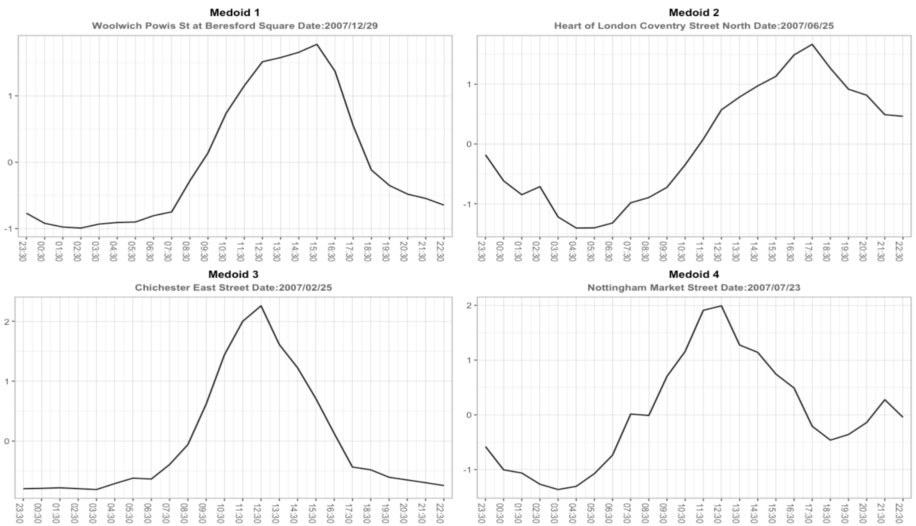


Figure 14.2 - Results for 2007 Daily Fuzzy Analysis k=4

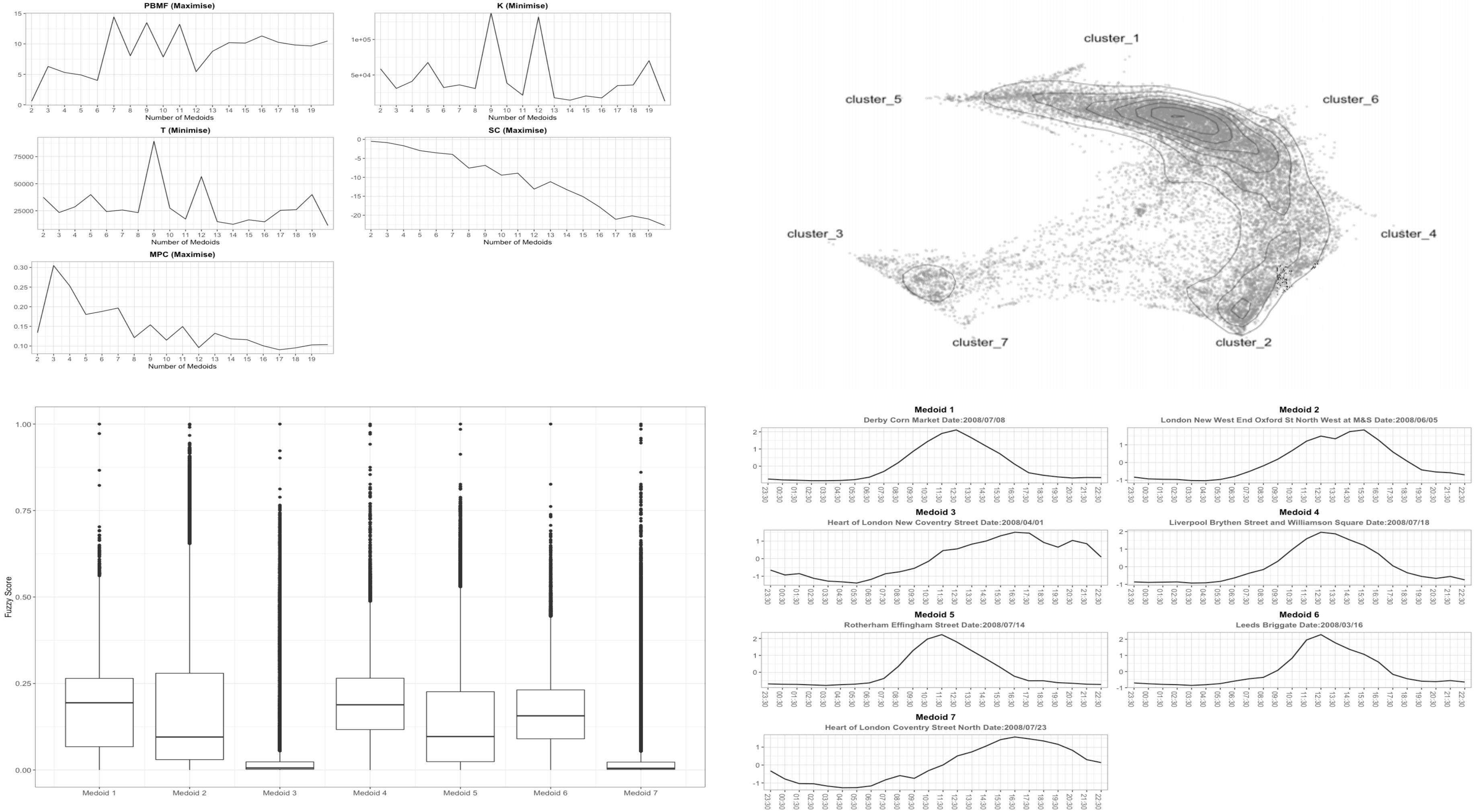


Figure 14.3 - Results for 2008 Daily Fuzzy Analysis k=7

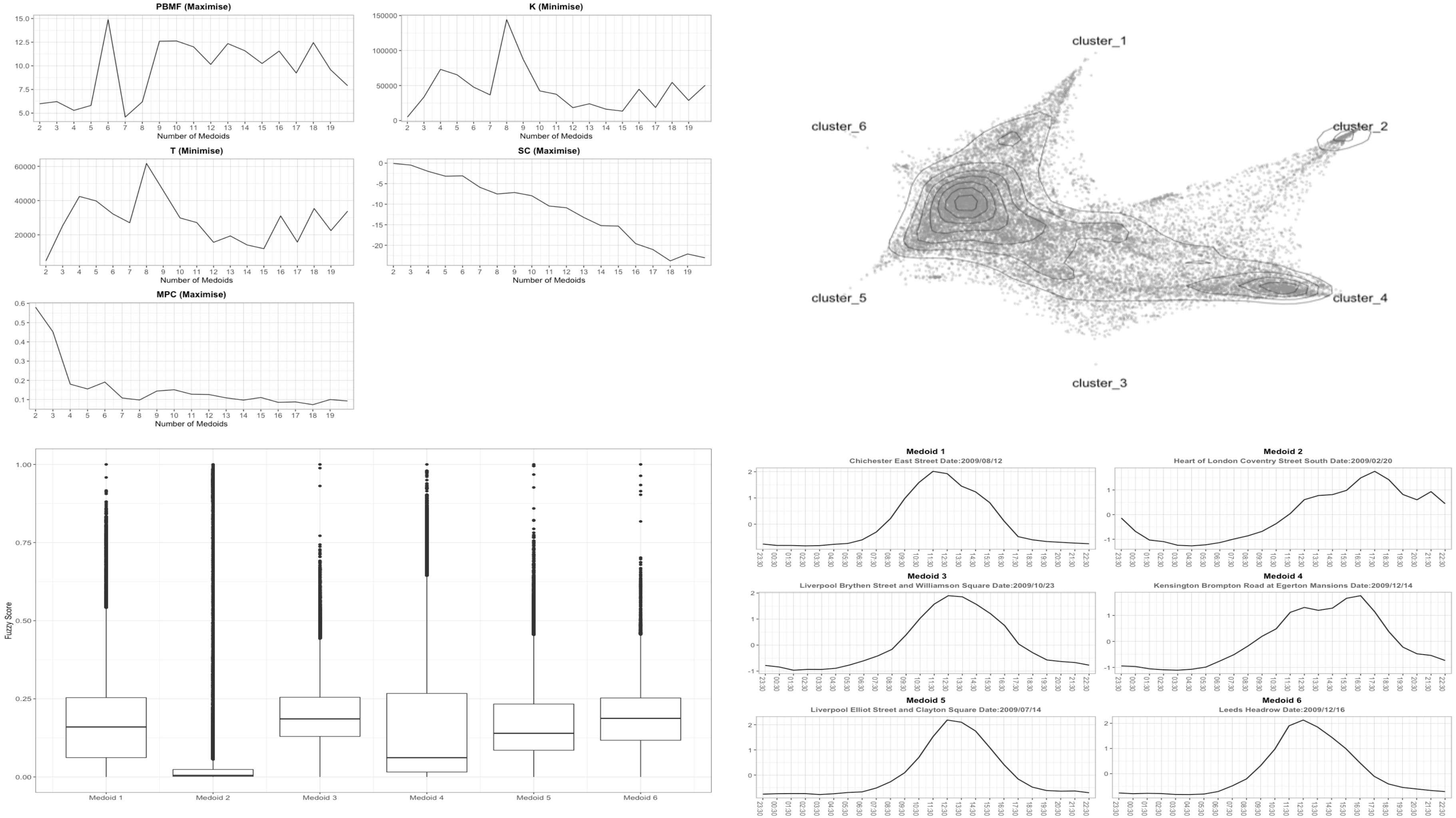


Figure 14.4 - Results for 2009 Daily Fuzzy Analysis k=6

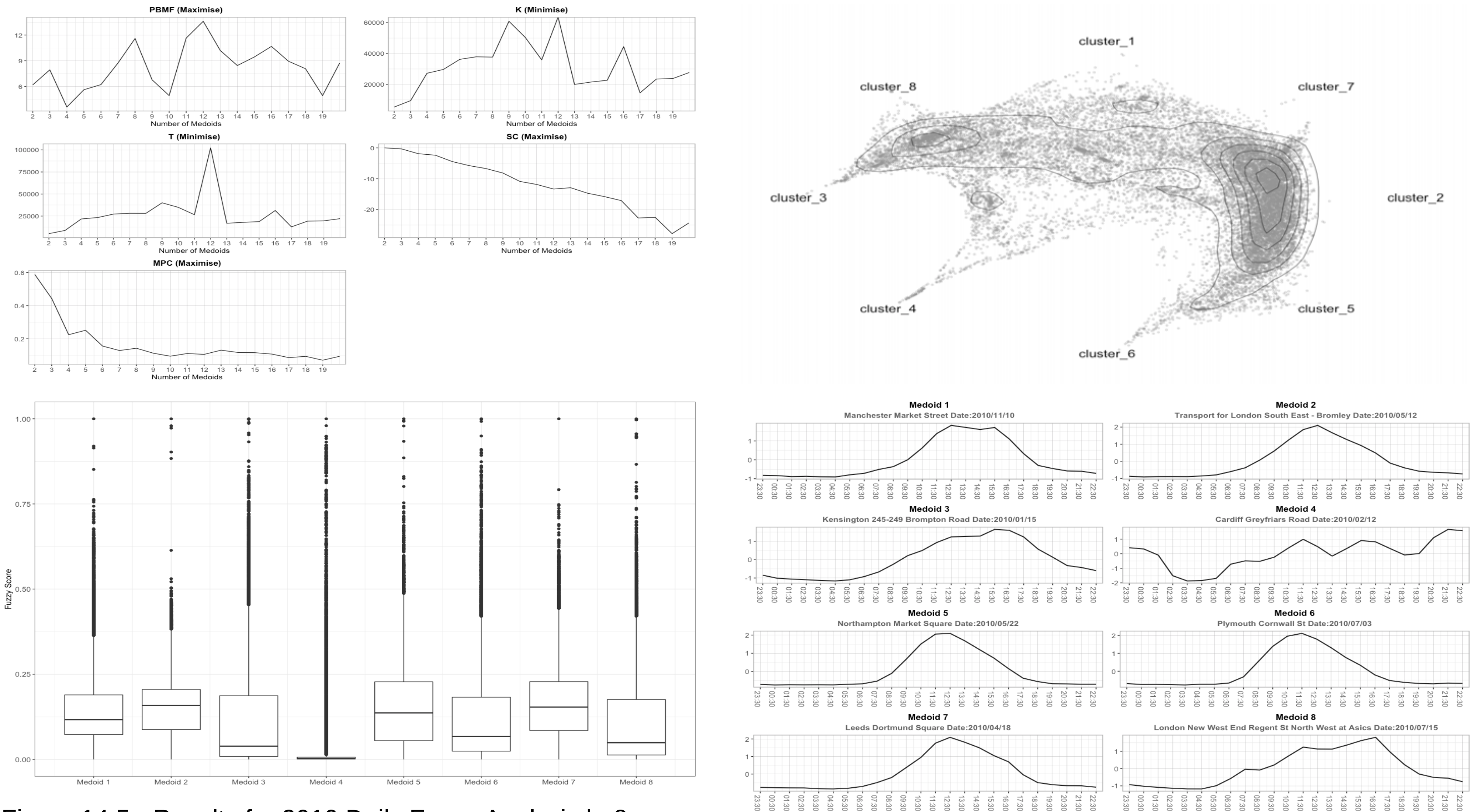


Figure 14.5 - Results for 2010 Daily Fuzzy Analysis k=8

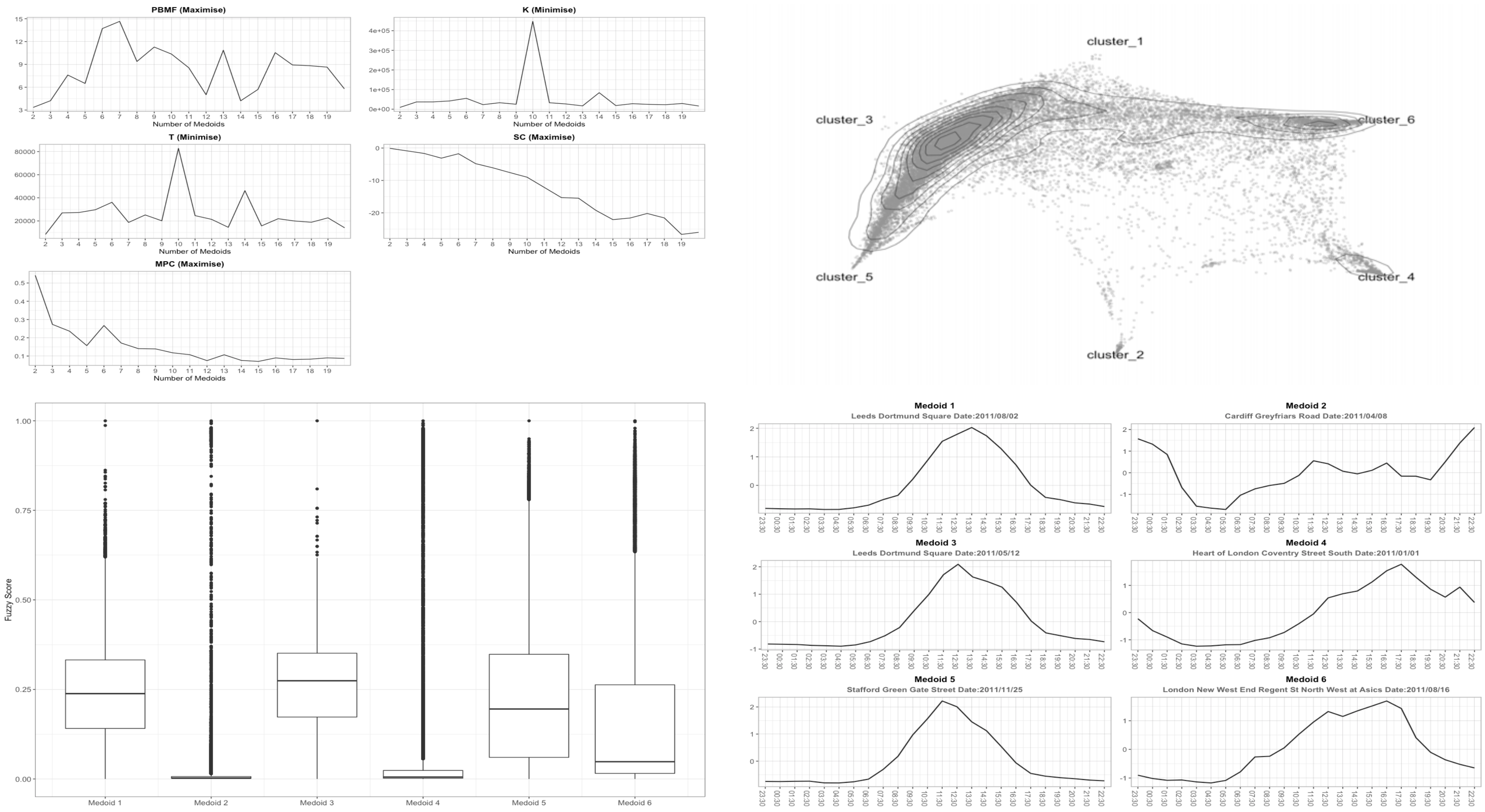


Figure 14.6 - Results for 2011 Daily Fuzzy Analysis k=6

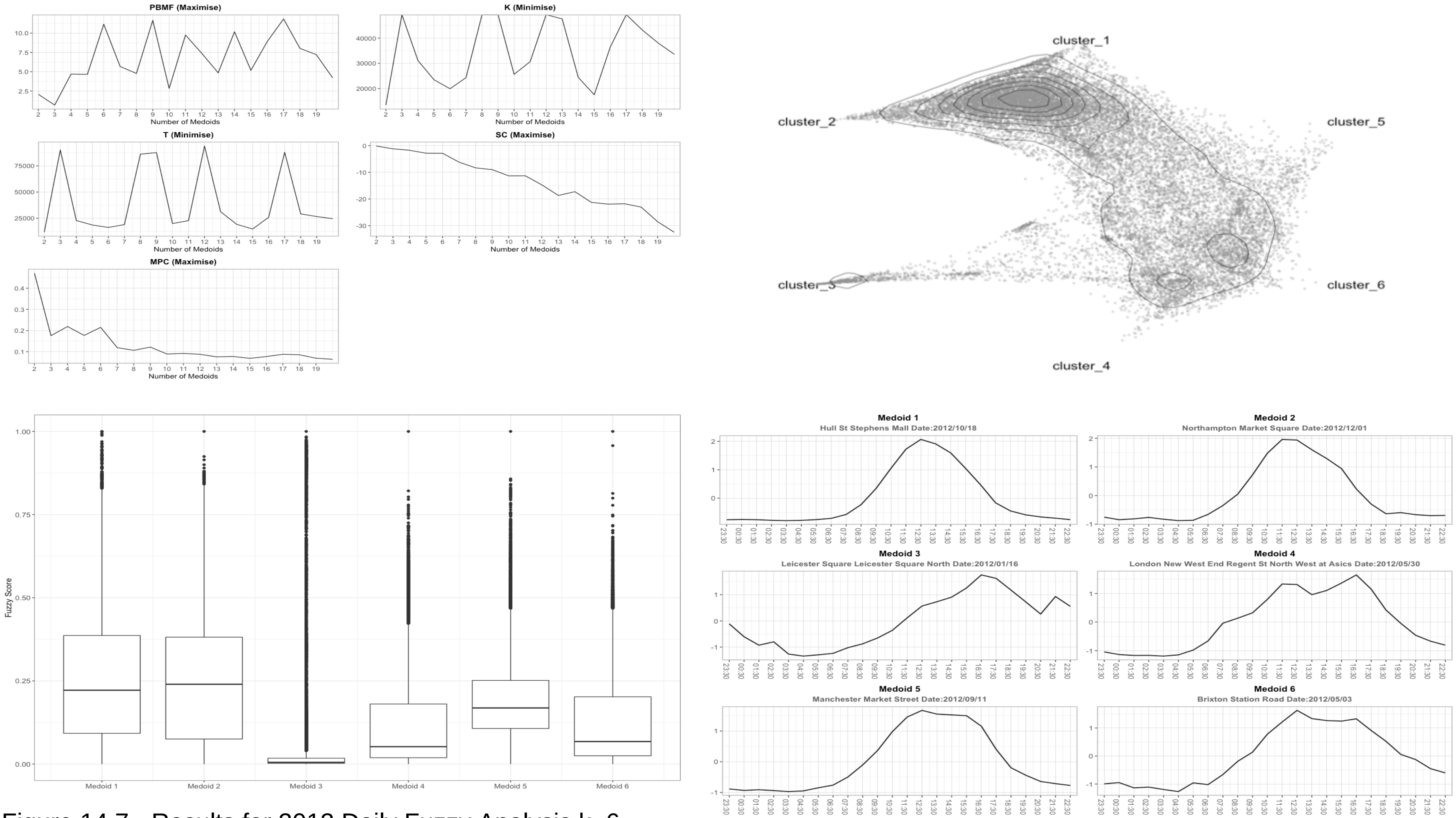


Figure 14.7 - Results for 2012 Daily Fuzzy Analysis k=6

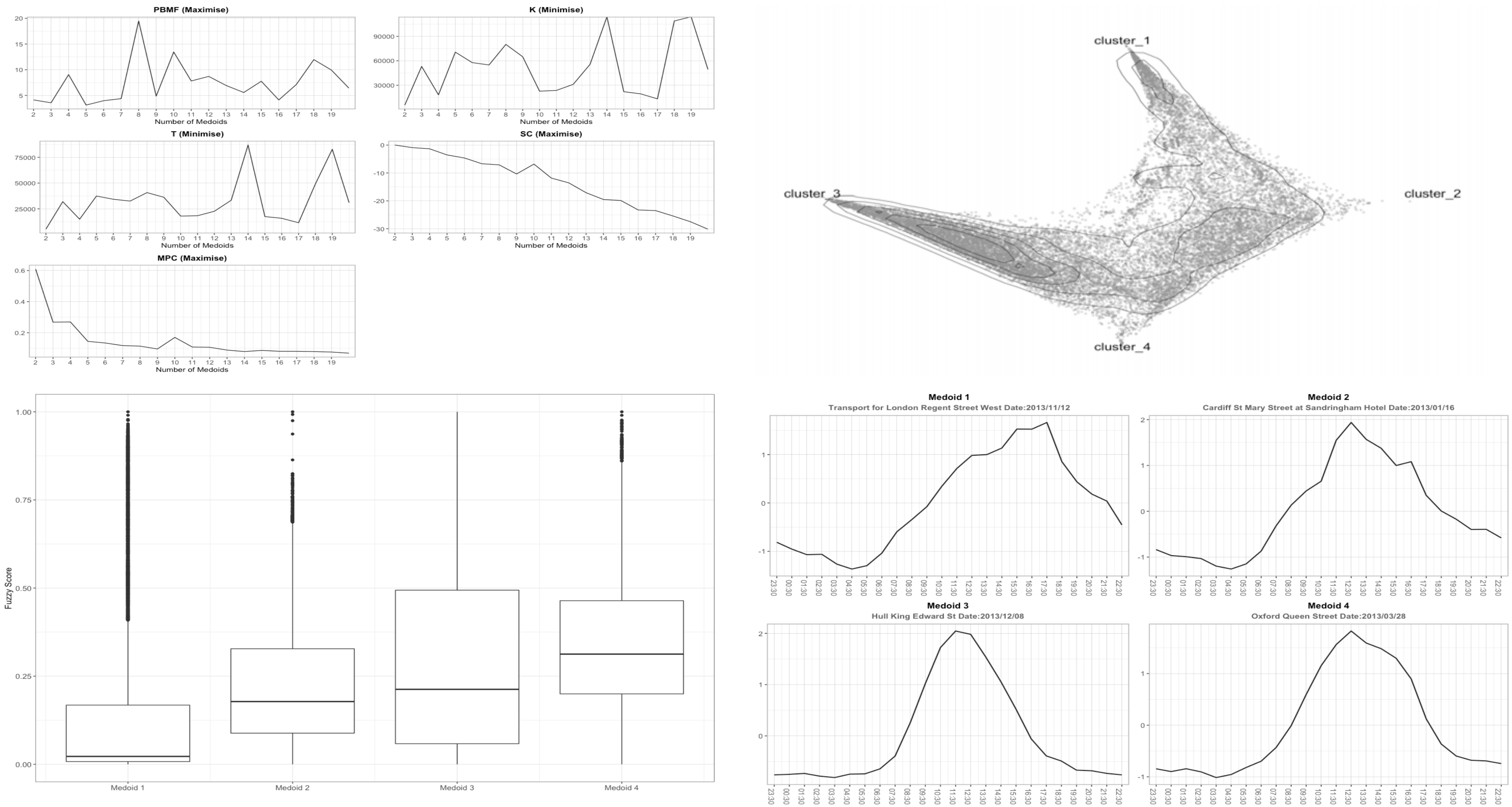
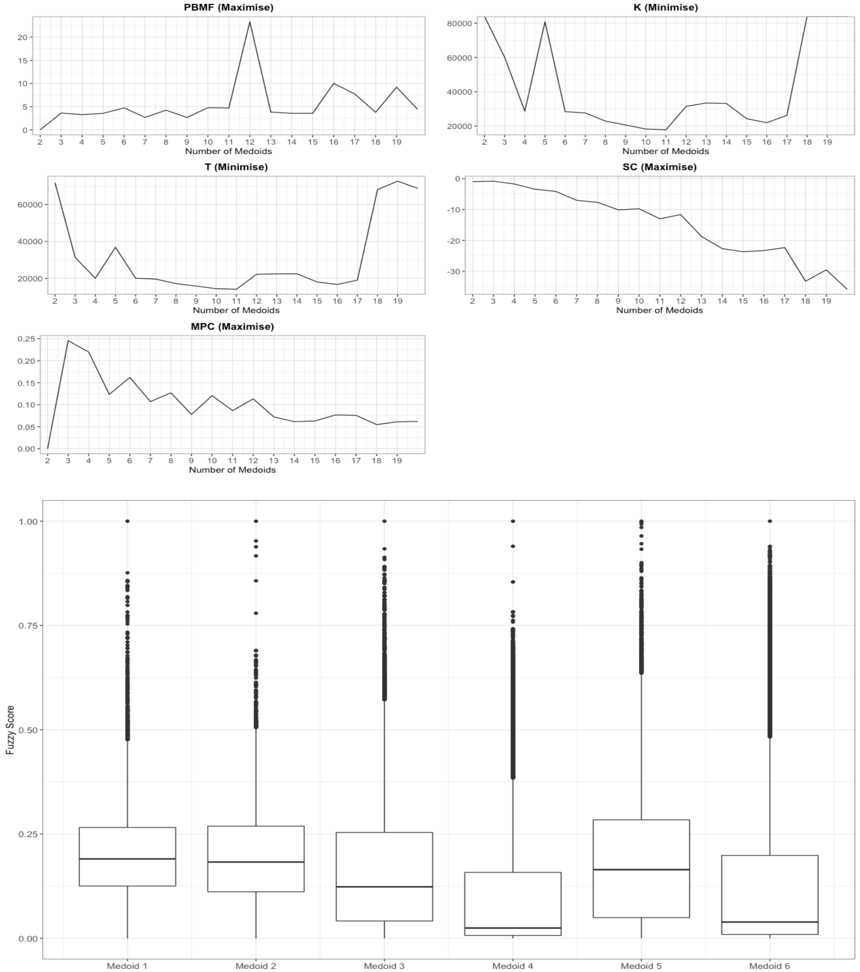


Figure 14.8 - Results for 2013 Daily Fuzzy Analysis k=4



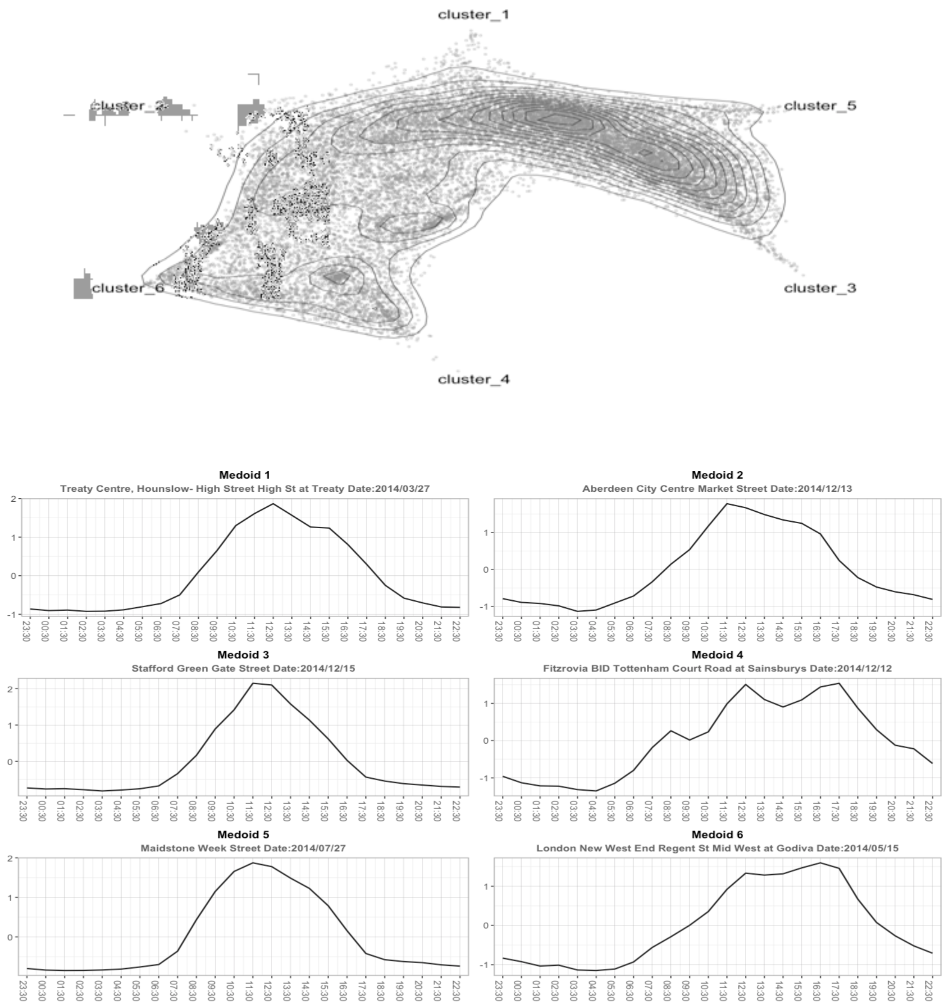


Figure 14.9 - Results for 2014 Daily Fuzzy Analysis k=6

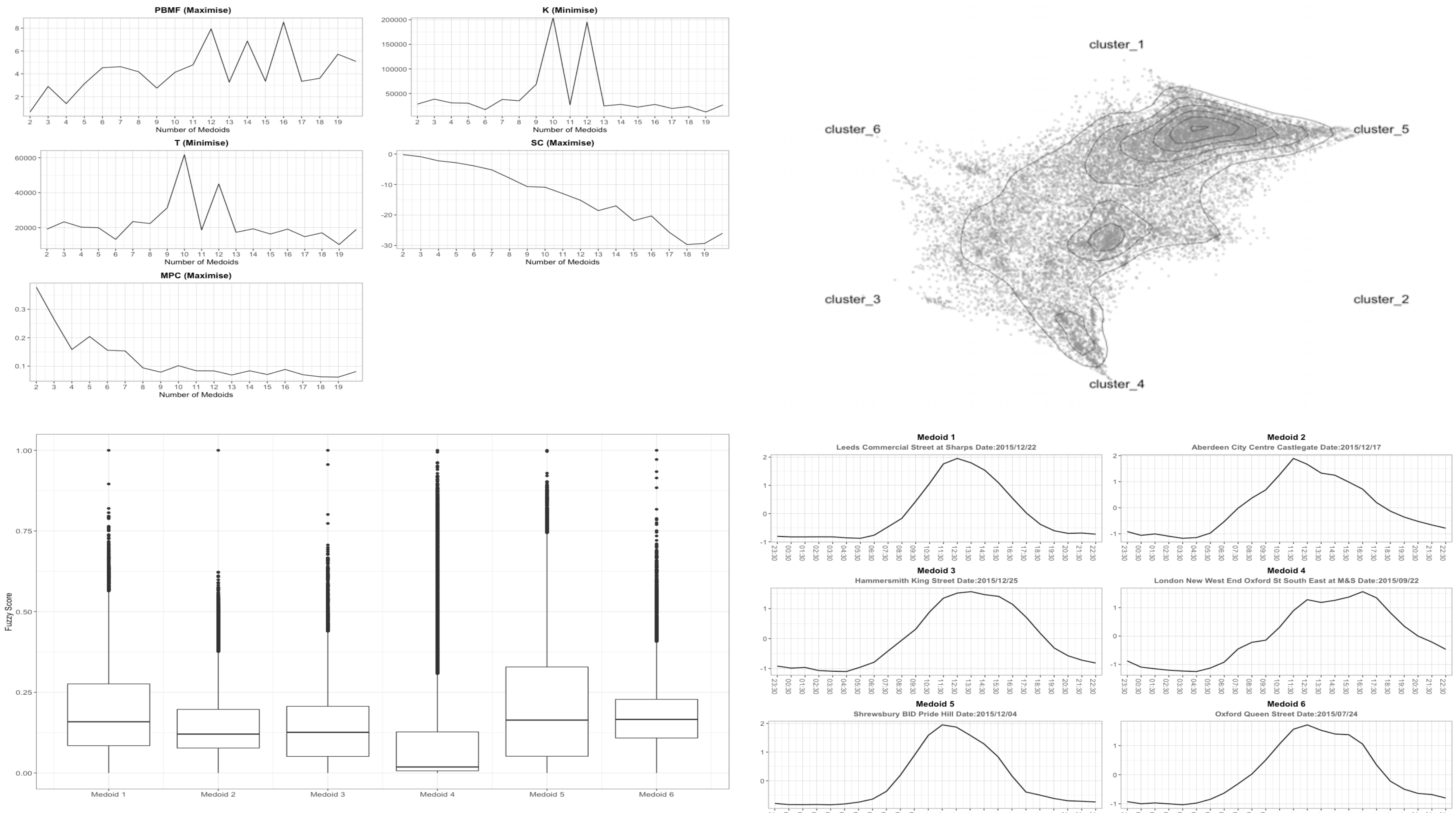
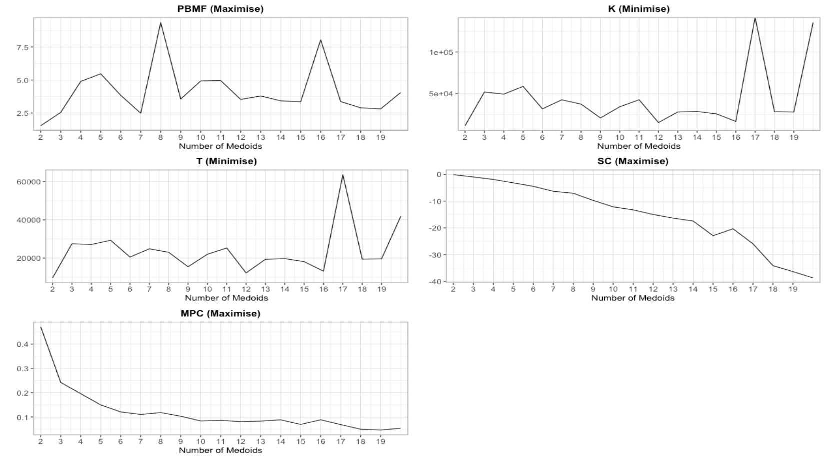
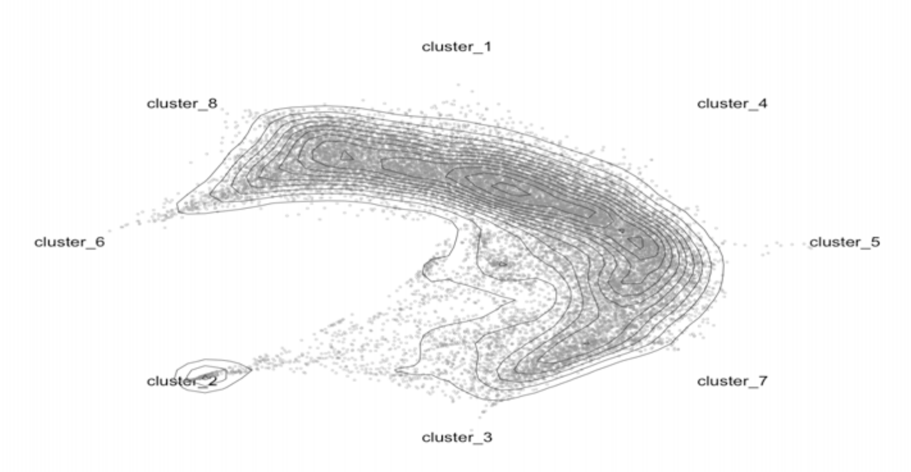
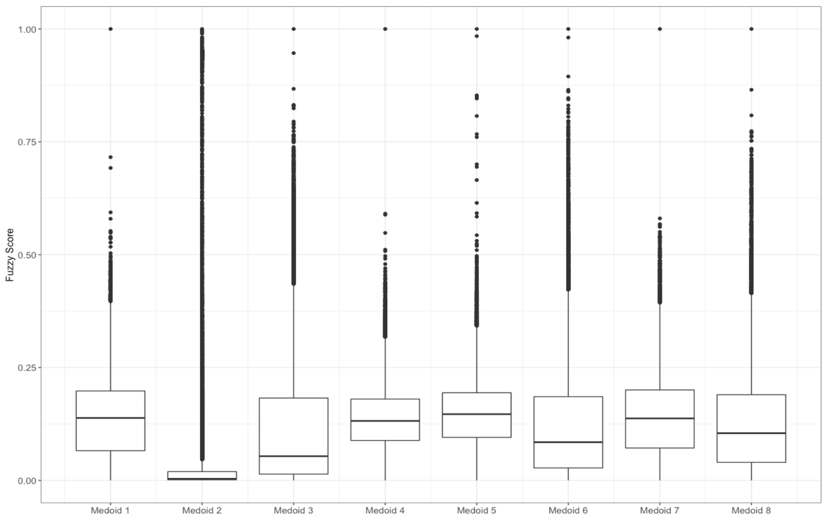


Figure 14.10 - Results for 2015 Daily Fuzzy Analysis k=6







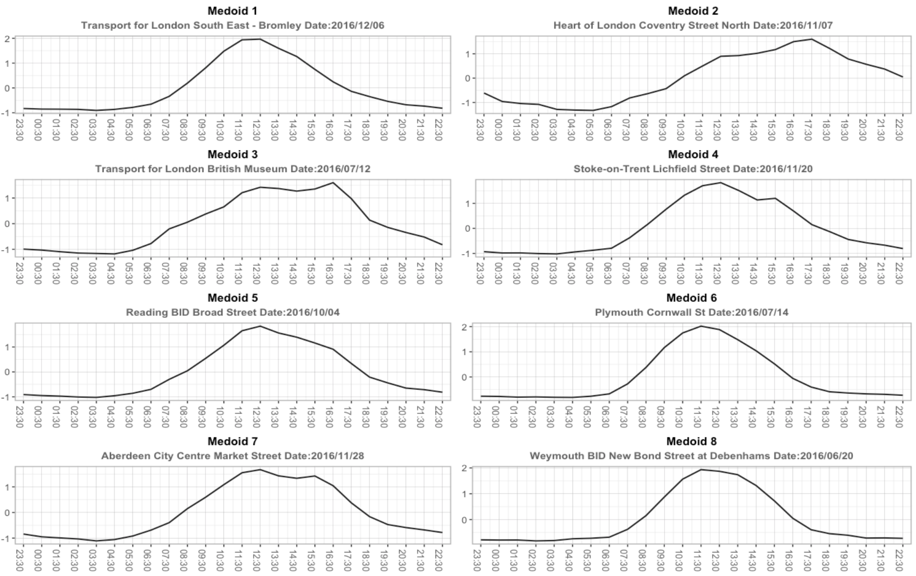


Figure 14.11 - Results for 2016 Daily Fuzzy Analysis k=8

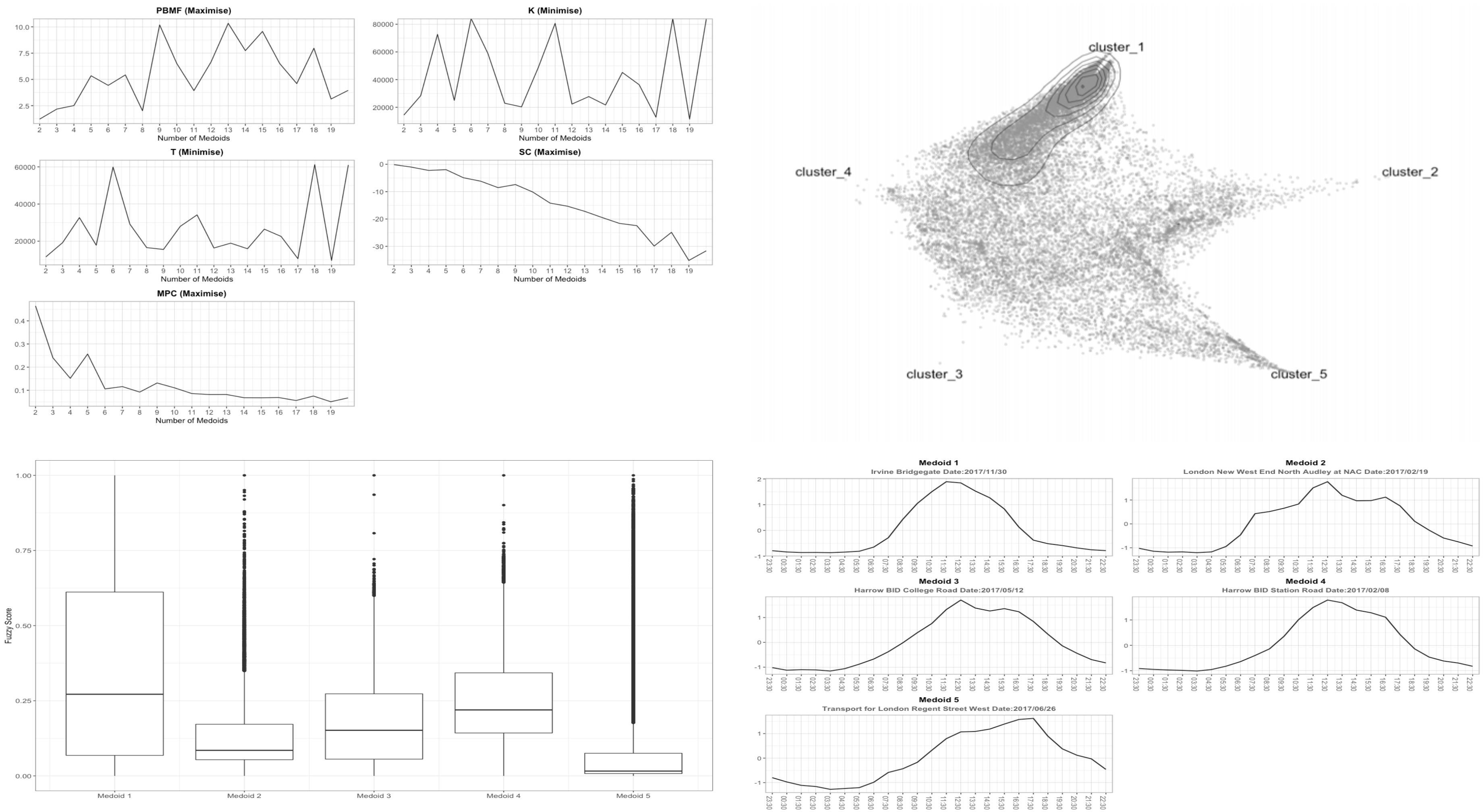
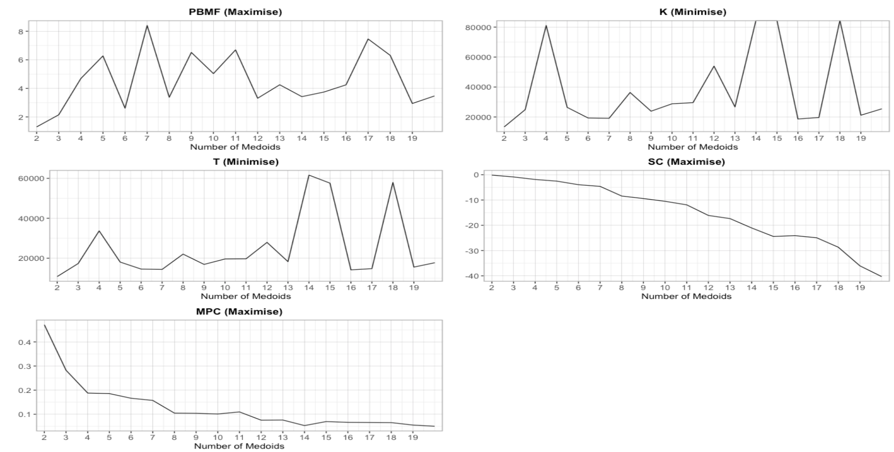
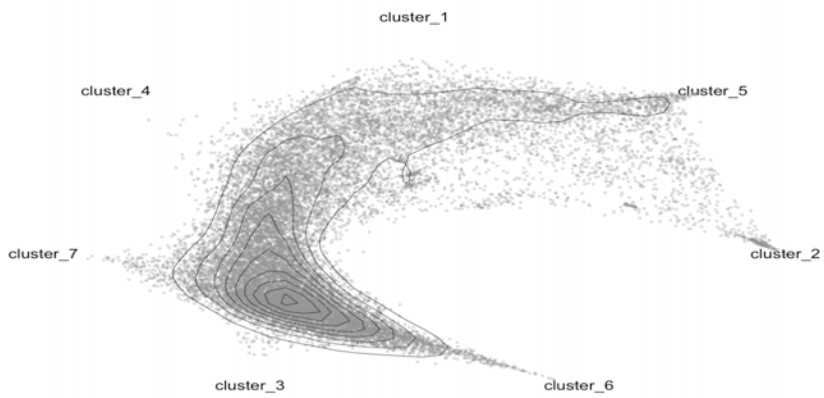
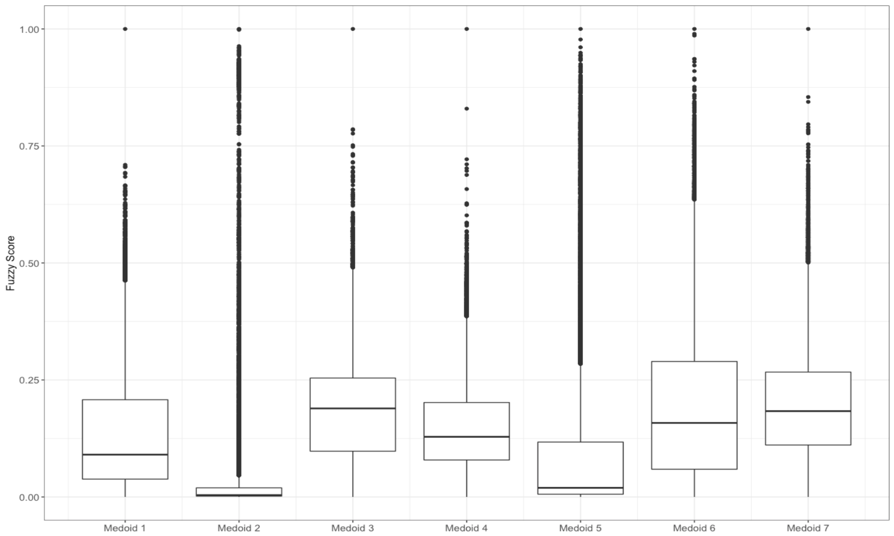


Figure 14.12 - Results for 2017 Daily Fuzzy Analysis k=5







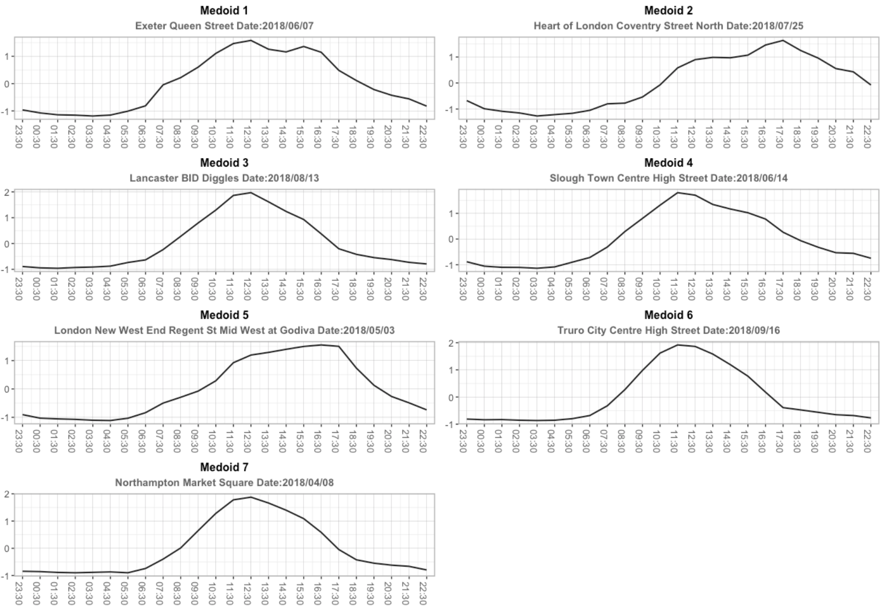


Figure 14.13 - Results for 2018 Daily Fuzzy Analysis k=7

14.2 Fuzzy Cluster Descriptive Analyses

14.2.1 Daily Results for 2007

Figure 14.2 displays the medoids identified from the 2007 daily signatures. Figure 14.2 shows the four medoids allocated for 2007 daily signatures. Medoid 3 is an amalgam of signatures 1 and 3 from 2006, with peak territorialisation at lunchtime 12:00 to 13:00. Medoid 1 is very similar to medoid 2 with an extended period through to the afternoon. Medoid 2 mirrors medoid 4 (2006) with afternoon/evening peaks and night-time territorializations. Medoid 4 (2007), has a lunchtime peak, but adds a minor peak at night-time.

To categorise the medoids then, the following descriptions were assigned:

- Medoid 1 - morning, lunchtime, and mid-afternoon peak
- Medoid 2 - morning, lunchtime, late afternoon peak, night-time
- Medoid 3 - morning, lunchtime peak
- Medoid 4 - morning, 2-hour lunchtime peak, early evening inflection point and night-time mini peak

Table 14.1. Best and next best fitting medoid allocations for 2007

	Secondary Medoid					
Primary Medoid	1	2	3	4	<10%	Total
1	0.00%	4.13%	15.79%	6.42%	5.79%	32.13%
2	5.00%	0.00%	0.01%	1.93%	3.28%	10.22%
3	27.40%	0.00%	0.00%	17.79%	4.68%	49.87%
4	3.23%	0.27%	4.08%	0.00%	0.21%	7.78%
Total	35.63%	4.40%	19.88%	26.14%	13.95%	100.00%

Table 14.1 shows that over 80% of sensors have medoids 3 or 1 assigned as their primary assigned daily signature. This maintains the dominance of the lunchtime territorialisation period with the peak period extending to late afternoon for some places. Table 14.2 below, provide a view of how the medoid assignments relate to urban classification types. Table 14.2 identifies that medoid 3, the lunchtime peak

daily signature, is the only signature assigned to towns - although note the sample of towns is still 1. There is a visible change from town to major city with medoid 3 being more significant for the smaller places just as was evident in 2006. Like in 2006, as place size (complexity) increases, so does the tendency for there to be afternoon, evening and night-time intensities of territorialisation.

Table 14.2. Urban classification and medoid assignment for 2007 daily medoids

Primary Medoid	Major City	Regional Centre	Sub-Regional Centre	Major Town	Town	Total
1	50.05%	18.04%	9.42%	3.77%	0.00%	32.13%
2	18.19%	0.00%	0.06%	0.00%	0.00%	10.22%
3	25.06%	81.96%	74.08%	96.23%	100.00%	49.87%
4	6.70%	0.00%	16.45%	0.00%	0.00%	7.78%
Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

Figure 14.3 displays the medoids identified from the 2008 daily signatures. Figure 14.3 shows the seven medoids allocated for 2008 daily signatures. Medoid 5 repeats the late morning peak territorialisation seen in the 2006 data. Medoids 1, 4 and 6 both have lunchtime peaks but whereas Medoid 1 suggests a rate of territorialisation intensity increase that is similar before and after peak time, medoids 4 and 6 suggest a steeper rise in the morning followed by a more gradual decline in the afternoon. Medoid 2 has a lunchtime peak but also another late afternoon, and medoids 3 and 7 match previous medoids for afternoon, evening and night-time footfall volumes. Medoid 3 is an amalgam of signatures 1 and 3 from 2006, with a peak at lunchtime 12:00 to 13:00. Medoid 1 is very similar to medoid 2 with an extended period of traffic through to the afternoon. Medoid 2 mirrors medoid 4 (2006) with an afternoon/evening peak and night-time footfall volumes. Medoid 4 (2007), has a lunchtime peak, but adds a minor peak at night-time.

To categorise the medoids then, the following descriptions were assigned:

- Medoid 1 - lunchtime peak
- Medoid 2 - lunchtime to mid-afternoon peak

- Medoid 3 - morning, lunchtime, evening, and night-time
- Medoid 4 - lunchtime and night-time mini peak
- Medoid 5 - Late morning peak
- Medoid 6 - late morning to lunchtime peak
- Medoid 7 - morning, lunchtime, late afternoon peak, evening, and night-time

Table 14.3 with more medoids selected, shows more range of signature types with towns being assigned a combination of medoids 5, 1 and 4. So, a blend of late-morning, midday and a degree of afternoon and night-time footfall. The medoid allocations show a very similar pattern however with the previous 2 years with medoids 7 (exclusively) and medoids 2 and 3 being mostly assigned to major city locations.

Table 14.3. Urban classification and medoid assignment for 2008 daily medoids

Primary Medoid	Major City	Regional Centre	Sub-Regional Centre	Major Town	Town	Total
1	7.38%	26.42%	30.62%	41.38%	23.40%	18.07%
2	39.29%	7.95%	7.46%	0.00%	8.97%	24.55%
3	6.37%	0.78%	1.27%	0.00%	0.00%	3.90%
4	21.36%	19.97%	11.67%	8.11%	19.60%	17.79%
5	4.99%	18.42%	31.40%	39.07%	39.97%	16.43%
6	13.53%	26.47%	17.59%	11.45%	8.05%	15.34%
7	7.09%	0.00%	0.00%	0.00%	0.00%	3.94%
Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

14.2.2 Daily Results for 2009

Figure 14.4 displays the medoids identified from the 2009 daily signatures. Figure 14.4 shows the six medoids allocated for 2009 daily signatures. Following the same process of descriptive analysis for the previous years, the medoids have been categorised below:

- Medoid 1 - late morning peak and lunchtime
- Medoid 2 - lunchtime, late afternoon peak, evening, and night-time
- Medoid 3 - lunchtime peak (2 hours)
- Medoid 4 - lunchtime and late afternoon peak
- Medoid 5 - lunchtime peak (2 hours)
- Medoid 6 - late morning and lunchtime peak

Table 14.4 continues the trend of towns and major towns being dominated by the midday or late morning daily medoid signatures. Major cities have a larger range of signatures and, include signatures like medoids 2 and 4 where afternoon, evening and night-time footfall is identified in the signatures. Regional and Sub-Regional centres mostly have lunchtime focussed signatures but also appear to have more afternoon, evening, and night-time footfall.

Table 14.4. Urban classification and medoid assignment for 2009 daily medoids

Primary Medoid	Major City	Regional Centre	Sub-Regional Centre	Major Town	Town	Total
1	7.10%	20.31%	27.63%	55.18%	47.54%	18.05%
2	9.88%	5.95%	1.84%	0.00%	0.00%	6.50%
3	23.47%	16.33%	14.83%	7.26%	24.31%	19.46%
4	37.70%	11.94%	12.51%	0.00%	3.23%	24.83%
5	9.94%	24.54%	22.61%	24.79%	3.69%	15.64%
6	11.91%	20.93%	20.58%	12.77%	21.23%	15.51%
Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

14.2.3 Daily Results for 2010

Figure 14.5 displays the medoids identified from the 2010 daily signatures. Figure 14.5 shows the eight medoids allocated for 2010 daily signatures. Following the same process of descriptive analysis for the previous years, the medoids have been categorised below:

- Medoid 1 - lunchtime peak and extended afternoon
- Medoid 2 - lunchtime peak
- Medoid 3 - lunchtime, mid to late afternoon peak and evening
- Medoid 4 - morning, late morning, mid-afternoon, evening, and night-time peak
- Medoid 5 - late morning and lunchtime peak
- Medoid 6 - late morning peak
- Medoid 7 - lunchtime peak (minor afternoon peak)
- Medoid 8 - morning, late morning (lunchtime), late afternoon peak, evening

Of the eight medoids, medoid 4 suggests locations where there is a morning, lunchtime, afternoon, and night-time peak of footfall in a way that looks unique. However, only 4.17% of locations assigned this signature as the primary medoid.

Table 14.5 identifies those cities that continue to sustain more footfall traffic after lunchtime than the other urban types. Medoid 8 also indicates that a daily signature showing the commuter inflows and outflows of population plus lunchtime can be identified for major cities predominantly. The pattern also persists for locations that are not major cities also having a more lunchtime dominated signature.

Table 14.5. Urban classification and medoid assignment for 2010 daily medoids

Primary Centroid	Major City	Regional Centre	Sub-Regional Centre	Major Town	Town	Total
1	16.54%	9.80%	11.53%	13.13%	9.09%	13.84%
2	11.93%	12.27%	13.79%	5.27%	19.23%	12.30%
3	23.01%	8.47%	7.17%	0.00%	2.53%	14.67%
4	4.69%	4.51%	4.48%	0.00%	0.00%	4.17%
5	6.28%	26.91%	20.99%	29.08%	11.33%	14.59%
6	2.91%	10.98%	16.91%	30.76%	30.55%	10.44%
7	15.25%	23.73%	20.13%	21.53%	22.95%	18.33%
8	19.38%	3.33%	5.01%	0.23%	4.32%	11.67%
Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

14.2.4 Daily Results for 2011

Figure 14.6 displays the medoids identified from the 2011 daily signatures. Figure 14.6 shows the eight medoids allocated for 2011 daily signatures. Following the same process of descriptive analysis for the previous years, the medoids have been categorised below:

- Medoid 1 - extended lunchtime peak
- Medoid 2 - morning, late morning (lunchtime), late afternoon, evening, and night-time peak
- Medoid 3 - lunchtime peak with minor afternoon inflection point
- Medoid 4 - lunchtime, late afternoon peak, evening, and night-time
- Medoid 5 - late morning peak plus lunchtime
- Medoid 6 - morning, lunchtime and late afternoon peak and evening

Like in 2010 (medoid 4), medoid 2 presents a unique signature and is only applicable to 1.39% of locations. The other medoids follow the now familiar pattern of midday territorialisation peaks with variation for the afternoon, evening, and night-time periods. Also, minor peaks are evident suggestive of commuter traffic peaks. Table 14.6 continues previous patterns but, interesting that medoids 6 and 3 appears to contribute more to towns than major towns with a suggestion of some towns having more afternoon and evening territorialisation periods than major towns?

Table 14.6. Urban classification and medoid assignment for 2011 daily medoids

Primary Medoid	Major City	Regional Centre	Sub-Regional Centre	Major Town	Town	Total
1	17.16%	25.06%	20.13%	32.17%	15.83%	20.03%
2	0.27%	4.68%	2.22%	0.00%	0.00%	1.39%
3	24.43%	30.12%	25.59%	19.37%	31.56%	25.54%
4	10.27%	0.55%	1.57%	0.00%	0.00%	5.31%
5	9.93%	28.63%	39.34%	48.39%	48.36%	25.20%
6	37.94%	10.95%	11.15%	0.07%	4.25%	22.53%
Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

14.2.5 Daily Results for 2012

Figure 14.7 displays the medoids identified from the 2012 daily signatures. Figure 14.7 shows the eight medoids allocated for 2012 daily signatures. Following the same process of descriptive analysis for the previous years, the medoids have been categorised below:

- Medoid 1 - lunchtime peak
- Medoid 2 - late morning and lunchtime peak
- Medoid 3 - lunchtime, late afternoon peak, evening, and night-time
- Medoid 4 - morning, late morning and lunchtime and late afternoon peak plus evening
- Medoid 5 - lunchtime peak and extended afternoon
- Medoid 6 - lunchtime peak and extended afternoon with minor night-time

Table 14.7 continues to show previous mentioned patterns. Note that again, town types have a very slight tendency to show an afternoon extension in territorialisation than major towns. Else, all the same.

Table 14.7. Urban classification and medoid assignment for 2012 daily medoids

Primary Medoid	Major City	Regional Centre	Sub-Regional Centre	Major Town	Town	Total
1	16.97%	34.22%	31.46%	39.76%	31.64%	26.17%
2	12.94%	29.99%	40.34%	55.53%	49.87%	28.34%
3	9.68%	4.59%	1.15%	0.00%	0.00%	5.26%
4	21.29%	3.62%	6.20%	0.07%	0.89%	11.65%
5	21.85%	16.26%	9.79%	4.63%	14.66%	15.96%
6	17.27%	11.32%	11.06%	0.00%	2.95%	12.61%
Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

14.2.6 Daily Results for 2013

Figure 14.8 displays the medoids identified from the 2013 daily signatures. Figure 14.8 shows the four medoids allocated for 2013 daily signatures. Following the same process of descriptive analysis for the previous years, the medoids have been categorised below:

- Medoid 1 - lunchtime, late afternoon peak, evening, and night-time
- Medoid 2 - lunchtime peak and extended afternoon, evening, and night-time
- Medoid 3 - late-morning peak and lunchtime
- Medoid 4 - lunchtime peak and extended afternoon

With only four medoids assigned to 2013, Table 14.8 shows a sharp contrast between major towns and towns with only lunchtime and to a lesser degree afternoon signatures vs the other urban types where evening footfall is picked up by the signatures. Table 14.8 also suggests that sub-regional centres have a more intense territorialisation lunchtime period than regional centres which demonstrate a more extended territorialisation period into the afternoons.

Table 14.8. Urban classification and medoid assignment for 2013 daily medoids

Primary Medoid	Major City	Regional Centre	Sub-Regional Centre	Major Town	Town	Total
1	27.79%	8.04%	10.54%	0.26%	0.08%	15.70%
2	25.96%	21.58%	19.53%	4.22%	5.98%	20.57%
3	13.48%	32.08%	42.82%	64.03%	56.02%	31.62%
4	32.77%	38.30%	27.11%	31.49%	37.91%	32.11%
Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

14.2.7 Daily Results for 2015

Figure 14.10 displays the medoids identified from the 2015 daily signatures. Figure 14.10 shows the six medoids allocated for 2015 daily signatures. Following the same process of descriptive analysis for the previous years, the medoids have been categorised below:

- Medoid 1 - lunchtime peak slightly extending into the afternoon
- Medoid 2 - late-morning peak and extended afternoon plus evening
- Medoid 3 - late morning and lunchtime peak and afternoon plus degree of evening
- Medoid 4 - morning, lunchtime, and evening peaks plus minor night-time
- Medoid 5 - late-morning peak slightly extending into the afternoon
- Medoid 6 - lunchtime peak, afternoon, and evening plus minor night-time

The results in Table 14.9 suggest the idea that regional and especially sub-regional places are a mixture of all the medoids but with the lunchtime dominated signatures perhaps more significant.

Table 14.9. Urban classification and medoid assignment for 2015 daily medoids

Primary Medoid	Major City	Regional Centre	Sub-Regional Centre	Major Town	Town	Total
1	10.63%	20.69%	20.20%	22.95%	27.54%	18.39%
2	16.27%	18.91%	17.11%	14.20%	4.76%	15.93%
3	19.20%	9.27%	8.19%	1.94%	0.62%	10.41%
4	25.17%	12.65%	14.83%	0.63%	0.00%	15.06%
5	11.87%	20.69%	27.63%	56.16%	59.89%	26.78%
6	16.86%	17.79%	12.04%	4.13%	7.20%	13.43%
Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

14.2.8 Daily Results for 2016

Figure 14.11 displays the medoids identified from the 2016 daily signatures. Figure 14.11 shows the eight medoids allocated for 2016 daily signatures. Following the same process of descriptive analysis for the previous years, the medoids have been categorised below:

- Medoid 1 - late morning and lunchtime peak
- Medoid 2 - morning, lunchtime, and late afternoon peak plus night-time
- Medoid 3 - morning, lunchtime, and late afternoon peak plus minor night-time
- Medoid 4 - lunchtime peak, afternoon, and evening
- Medoid 5 - lunchtime peak, afternoon, and evening
- Medoid 6 - early lunchtime peak
- Medoid 7 - early lunchtime and lunchtime peak plus extended afternoon
- Medoid 8 - early lunchtime peak and lunchtime

14.2.9 Daily Results for 2017

Figure 14.12 displays the medoids identified from the 2017 daily signatures. Figure 14.12 shows the five medoids allocated for 2017 daily signatures. Following the same process of descriptive analysis for the previous years, the medoids have been categorised below:

- Medoid 1 - late morning and lunchtime peak
- Medoid 2 - morning, lunchtime peak and late afternoon, evening plus minor night-time
- Medoid 3 - lunchtime peak and extended afternoon and evening
- Medoid 4 - lunchtime peak and extended afternoon
- Medoid 5 - morning, lunchtime, and late afternoon/early evening peak plus minor night-time

Table 14.10, like all the other years, the town and major towns all show a distinct lunchtime signature which is a mixture of medoid 1 predominantly and then secondarily, medoid.

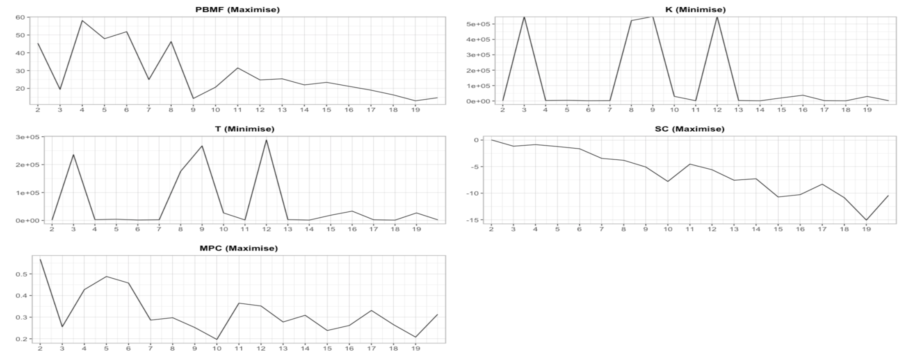
Table 14.10. Urban classification and medoid assignment for 2017 daily medoids

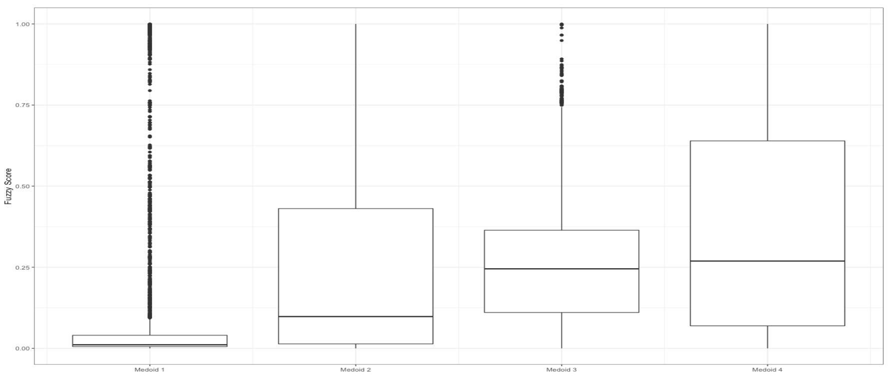
Best Fitting Medoid	Major City	Regional Centre	Sub-Regional Centre	Major Town	Town	Total
1	13.63%	28.74%	45.21%	78.51%	89.62%	41.94%
2	19.49%	12.30%	8.71%	4.80%	1.55%	10.91%
3	23.72%	17.34%	17.00%	2.78%	0.98%	15.71%
4	20.95%	31.76%	22.83%	13.67%	7.39%	21.85%
5	22.21%	9.87%	6.24%	0.24%	0.46%	9.59%
Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

15 Appendix D – Combined Sensor Weekly Results

15.1 Fuzzy Cluster Outputs

Below, are listed in order of year, all the CVI, Radviz, Boxplot and Medoid plots for the weekly signatures.





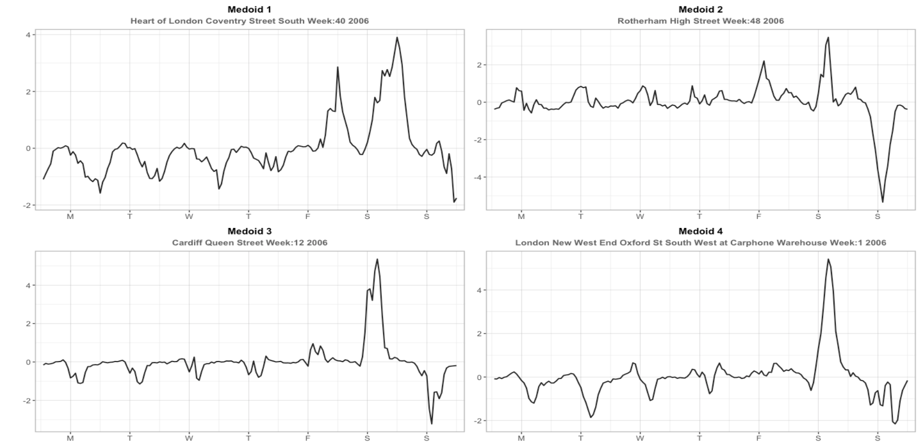
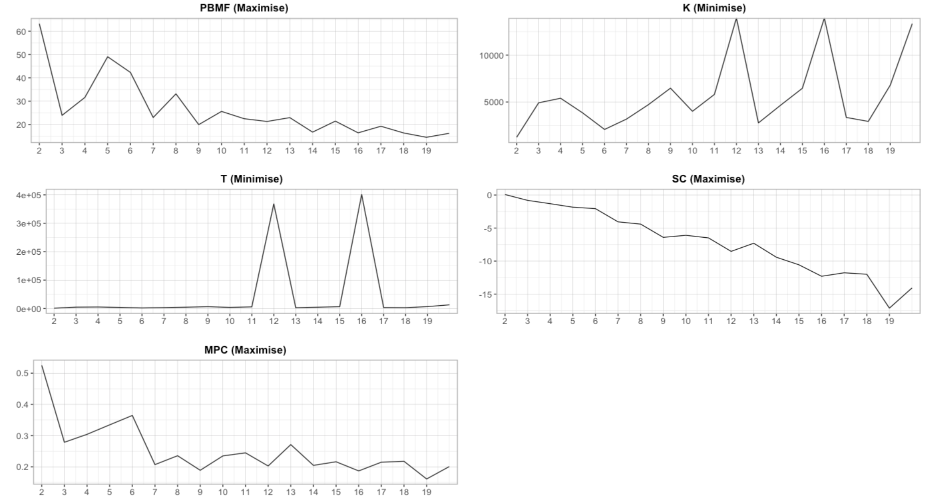


Figure 15.1 - Results for 2006 Weekly Fuzzy Analysis k=4



As number of medoids chosen is 2, there is no Radviz diagram

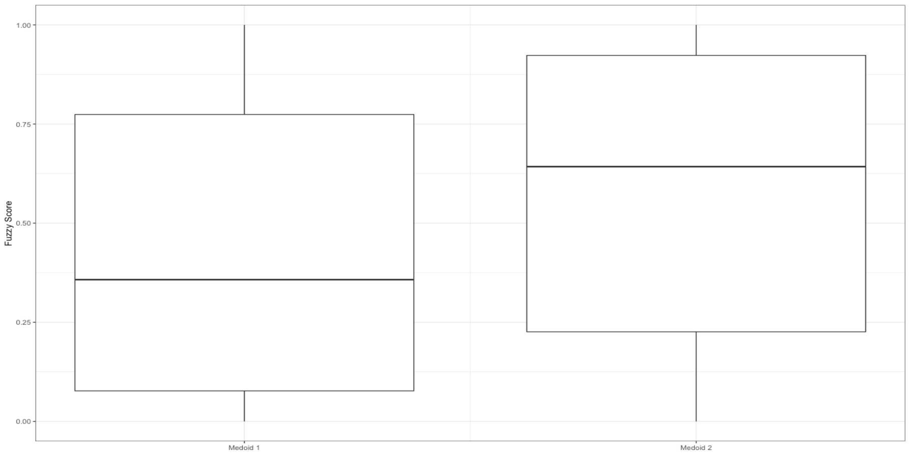
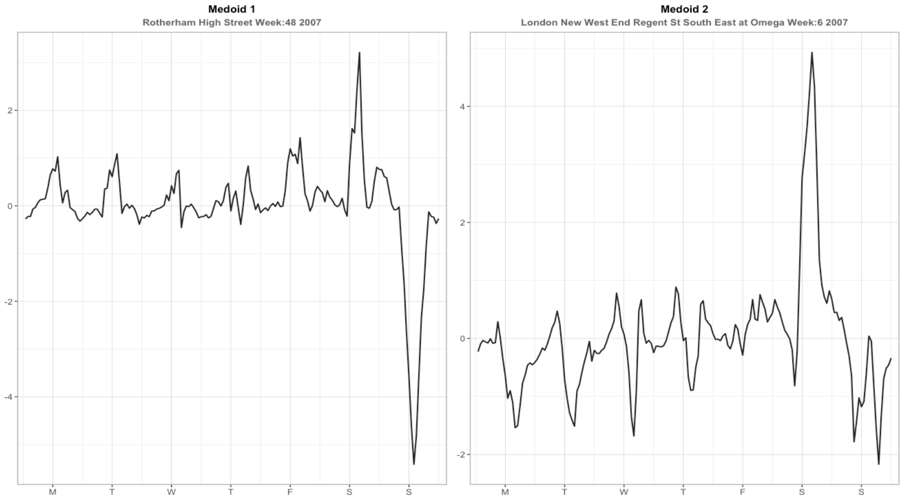


Figure 15.2 - Results for 2007 Weekly Fuzzy Analysis k=2



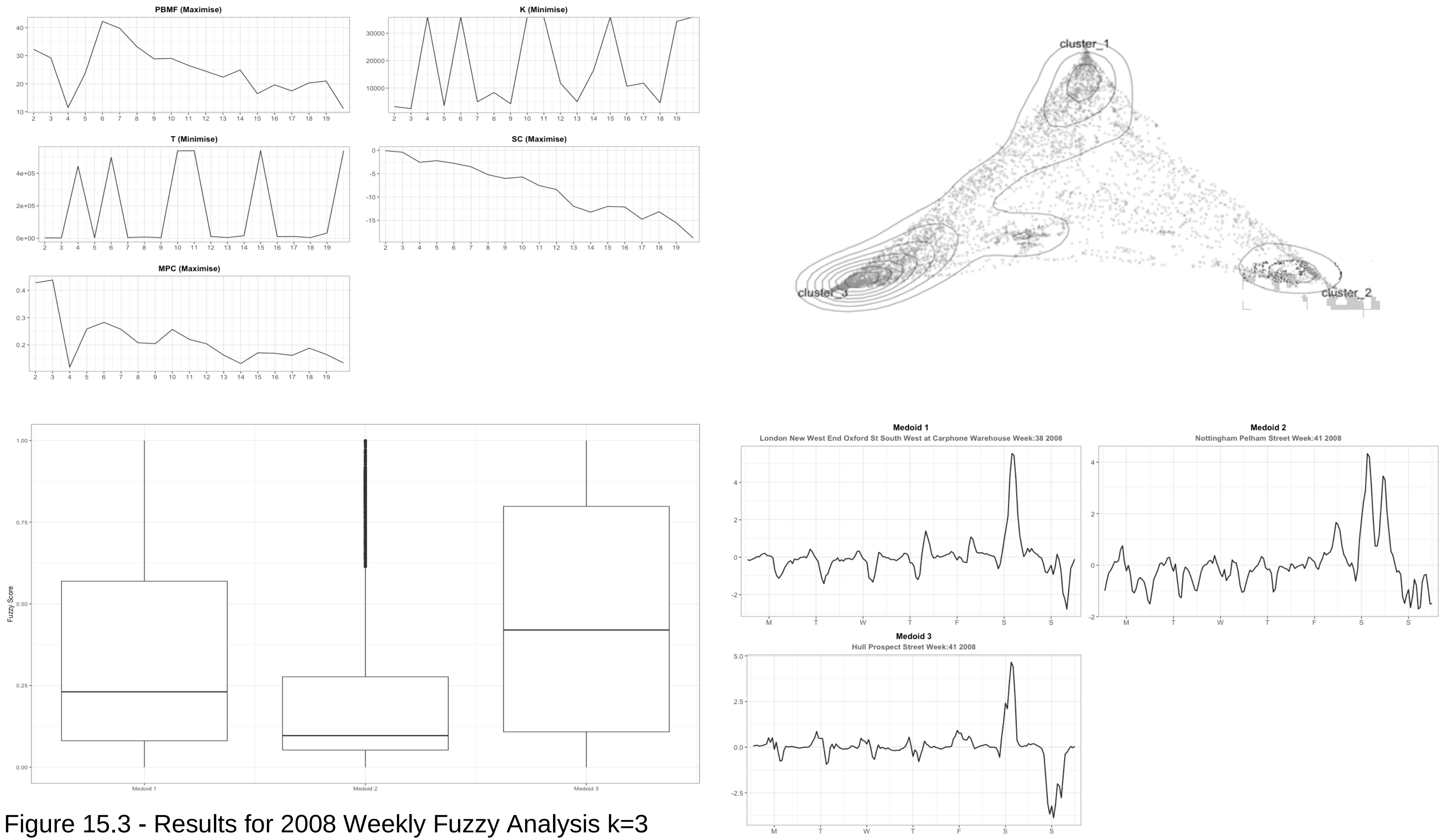
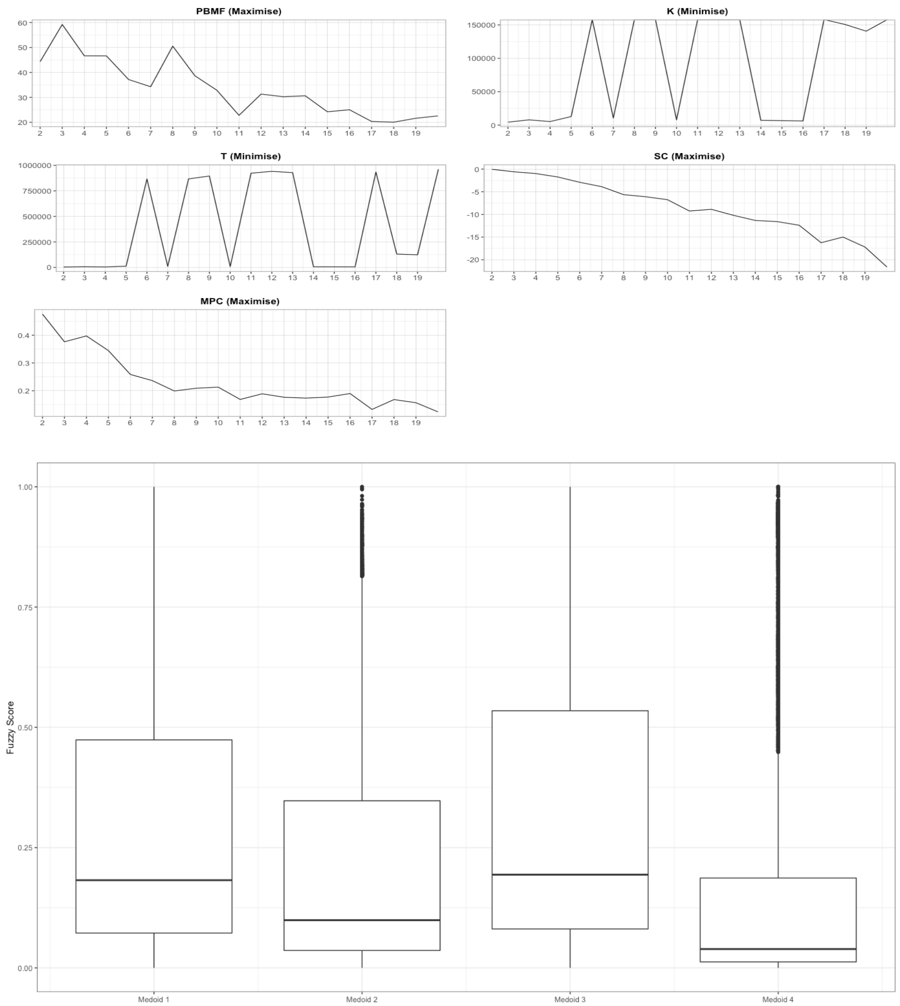


Figure 15.3 - Results for 2008 Weekly Fuzzy Analysis k=3



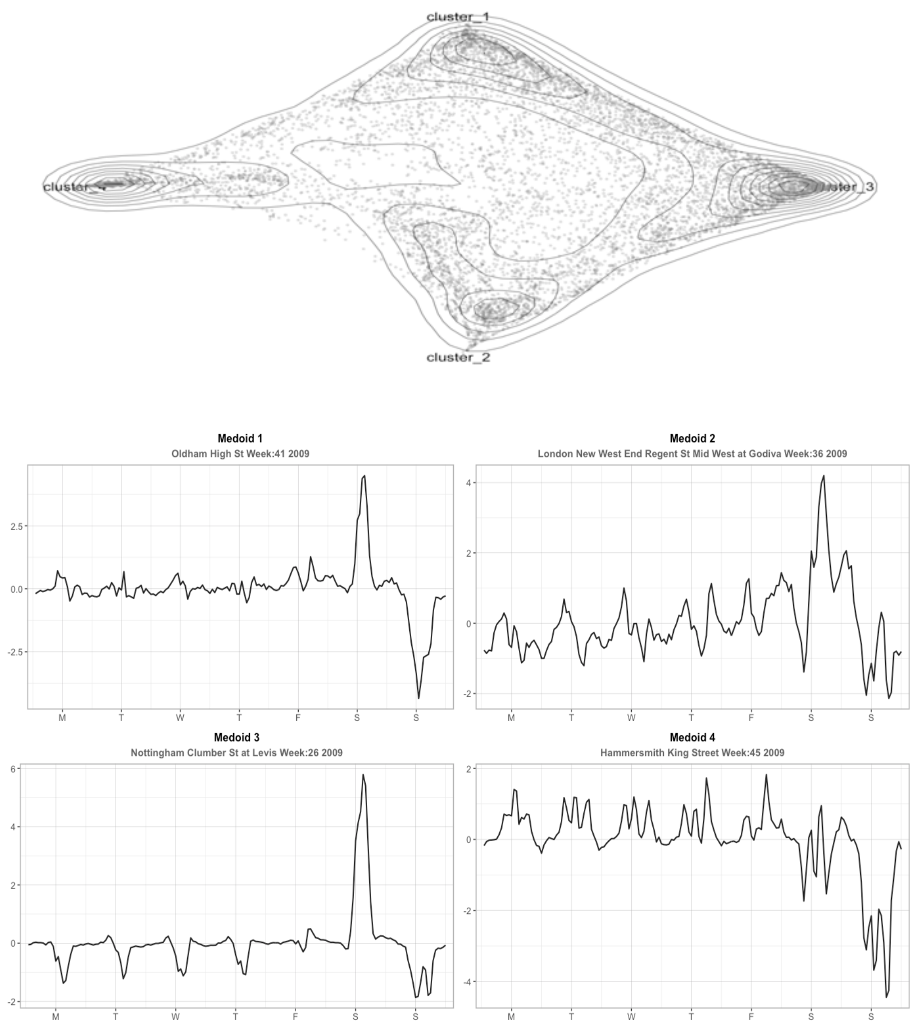
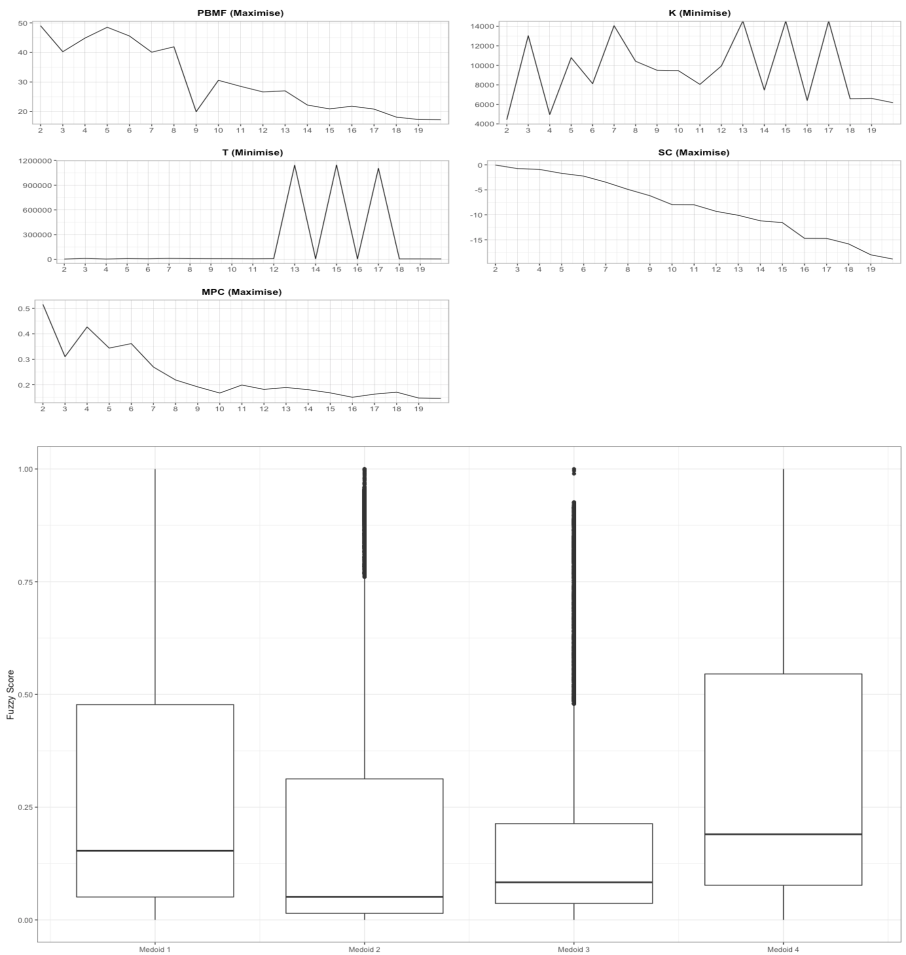


Figure 15.4 - Results for 2009 Weekly Fuzzy Analysis k=4



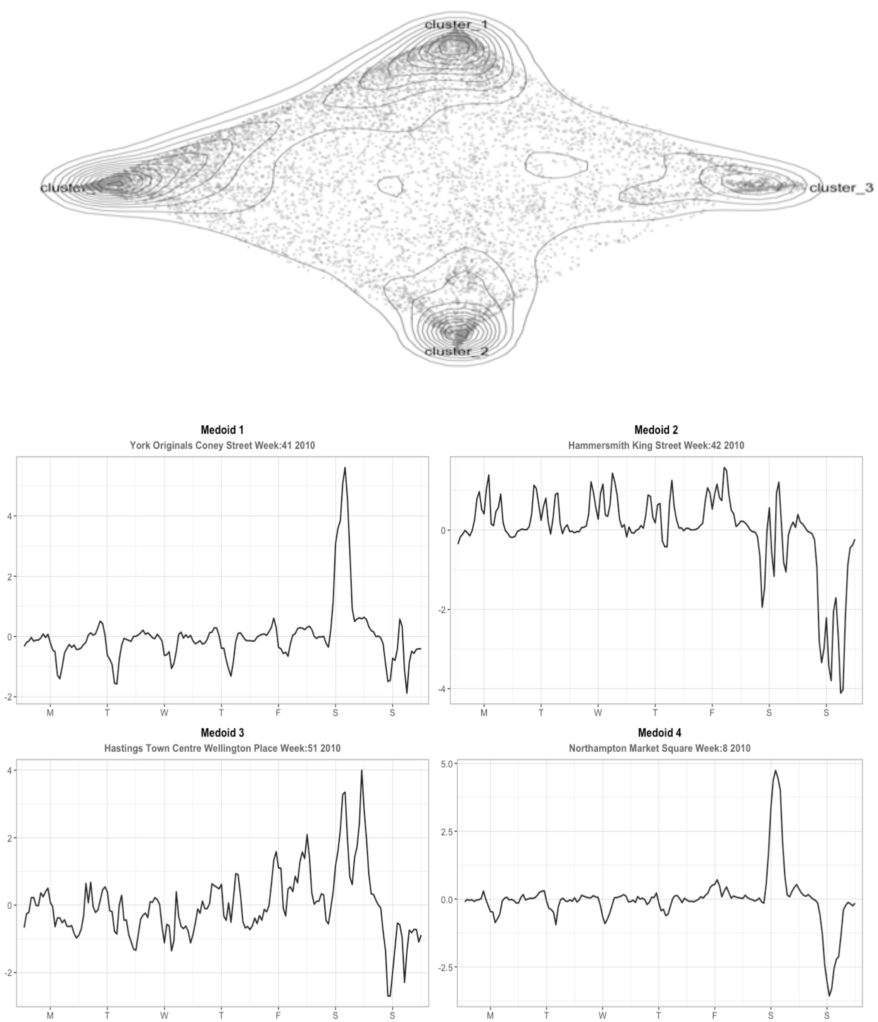
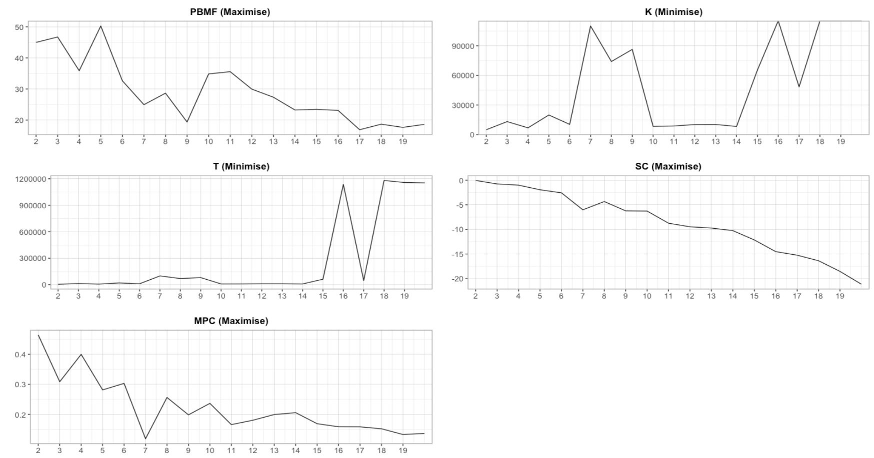
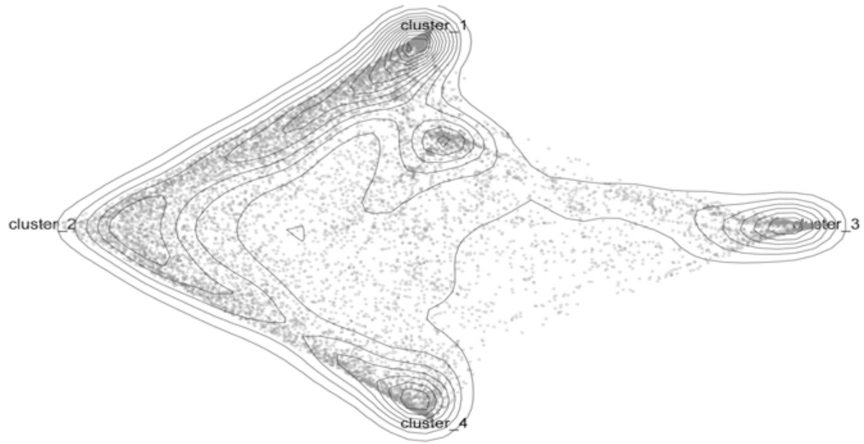
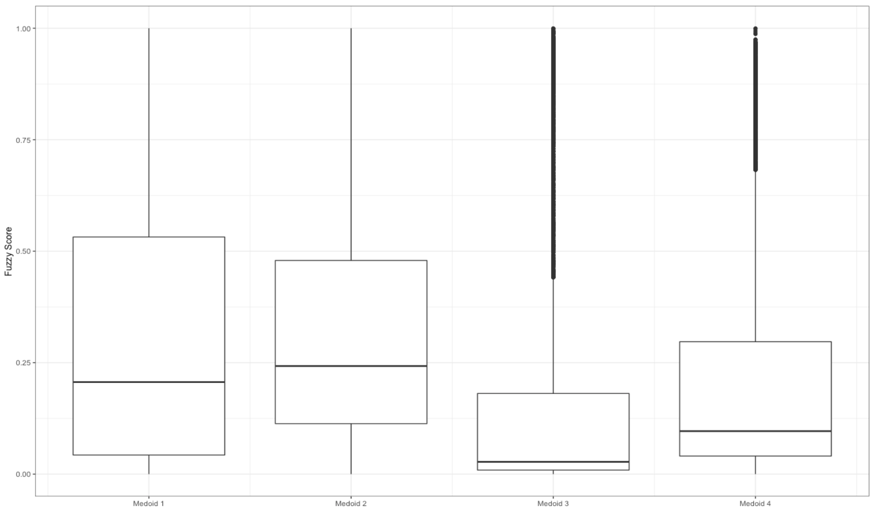


Figure 15.5 - Results for 2010 Weekly Fuzzy Analysis k=4







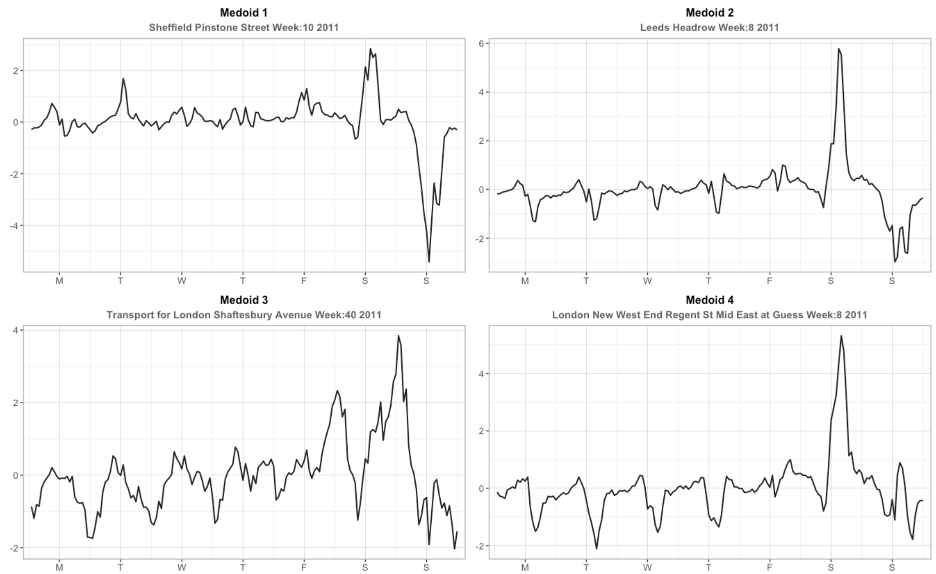
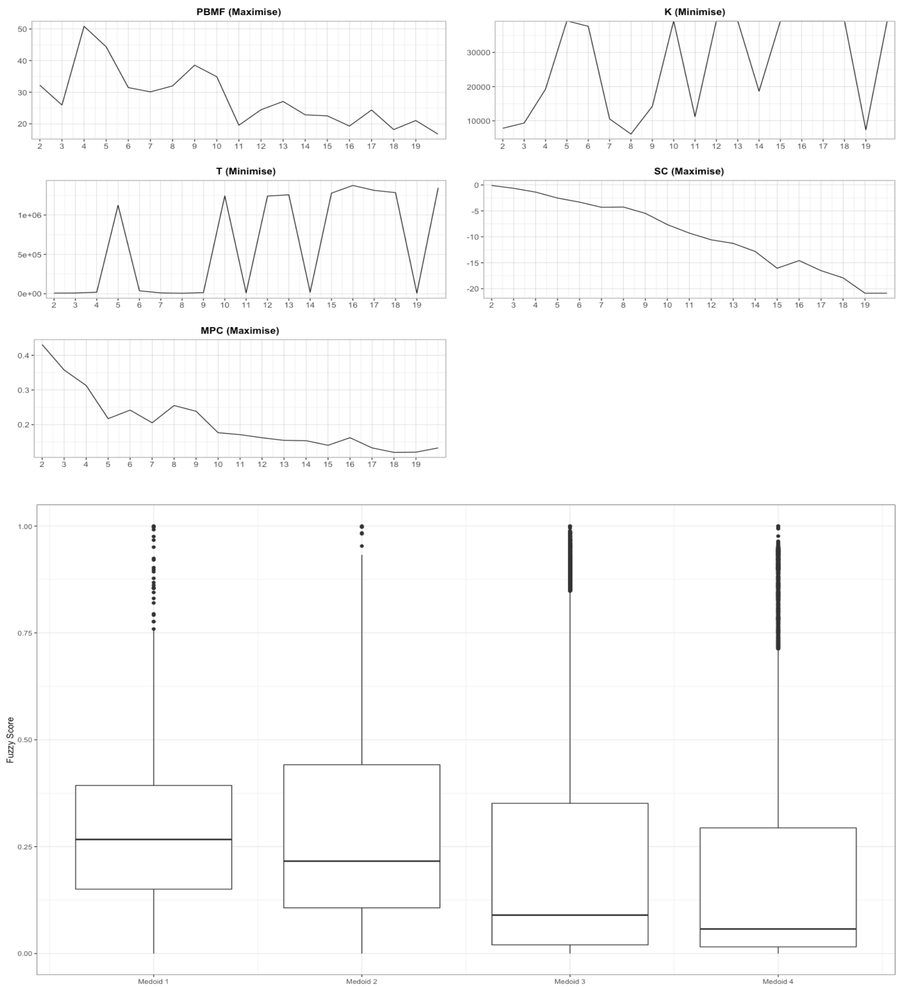


Figure 15.6 - Results for 2011 Weekly Fuzzy Analysis k=4



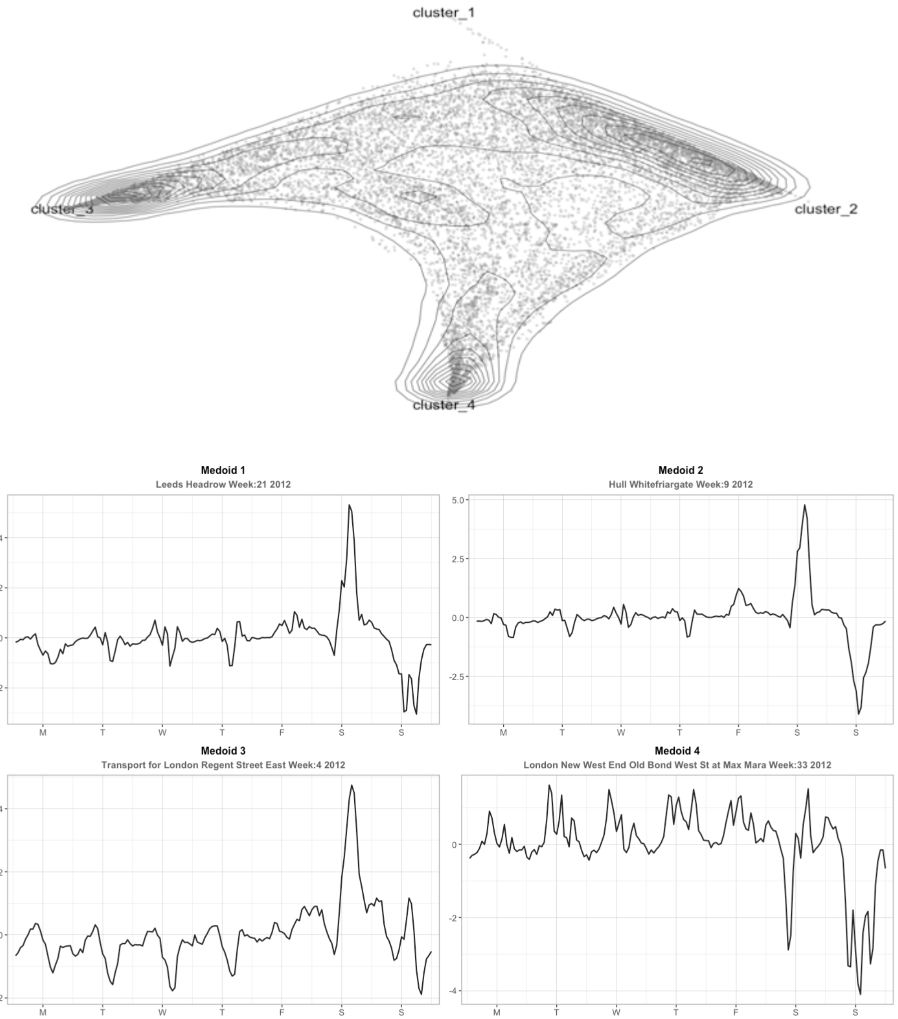


Figure 15.7 - Results for 2012 Weekly Fuzzy Analysis k=4

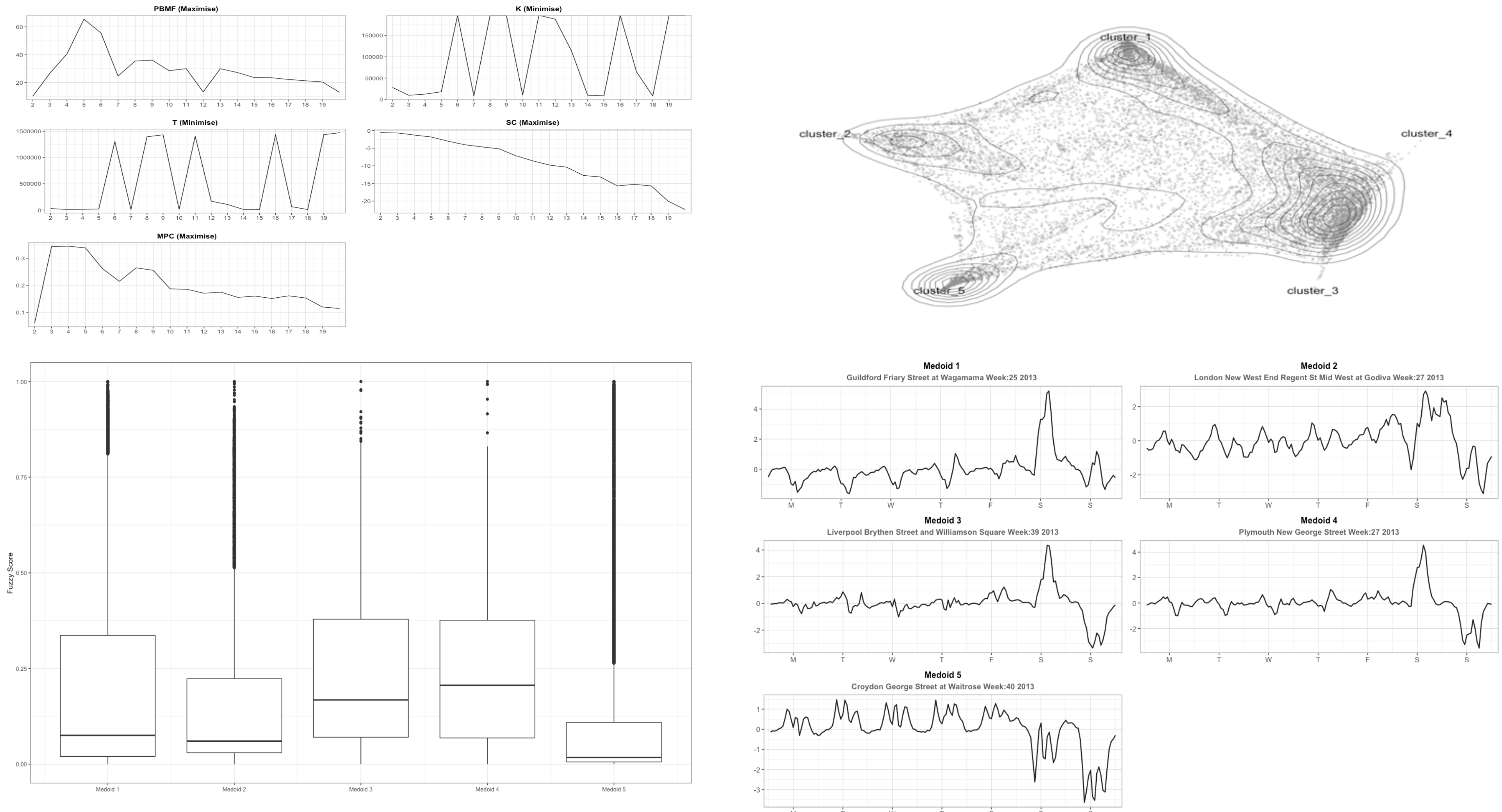
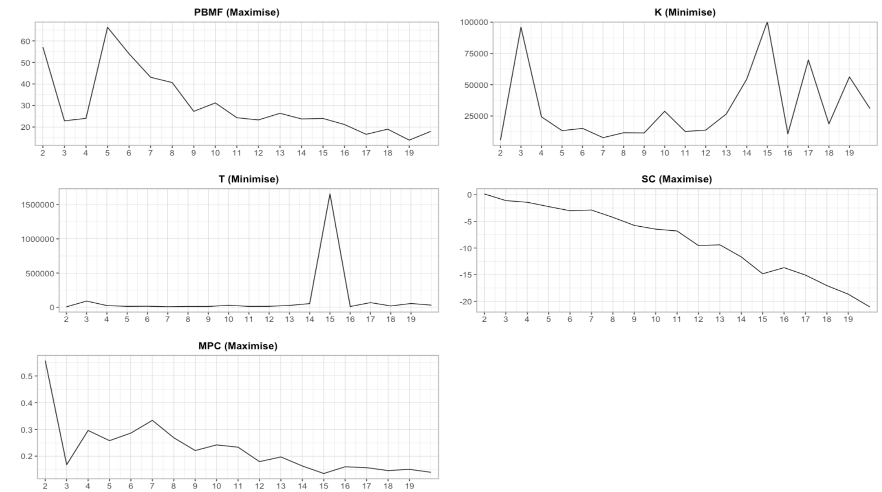
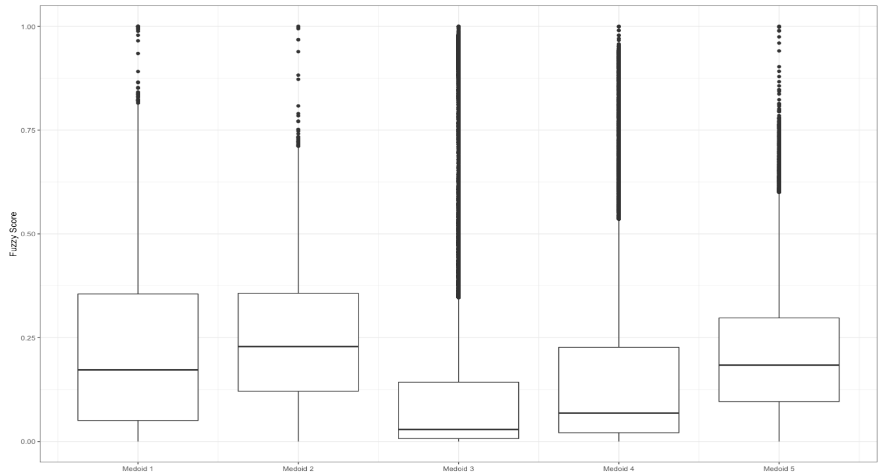
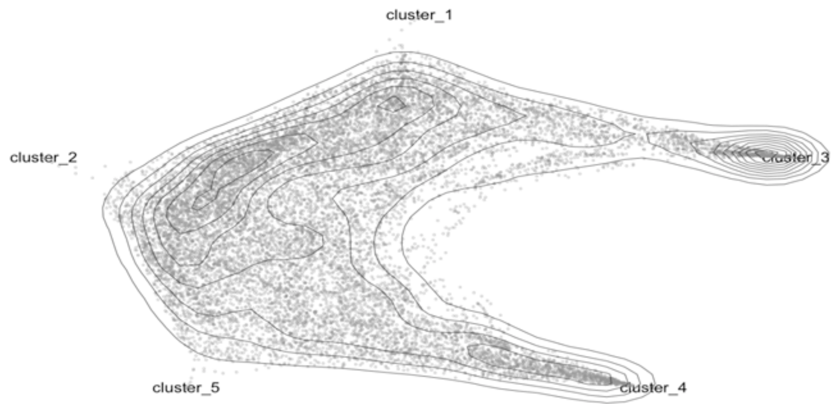


Figure 15.8 - Results for 2013 Weekly Fuzzy Analysis k=5







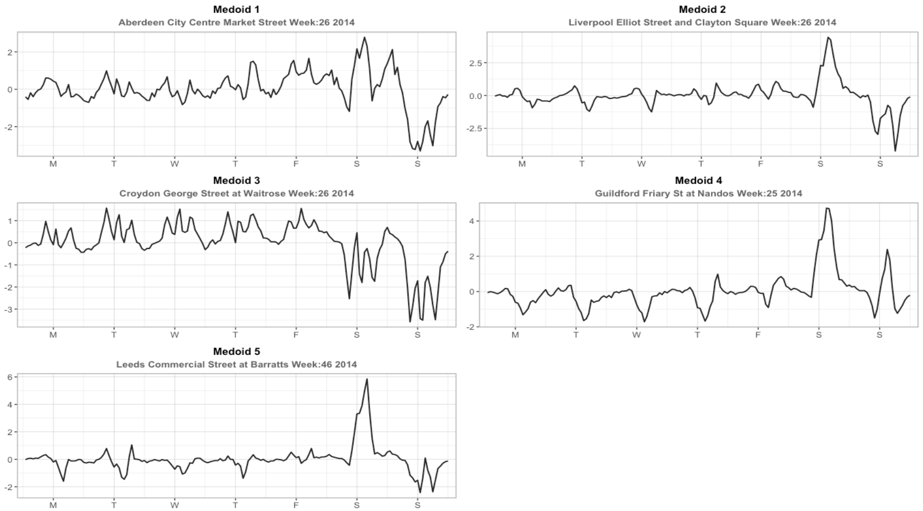
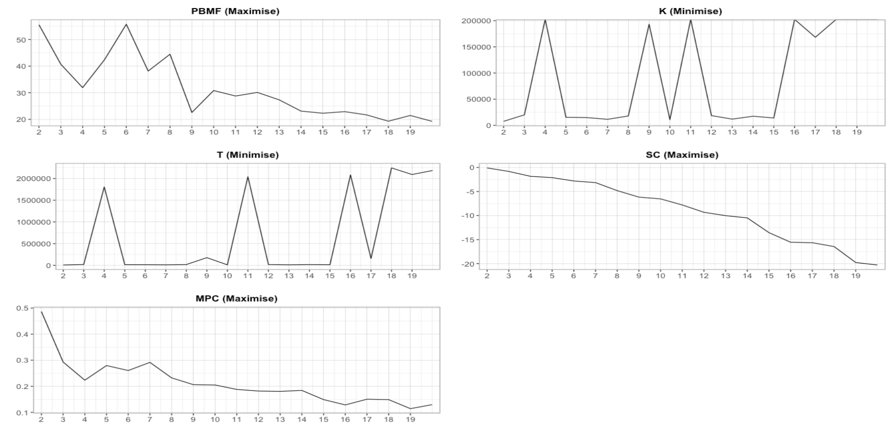


Figure 15.9 - Results for 2014 Weekly Fuzzy Analysis k=5



As number of medoids is 2, there is no Radviz Diagram

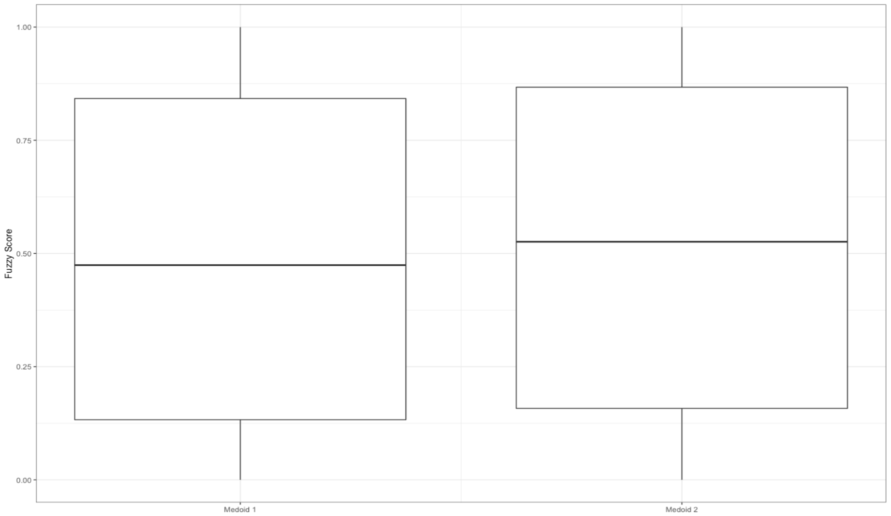
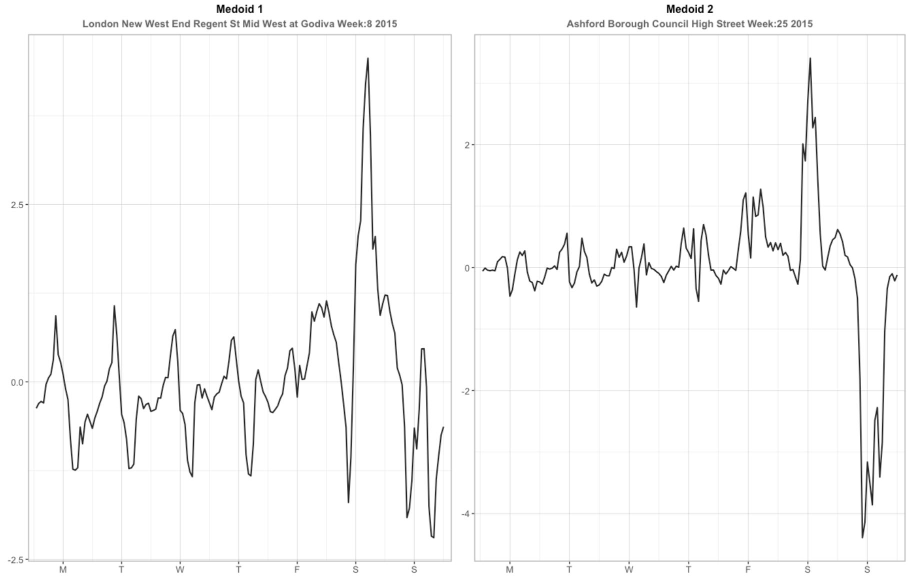
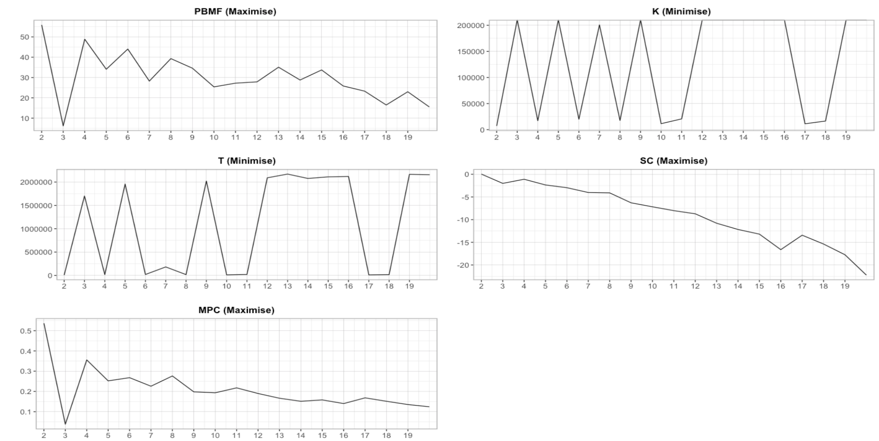
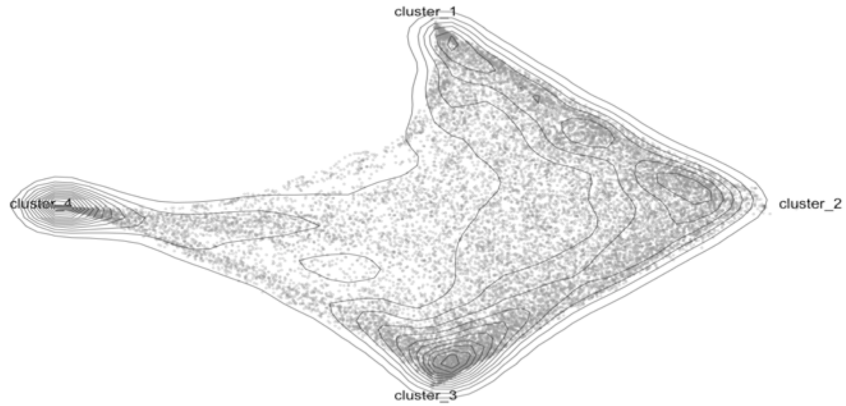
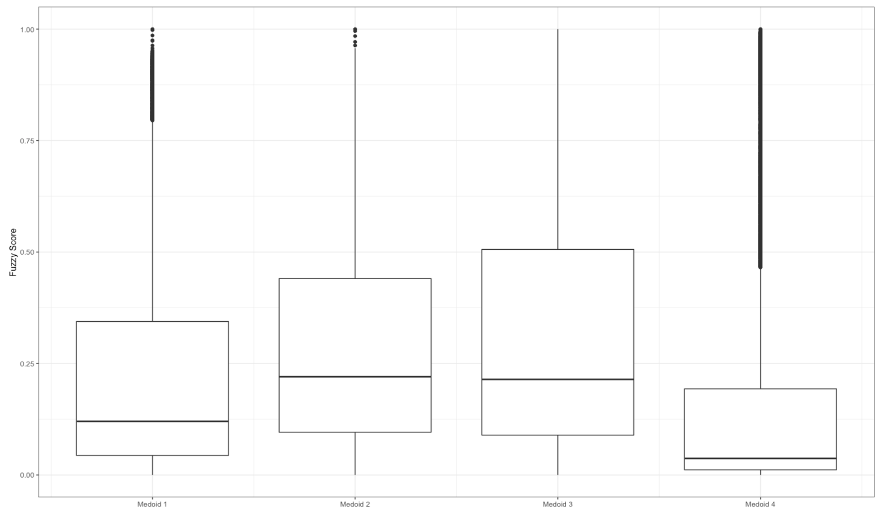


Figure 15.10 - Results for 2015 Weekly Fuzzy Analysis k=2









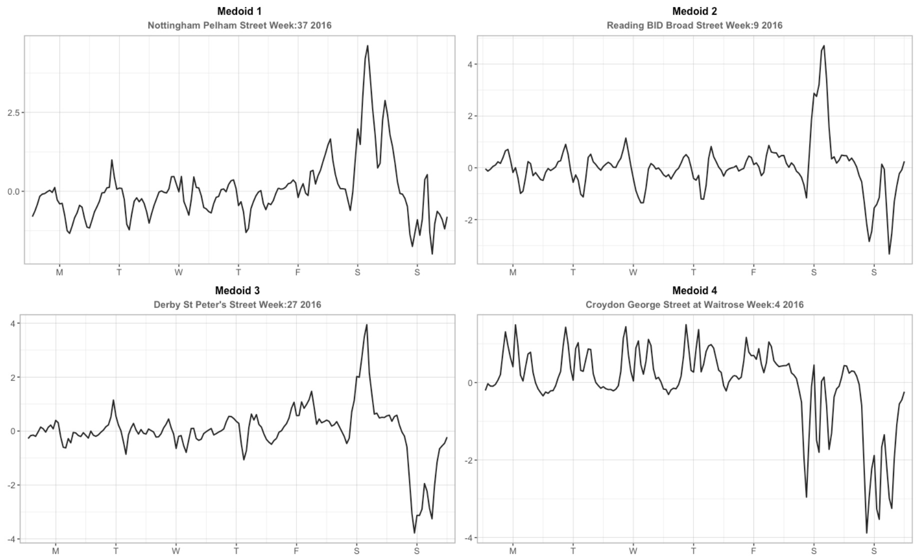
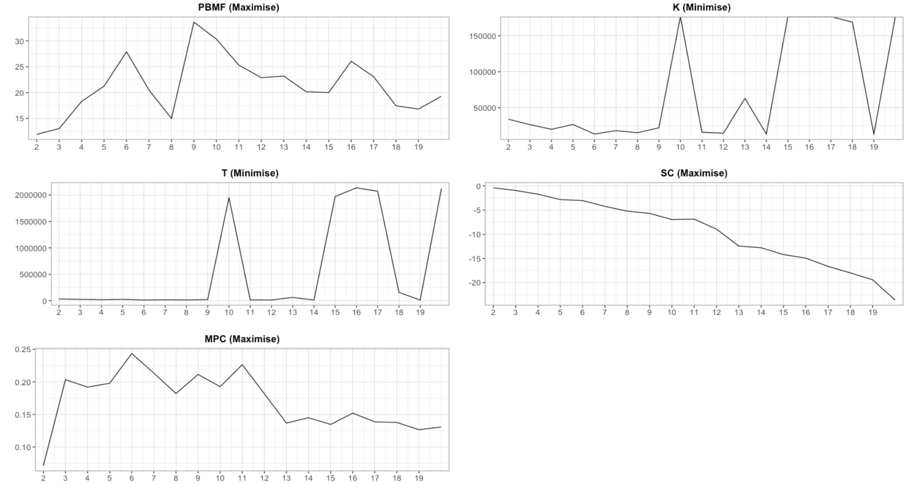
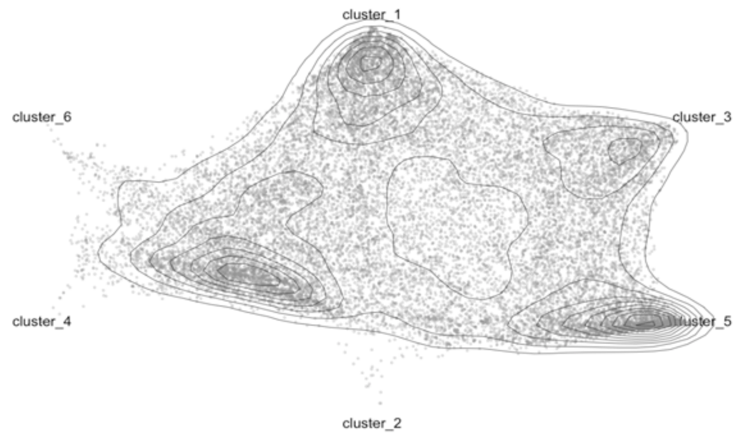
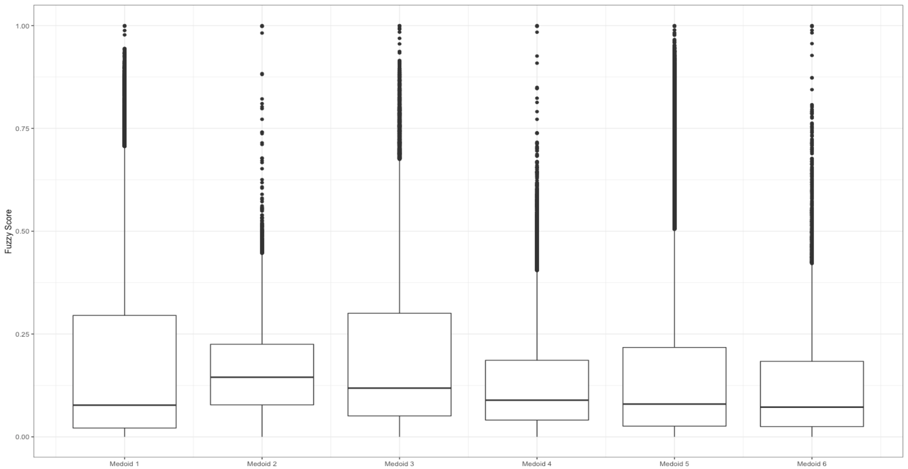


Figure 15.11 - Results for 2016 Weekly Fuzzy Analysis k=4







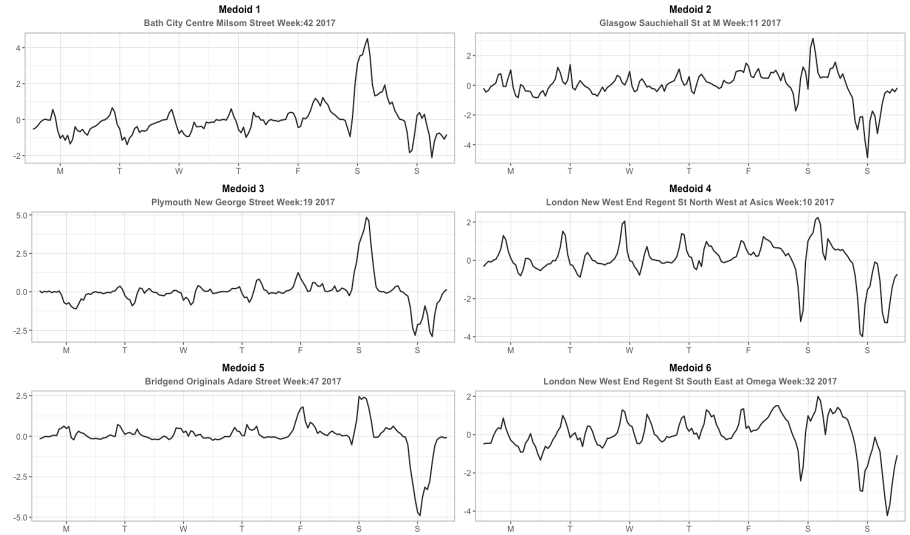


Figure 15.12 - Results for 2017 Weekly Fuzzy Analysis k=6

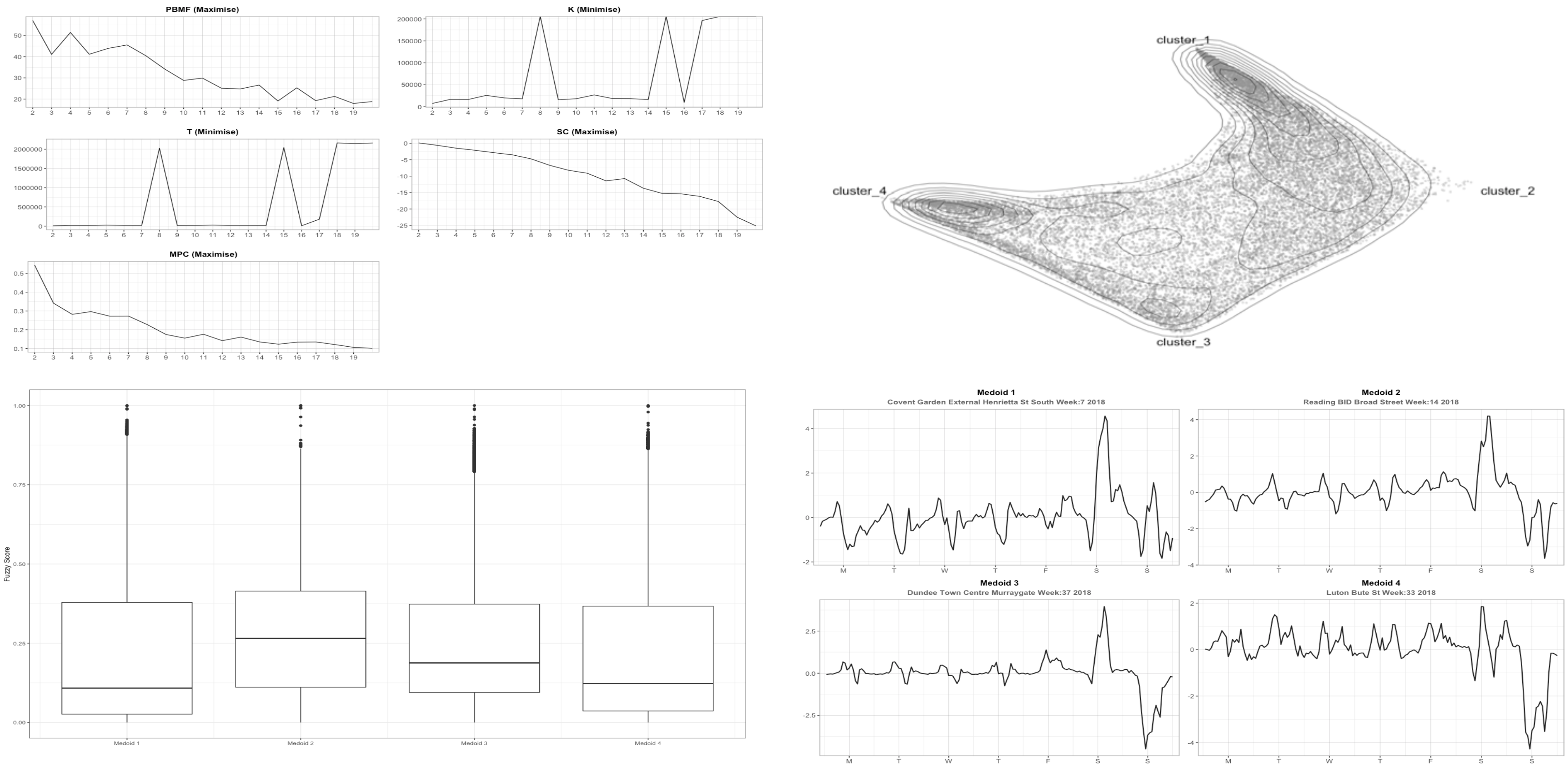


Figure 15.13 - Results for 2018 Weekly Fuzzy Analysis k=4

16 Appendix E – Exemplar Results

Below are the cluster analyses used to determine the optimal number of clusters to be used by each exemplar location.

16.1 Manchester

There are two sets of analyses for the daily and weekly cluster analyses.

16.1.1 Daily Analysis Results

Using the same parameter configurations for performing the daily fuzzy analysis as identified in Appendix A – Data Mining for all camera locations, the following results for the Manchester cameras were generated.

Following the same process as used for the collective results, the first check was to identify the number of clusters that best fitted the data using the cluster validation indices check displayed by Figure 16.1 below.

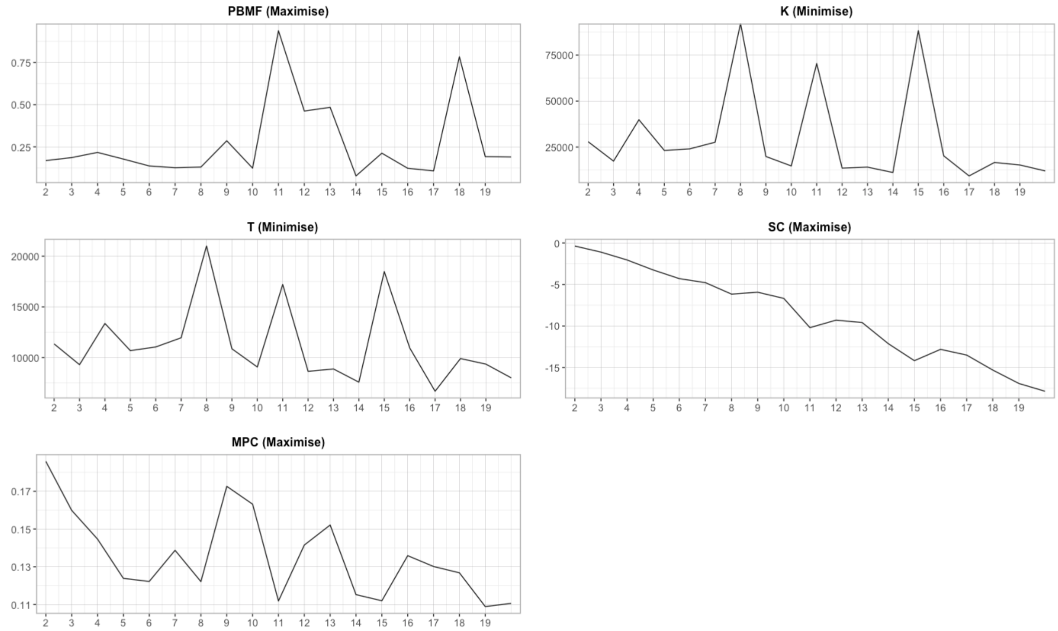


Figure 16.1. Cluster Validation indices for the Manchester sensors daily signatures

From Figure 16.1, there is very little convergence between the cluster validity indices apart from k = 2. As a quick check to view the distribution of the fuzzy clusters as displayed in Figure 16.2, these looked well defined and not dispersed around the middle area of the plot, the area where no real match with any cluster has been determined by the fuzzy clustering algorithm. For this reason, k=6 was the chosen number of clusters.

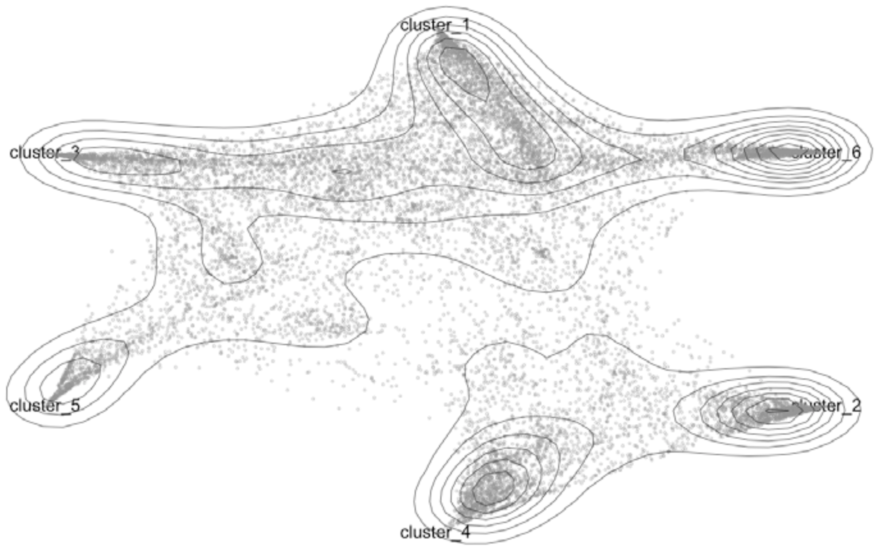


Figure 16.2. Radviz diagram for k=6 of the Manchester camera daily signature fuzzy cluster analysis.

16.1.2 Weekly Analysis Results

Using the same parameter configurations for performing the weekly fuzzy analysis as identified in Appendix A – Data Mining for all camera locations, the following results for the Manchester cameras were generated. Note that the weekly signatures provide the adjustment that should be made to the daily signatures for each weekday.

The first check was to identify the number of clusters that best fitted the data using the cluster validation indices check displayed by Figure 16.3 below.

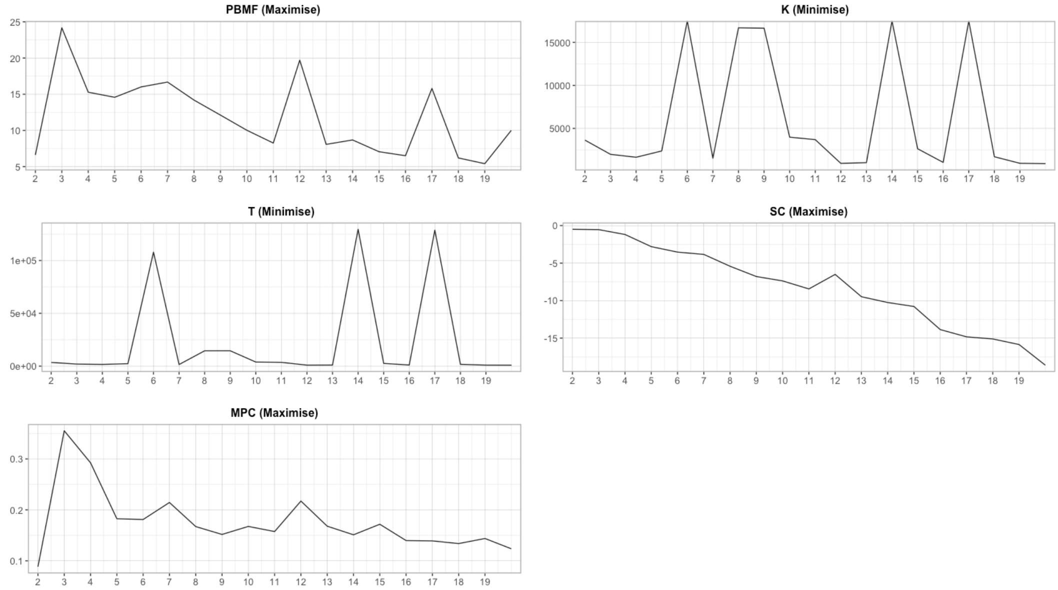


Figure 16.3. Cluster Validation indices for the Manchester camera weekly signatures.

From Figure 16.3, the best fitting option was clearly k=3. To confirm this, Figure 16.4 shows the three cluster centres but, there is a degree of allocation of weeks in the middle of the diagram, identifying undefined weekly periods.

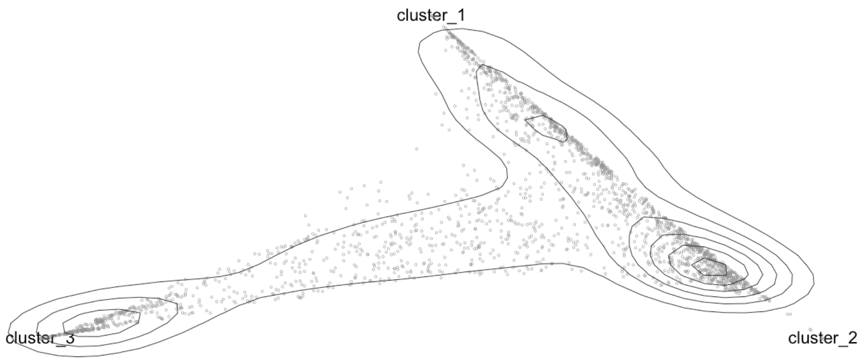


Figure 16.4. Radviz diagram for k=3 of the Manchester camera weekly signature fuzzy cluster analysis.

16.2 Rotherham

There are two sets of analyses for the daily and weekly cluster analyses.

16.2.1 Daily Decomposed Analysis Results

Using the same parameter configurations for performing the daily fuzzy analysis as identified in Appendix A – Data Mining for all camera locations, the following results for the Rotherham footfall sensors were generated.

The first check was to identify the number of clusters that best fitted the data using the cluster validation indices check displayed by Figure 16.5 below.

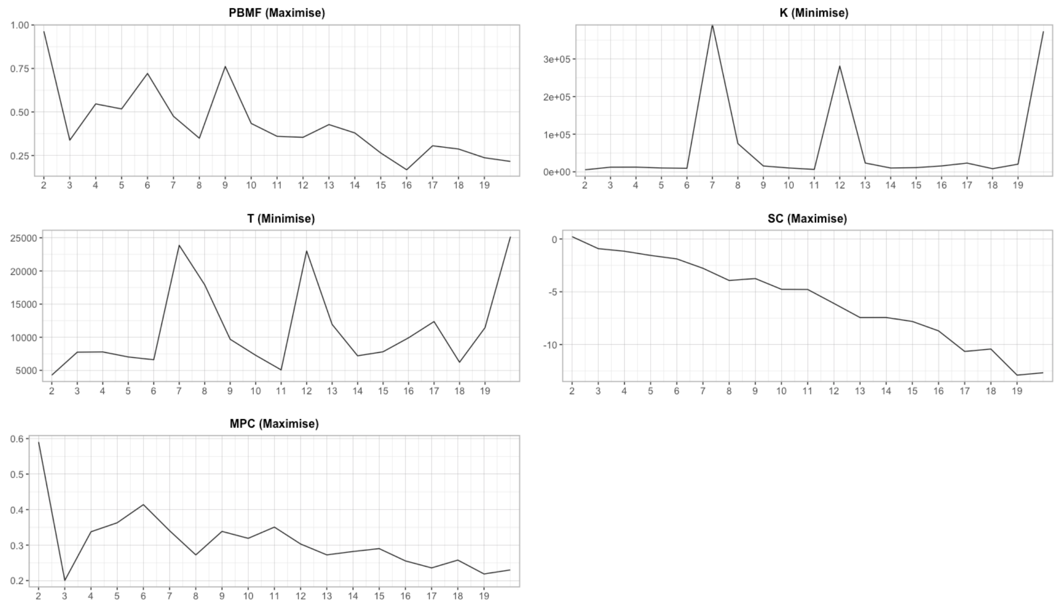


Figure 16.5. Cluster Validation indices for the Rotherham camera daily decomposed signatures.

From Figure 16.5, the two options were k = 2 or 6. Looking at the distribution of the fuzzy clusters as displayed in Figure 16.6, these are poorly defined and dispersed around the middle area of the plot, the area where no real match with any cluster has been determined by the fuzzy clustering algorithm. This suggests therefore that using the decomposed daily signatures, the best fitting daily signature is either k = 1 or 2 and that the shape of the medoids is very similar.

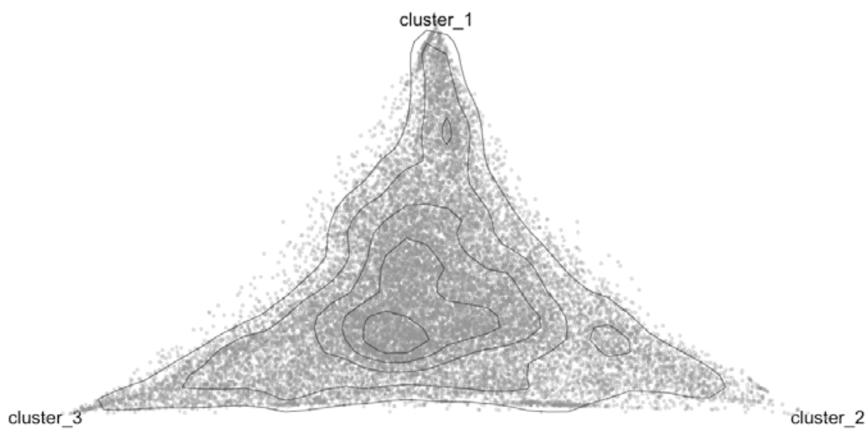


Figure 16.6. Radviz diagram for k=3 of the Rotherham daily signature fuzzy cluster analysis

Figure 16.7 below displays the medoids that represent each daily fuzzy cluster. The Medoids all focus on a peak intensity of territorialisation before mid-day or at midday confirming the daily signatures associated with Towns and Major Towns found in Chapter 7.

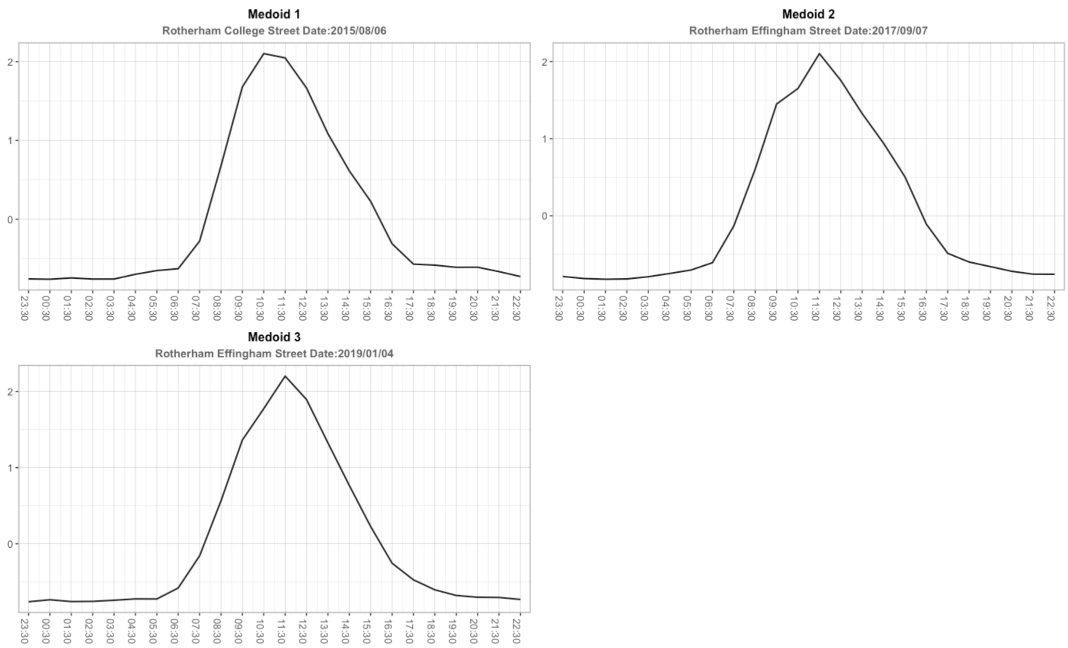


Figure 16.7. Daily Medoids for the Rotherham sensors where k=3

However, inspection of the cluster validation indices and Radviz diagrams failed to suggest a valid number of clusters – see Appendix A. As a result, the cluster analysis results using the decomposed daily signatures were not analysed further.

16.2.2 Weekly Analysis Results

Using the same parameter configurations for performing the weekly fuzzy analysis as identified in Appendix A – Data Mining for all camera locations, the following results for the Rotherham sensors were generated. Note that the weekly signatures provide the adjustment that should be made to the daily signatures for each weekday.

The first check was to identify the number of clusters that best fitted the data using the cluster validation indices check displayed by Figure 16.8 below.

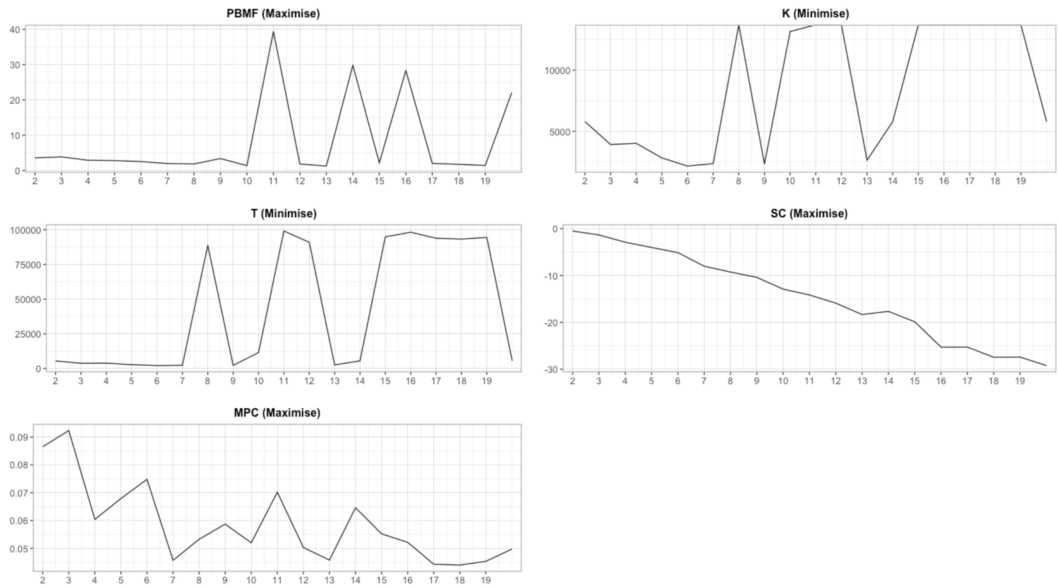


Figure 16.8. Cluster Validation indices for the Rotherham weekly signatures

From Figure 16.8, the best fitting option was viewed to be k=3, although not validated by all the indices. To confirm this, Figure 16.9 shows the three cluster centres but, there is a significant degree of allocation of weeks in the middle of the diagram, identifying undefined weekly periods. Like the Daily results, the cluster algorithm found it difficult to identify discrete cluster centres.

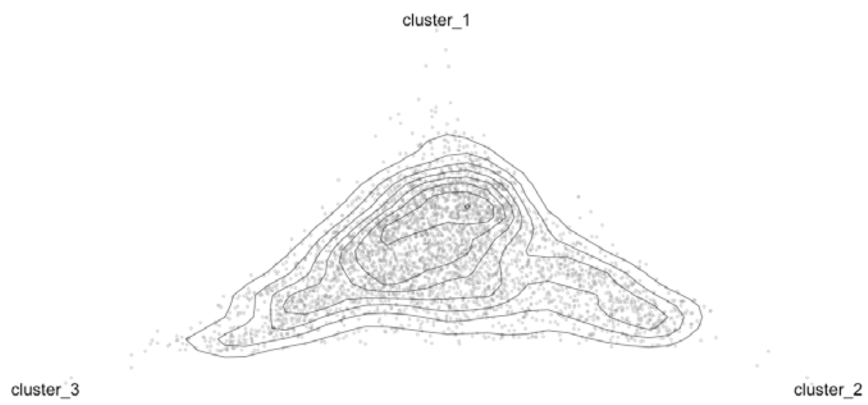


Figure 16.9. Radviz diagram for k=3 of the Rotherham weekly signature fuzzy cluster analysis

16.2.3 Imputed Data Daily Patterns – option 1

Results for the fuzzy analysis processing where imputed footfall data replaced the decomposed daily component values. Following exactly the same process as used for the collective results, the first check was to identify the number of clusters that best fitted the data using the cluster validation indices check displayed by Figure 16.10 below.

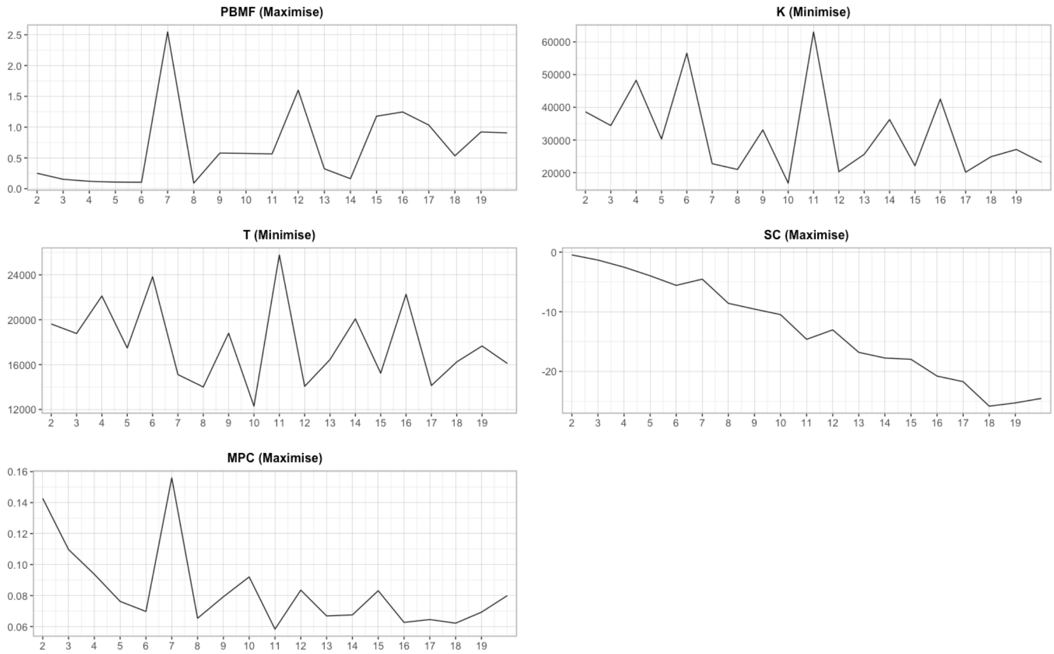


Figure 16.10. Cluster Validation indices for the Rotherham imputed footfall results

From Figure 16.10, the best fitting option was identified as k=7, a much better result from all the indices that identified using the decomposed signatures. To confirm this, Figure 16.11 shows the seven cluster centres with a cluster centre based upon clusters 1,2,5 and 7. Note how Medoid 6, which represented Sunday footfall, forms a distinct cluster centre.

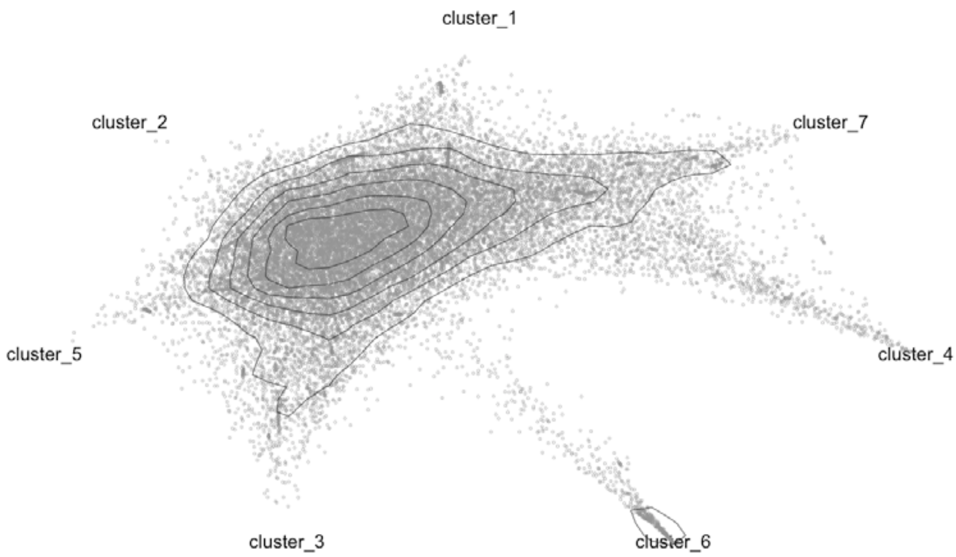


Figure 16.11. Radviz diagram for k=7 of the Rotherham imputed data fuzzy cluster analysis.

16.2.4 Imputed Data Daily Results – option 2

Below are the fuzzy analysis outputs where the distance time warping was switched off and replaced by Euclidean distance.

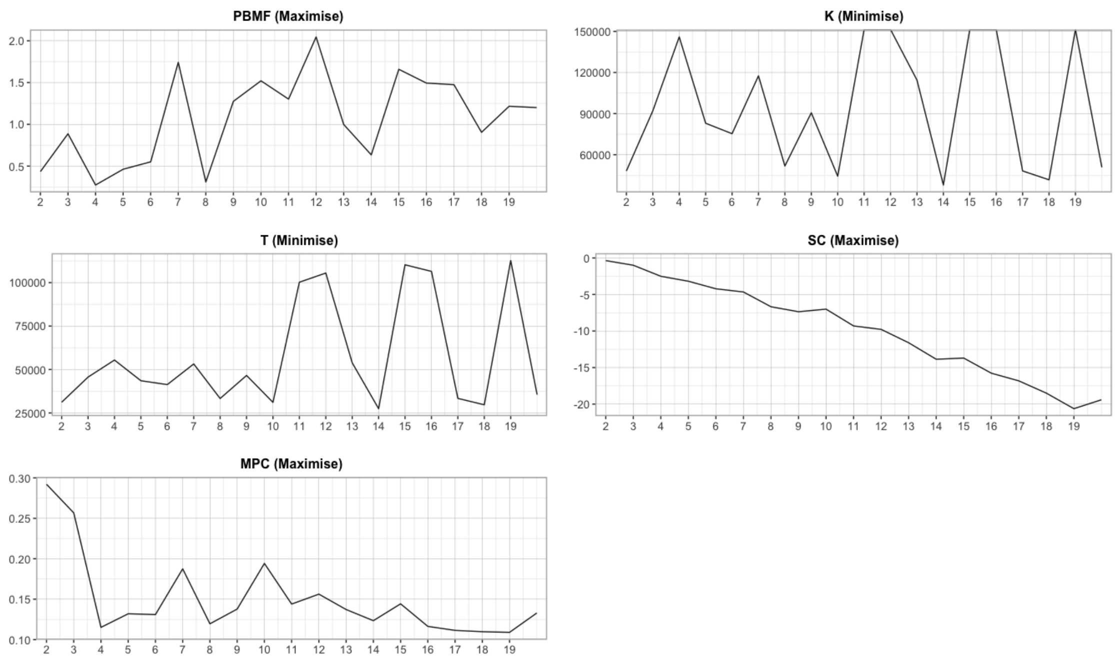


Figure 16.12. Cluster Validation indices for Rotherham imputed daily results using Euclidean distance

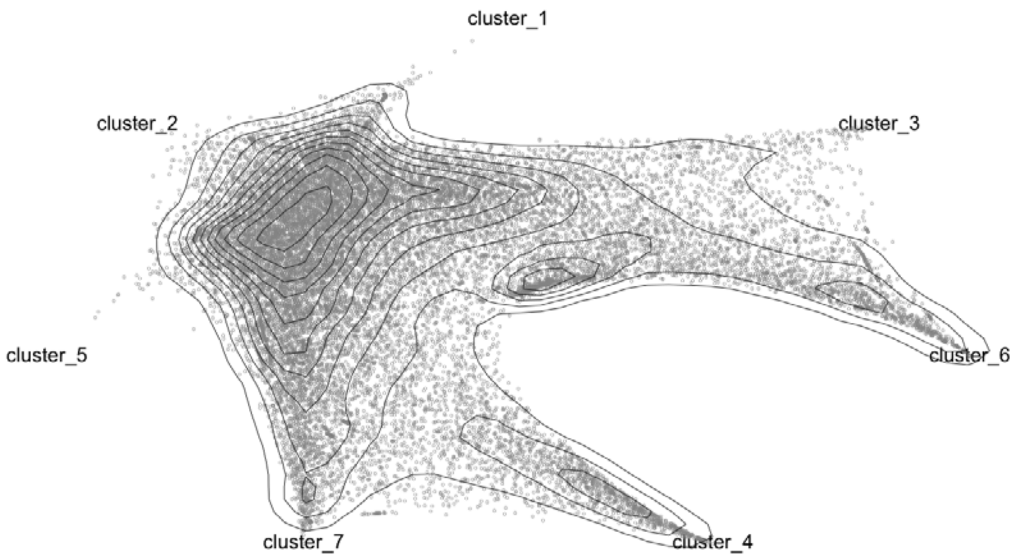


Figure 16.13. Radviz diagram for k=7 for the Rotherham imputed daily results using Euclidean distance

16.2.5 Imputed Weekly Footfall Patterns

Using the same parameter configurations for performing the weekly fuzzy analysis as identified in Appendix A – Data Mining for all camera locations, the following results for the Rotherham sensors were generated. The first check was to identify the number of clusters that best fitted the data using the cluster validation indices check displayed by Figure 16.14 below.

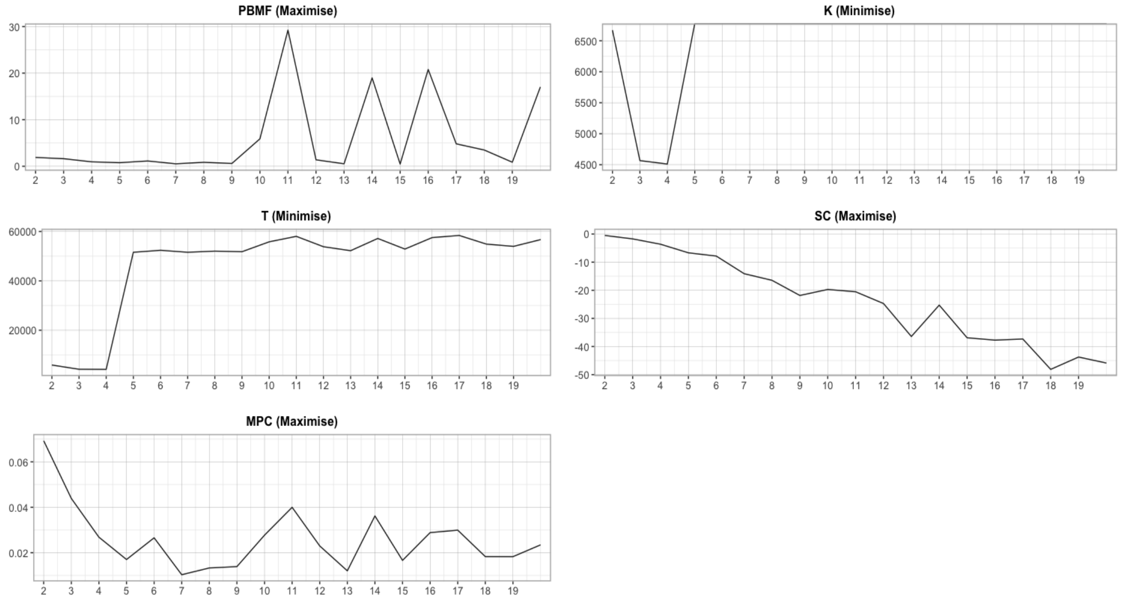


Figure 16.14. Cluster Validation indices for Rotherham weekly imputed clusters

The validation indices suggest that k=3 is the best fitting option, and the associated Radviz diagram is provided below to validate this finding. As shown in Figure 16.15, the differential between the clusters is not sufficient for the clusters to be used for analysis.

Figure 16.15. Rotherham Imputed Weekly Cluster Radviz Diagram for k=3

17 References

Abdolvand, N., Albadvi, A. and Aghdasi, M. (2015) 'Performance management using a value-based customer-centered model.' *International Journal of Production Research*, 53(18) pp. 5472-5483.

Abraham, Y. (2016) *Radviz: Project Multidimensional Data in 2D Space (R package version 0.7.0)*. [Online] [Accessed on 21/02/2017] https://CRAN.R-project.org/package=Radviz

Abraham, Y. (2020) *Visualizing Multivariate Data with Radviz*. [Online] [Accessed on 17/04/2020] https://cran.r-project.org/web/packages/Radviz/vignettes/single_cell_projections.html

Abuadbba, A. and Khalil, I. (2015) 'Wavelet based steganographic technique to protect household confidential information and seal the transmitted smart grid readings.' *Information Systems*, 53 pp. 224-236.

ACTM. (2020) *Association of Town Centre Management*. [Online] [Accessed on 17/09/2020] https://www.atcm.org

Aghabozorgi, S., Seyed Shirkhorshidi, A. and Ying Wah, T. (2015) 'Time-series clustering – A decade review.' *Information Systems*, 53 pp. 16-38.

Agrawal, R., Faloutsost, C. and Swami, A. (1993) 'Efficient similarity search in sequence databases.' *In International Conference on Foundations of Data Organization and Algorithms* pp. 69-84.

Agryzkov, T., Martí, P., Tortosa, L. and Vicent, J. F. (2016) 'Measuring urban activities using Foursquare data and network analysis: a case study of Murcia (Spain).' *International Journal of Geographical Information Science*, pp. 1-22.

Ahn, H. (2001) 'Applying the Balanced Scorecard Concept: An Experience Report.' *Long Range Planning*, 34(4) pp. 441-461.

Aldrich, E. (2020) 'R Package Wavelets: Functions for Computing Wavelet Filters, Wavelet Transforms and Multiresolution Analyses - ' CRAN. [Accessed on 01/07/2020].

Alfonzo, M. A. (2016) 'To Walk or Not to Walk? The Hierarchy of Walking Needs.' *Environment and Behavior*, 37(6) pp. 808-836.

Ali, M., Alqahtani, A., Jones, M. W. and Xie, X. (2019) 'Clustering and Classification for Time Series Data in Visual Analytics: A Survey.' *IEEE Access*, 7 pp. 181314-181338.

Allen, J. (2011) 'Powerful assemblages?' *Area*, 43(2) pp. 154-157.

Amin, A. (2013) 'Surviving the turbulent future.' *Environment and Planning D: Society and Space*, 31(1) pp. 140-156.

Anderson, B. and McFarlane, C. (2011) 'Assemblage and geography.' *Area*, 43(2) pp. 124-127.

Anderson, B., Kearnes, M., McFarlane, C. and Swanton, D. (2012) 'On assemblages and geography.' *Dialogues in Human Geography*, 2(2) pp. 171-189.

Anderson, K., Domosh, M., Pile, S. and Thrift, N. (2003) Handbook of Cultural Geography: A Rough Guide. In: Anderson, K., Domosh, M., Pile, S. and Thrift, N. *Handbook of Cultural Geography*. London: SAGE Publications Ltd.

Andiojaya, A. and Demirhan, H. (2019) 'A bagging algorithm for the imputation of missing values in time series.' *Expert Systems with Applications*, 129 pp. 10-26.

Angstenberger, L. (2001) *Dynamic Fuzzy Pattern Recognition with Applications to Finance and Engineering.* Internatonal Series in Intelligent Technologies. Boston/London/Dordrecht: Kluwer Academic Publishers.

Anhoej, J. (2015) 'Diagnostic value of run chart analysis: using likelihood ratios to compare run chart rules on simulated data series.' *PLoS One*, 10(3) 2015/03/24, p. e0121349.

Anhoej, J. (2020) *qicharts2: Quality Improvement Charts*. [Online] [Accessed on 02/03/2020] https://CRAN.R-project.org/package=qicharts2

Anthony, R. N. (1965) *Management Planning and Control Systems: A Framework for Analysis.* Harvard Business School Press.

Antonini, G., Bierlaire, M. and Weber, M. (2006) 'Discrete choice models of pedestrian walking behavior.' *Transportation Research Part B*, 40 pp. 667-687.

Antunes, C. M. and Olivera, A. L. (2001) 'Temporal Data Mining: an overview.' *In KDD Workshop on Temporal Data Mining* pp. 1-13.

Applebaum, W. (1965) 'Can Store Location Research Be a Science?' *Economic Geography*, 41(3) pp. 234-237.

Arellana, J., Saltarín, M., Larrañaga, A. M., Alvarez, V. and Henao, C. A. (2019) 'Urban walkability considering pedestrians’ perceptions of the built environment: a 10-year review and a case study in a medium-sized city in Latin America.' *Transport Reviews*, 40(2) pp. 183-203.

Arentze, T., Borgers, A. and Timmermans, H. (1993) 'A model of Multi-Purpose Shopping Trip Behavior.' *Papers in Regional Science*, 72(3) pp. 239-256.

Argyris, C. (1991) 'Teaching Smart People How to Learn.' *Harvard Business Review*, 4(2) pp. 4-15.

Armstrong, M. (2014) Armstrong's handbook of performance management: an evidence-based guide to delivering high performance. Kindle. (12/12/2017) 5th Editiion ed. London: Kogan Page.

Arranz-López, A., Soria-Lara, J. A. and Pueyo-Campos, Á. (2019) 'Social and spatial equity effects of non-motorised accessibility to retail.' *Cities*, 86 pp. 71-82.

Askarizad, R. and Safari, H. (2020) 'The influence of social interactions on the behavioral patterns of the people in urban spaces (case study: The pedestrian zone of Rasht Municipality Square, Iran).' *Cities*, 101 pp. 1-16.

Astbury, G. and Thurstain-Goodwin, M. (2014) 'Measuring the Impact of Out-of-town Retail Development on Town Centre Retail Property in England and Wales.' *Applied Spatial Analysis and Policy*, 7(4) pp. 301-316.

Atkinson, C. L. (2017) 'Performance Management for Learning, Reform, and Change: A Review of Three Recent Books.' *International Journal of Public Administration*, 41(8) pp. 645-649.

Auguie, B. (2017) *gridExtra: Miscellaneous Functions for "Grid" Graphics (R package version 2.3)*. [Online] [Accessed on 04/06/2018] https://CRAN.R-project.org/package=gridExtra

Aurousseau, M. (1921) 'The Distribution of Population: A Constructive Problem.' *Geographical Review*, 11(4) pp. 563-592.

Azhar, M., Huang, J. Z., Masud, M. A., Li, M. J. and Cui, L. (2020) 'A hierarchical Gamma Mixture Model-based method for estimating the number of clusters in complex data.' *Applied Soft Computing*, 87

Bacon, R. W. (1995) 'Combined trips and the frequency of shopping.' *Journal of Retailing and Consumer Services*, 2(3) pp. 175-183.

Bagnall, A., Lines, J., Hills, J. and Bostrom, A. (2015) 'Time-Series Classification with COTE: The Collective of Transformation-Based Ensembles.' *IEEE Transactions on Knowledge and Data Engineering*, 27(9) pp. 2522-2535.

Bagnall, A., Lines, J., Bostrom, A., Large, J. and Keogh, E. (2016) 'The great time series classification bake off: a review and experimental evaluation of recent algorithmic advances.' *Data Mining and Knowledge Discovery*, 31(3) pp. 606-660.

Bajde, D. (2013) 'Consumer culture theory (re)visits actor–network theory.' *Marketing Theory*, 13(2) pp. 227-242.

Balsas, C. J. L. (2010) 'Measuring the livability of an urban centre: an exploratory study of key performance indicators.' *Planning, Practice & Research*, 19(1) pp. 101-110.

Batty, M. (1997) 'The Retail Revolution.' *Environment and Planning B: Planning and Design*, 24(1) pp. 1-2.

Batty, M. (2002) 'Thinking about Cities as Spatial Events.' *Environment and Planning B: Planning and Design*, 29(1) pp. 1-2.

Batty, M., Axhausen, K. W., Giannotti, F., Pozdnoukhov, A., Bazzani, A., Wachowicz, M., Ouzounis, G. and Portugali, Y. (2012) 'Smart cities of the future.' *The European Physical Journal Special Topics*, 214(1) pp. 481-518.

Bennett, V. W. (1944) 'Consumer Buying Habits in a Small Town Located between Two Large Cities.' *Journal of Marketing*, 8(4) pp. 405-416.

Bennison, D. and Daves, R. L. (1980) 'The Impact of Town Centre Shopping Schemes in Britain: Their Impact on traditional retail environments.' *Progress in Planning*, 14(1) pp. 1-104.

Bennison, D., Warnaby, G. and Pal, J. (2010) 'Local shopping in the UK: towards a synthesis of business and place.' *International Journal of Retail & Distribution Management*, 38(11) pp. 846-864.

Bergson, H. (1910) *Time and Free Will.* London: George Allen and Unwin.

Bergson, H. (1911) *Matter and Memory.* London: George Allen and Unwin.

Berndt, D. J. and Clifford, J. (1994) 'Using dynamic time warping to find patterns in time series.' *In Proceedings of the AAAI-94 Workshop: Knowledge Discovery in Databases*. Seattle, Washington, pp. 359–370.

Berry, B. (1967) *Geography of Market Centres and Retail Distrubution.* Englewood, N.J.: Prentice-Hall Inc.

Berry, T., Newing, A., Davies, D. and Branch, K. (2016) 'Using workplace population statistics to understand retail store performance.' *The International Review of Retail, Distribution and Consumer Research*, 26(4) pp. 375-395.

Bettencourt, L. M. and Lobo, J. (2016) 'Urban scaling in Europe.' *Journal Royal Society Interface*, 13(116), Mar,

Beveridge, S. (1992) 'Least squares estimation of missing values in time series.' *Communications in Statistics - Theory and Methods*, 21(12) pp. 3479-3496.

Bezdek, J. C. (1981) *Pattern Recognition with Fuzzy Objective Function Algorithms.* New York: Plenum Press.

Bhaskar, R. (2008) *A Realist Theory of Science.* 2nd ed., London: Verso.

BIPM. (2012) *International vocabulary of metrology - Basic and general concepts and associated terms (VIM).* 19/12/2017, 3rd Edition ed. Geneva: Bureau of Weights and Measures (BIPM). (JCGM 200:2012)

Birkin, M., Clarke, G. and Clarke, M. (2010) 'Refining and Operationalizing Entropy-Maximizing Models for Business Applications.' *Geographical Analysis*, 42(4) pp. 422-445.

BIS. (2011) *Understanding High Street Performance*. Department for Business Innovation & Skills. [Online] [Accessed on 21/08/2014] www.gov.uk/government/uploads/system/uploads/attachment_data/file/31823/11-1402-understanding-high-street-performance.pdf

BIS. (2012) *BIS Retail Strategy*. Department for Business Innovation & Skills. [Online] [Accessed on 21/08/2014] https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/34640/12-1197-bis-retail-strategy.pdf

Bititci, U., Carrie, A. S. and McDevitt, L. (1997) 'Integrated performance measurement systems: a development guide.' *International Journal of Operations & Production Management*, 17(5) pp. 522-534.

Bititci, U., Garengo, P., Dörfler, V. and Nudurupati, S. (2012) 'Performance Measurement: Challenges for Tomorrow*.' *International Journal of Management Reviews*, 14(3) pp. 305-327.

Bititci, U., Mendibil, K., Nudurupati, S., Garengo, P. and Turner, T. (2006) 'Dynamics of performance measurement and organisational culture.' *International Journal of Operations & Production Management*, 26(12) pp. 1325-1350.

Blaikie, N. (2004) 'Abduction.' *In* Lewis-Beck, M. S., Bryman, A. and Futing Liao, T. (eds.) *The SAGE Encyclopedia of Social Science Research Methods*. Thousand Oaks: SAGE Publications, Inc,

Blaikie, N. (2007) *Approaches to social enquiry.* 2nd ed., Cambridge: Polity.

Blaikie, N. (2009) *Designing social research: the logic of anticipation.* Vol. 2nd. Cambridge: Polity.

Blázquez, M. (2014) 'Fashion Shopping in Multichannel Retail: The Role of Technology in Enhancing the Customer Experience.' *International Journal of Electronic Commerce*, 18(4) pp. 97-116.

Bloch, P. H., Ridgway, N. M. and Dawson, S. (1994) 'The Shopping Mall as Consumer Habitat.' *Journal of Retailing*, 70(1) pp. 23-42.

Borchert, J. G. (1998) 'Spatial dynamics of retail structure and the venerable retail hierarchy.' *GeoJournal*, 45(4) pp. 327-336.

Borgers, A. and Timmermans, H. J. P. (1986) 'City Centre Entry Points, Store Location Patterns and Pedestrian Route Choice Behaviour: A Microlevel Simulation Model.' *Socio-Economic Planning Sciences*, 20(1) pp. 25-31.

Borgers, A. and Vosters, C. (2011) 'Assessing preferences for mega shopping centres: A conjoint measurement approach.' *Journal of Retailing and Consumer Services*, 18 pp. 322-332.

Borsekova, K., Koróny, S., Vaňová, A. and Vitálišová, K. (2018) 'Functionality between the size and indicators of smart cities: A research challenge with policy implications.' *Cities*, 78 pp. 17-26.

Bourne, M., Mills, J., Wilcox, M., Neely, A. and Platts, K. (2000) 'Designing, implementing and updating performance measurement systems.' *International Journal of Operations & Production Management*, 20(7) pp. 754-771.

Box, G. E. P., Jenkins, G. M. and Reinsel, G. C. (2008) *Time Series Analysis - Forecasting and Control.* 4th ed., Hoboken, New Jersey: Wiley & Sons.

Braudel, F. (1986) *The Perspective of the World.* New York: Harper and Row.

Briassoulis, H. (2017a) 'Why I fell for assemblages.' *Dialogues in Human Geography*, 7(2) pp. 212-220.

Briassoulis, H. (2017b) 'Response assemblages and their socioecological fit.' *Dialogues in Human Geography*, 7(2) pp. 166-185.

Bridge, G. (2020) 'On pragmatism, assemblage and ANT: Assembling reason.' *Progress in Human Geography*, 45(3) pp. 417-435.

Brighenti, A. (2006) 'On Territory as Relationship and Law as Territory.' *Canadian Journal of Law and Society*, 21(2) pp. 65-86.

Brighenti, A. (2010a) 'On Territorology: Towards a General Science of Territory.' *Theory, Culture & Society*, 27(1) pp. 52-72.

Brighenti, A. (2010b) 'Lines, barred lines. Movement, territory and the law.' *International Journal of Law in Context*, 6(3) pp. 217-227.

Brighenti, A. (2010c) 'Tarde, Canetti, and Deleuze on crowds and packs.' *Journal of Classical Sociology*, 10(4) pp. 291-314.

Brighenti, A. (2013) 'Teoria dei territori. Theory of Territories.' *Scienza & Politica*, 48 pp. 175-183.

Brighenti, A. (2014) 'Mobilizing Territories, Territorializing Mobilities.' *Sociologica*, 8(1) pp. 1-25.

Brighenti, A. (2016) 'Visibility.' *Current Sociology*, 55(3) pp. 323-342.

Brighenti, A. (2018) 'The Social Life of Measures: Conceptualizing Measure–Value Environments.' *Theory, Culture & Society*, 35(1) pp. 23-44.

Brighenti, A. (2019) 'Umwelt-measures. On extensive and intensive measures: Introduction to the special issue ‘Theorising measures, rankings and metrics’.' *Social Science Information*, 58(2) pp. 224-237.

Brighenti, A. and Kärrholm, M. (2018) 'Beyond rhythmanalysis: towards a territoriology of rhythms and melodies in everyday spatial activities.' *City, Territory and Architecture*, 5(1) pp. 1-12.

Brinkmann, S. and Kvale, S. (2015) *Interviews. Learning the Craft of Qualitative Research Interviewing.* 3rd ed., London: Sage Publications Ltd.

British Retail Consortium. (2019) *Fall in retail employment likely to ensure*. British Retail Consortium. [Online] [Accessed on 25/04/2021] https://brc.org.uk/news/2019/2019-jul-25-retail-employment-monitor/

Bromley, R. A., Carrington, D. J. and Dargan, E. (1994) 'A comparison of the Limited-Area Model & the UK Mesoscale Model.' *In Numerical Weather Prediction 10th Conference (Nwp)*. Portland, OR, JUL 18-22.American Meteorological Society, 45 Beacon ST, Boston, MA 02108, pp. 415-416.

Bromley, R. D. F., Tallon, A. R. and Thomas, C. J. (2003) 'Disaggregating the space-time layers of city-centre activities and their users.' *Environment and Planning A* 35(10) pp. 1831 - 1851.

Brook, Q. (2006) *Six Sigma and Minitab - A complete toolbox guide for all Six Sigma Practioners.* UK: QSB Publishing Ltd.

Brown, S. (1991a) 'Retail location: the post hierarchical challenge.' *The International Review of Retail, Distribution and Consumer Research*, 1(3), 1991/04/01, pp. 367-381.

Brown, S. (1991b) 'Shopper Circulation in a Planned Shopping Centre.' *International Journal of Retail & Distribution Management*, 19(1) pp. 17-24.

Brown, S. (1992) *Retail location: a micro-scale perspective.* Aldershot: Avebury.

Brownrigg, R., Minka, T. P. and Deckmyn, A. (2018) *maps: Draw Geographical Maps (R package version 3.3.0)*. [Online] [Accessed on 10/11/2018] https://CRAN.R-project.org/package=maps

Brunsdon, C. (2016) 'Quantitative methods II.' *Progress in Human Geography*, 41(4) pp. 512-523.

Buchanan, I. (2015) 'Assemblage Theory and Its Discontents.' *Deleuze Studies*, 9(3) pp. 382-392.

Burgess, E. W. (1925) 'The Growth of a City.' *In* Park, R. E., Burgess, E. W. and McKenzie, R. D. (eds.) *The City*. Chicago: Chicago University Press, pp. 47-62.

Burney, L. L., Henle, C. A. and Widener, S. K. (2009) 'A path model examining the relations among strategic performance measurement system characteristics, organizational justice, and extra- and in-role performance.' *Accounting, Organizations and Society*, 34(3-4) pp. 305-321.

Buttimer, A. (1976) 'Grasping the Dynamism of Lifeworld.' *Annals of the Association of American Geographers*, 66(2) pp. 277-292.

Cadman, L. (2009) 'Autonomic non-representational theory/non-representational geographies.' *In* Kitchin, R. and Thrift, N. (eds.) *The International Encyclopedia of Human Geography*. Vol. 7. Oxford: Elsevier, pp. 456–463.

Callon, M. (1984) 'Some Elements of a Sociology of Translation: Domestication of the Scallops and the Fishermen of St Brieuc Bay.' *The Sociological Review*, 32(1) pp. 196-233.

Canonico, P., Harri Laihonen, P., De Nito, E., Esposito, V., Martinez, M., Mercurio, L. and Pezzillo iacono, M. (2015) 'The boundaries of a performance management system between learning and control.' *Measuring Business Excellence*, 19(3) pp. 7-21.

Carlin, J. B. and Dempster, A. P. (1989) 'Sensitivity Analysis of Seasonal Adjustments: Empirical Case Studies.' *Journal of the American Statistical Association*, 84(405) pp. 6-20.

Carmona, M. (2021) 'The existential crisis of traditional shopping streets: the sun model and the place attraction paradigm.' *Journal of Urban Design*, 29 Jul 2021,

Carruthers, I. (1957) 'A Classification of Service Centres in England and Wales.' *The Geographical Journal*, 123(3) pp. 371-385.

Carter, N. (1991) 'Learning to Measure Performance: The Use of Indicators in Organizations.' *Public Administration*, 69(1) pp. 85-101.

Castells, M. (2010) *The Rise of the Network Society.* 2nd - with new preface ed., Chichester, UK: Wiley-Blackwell.

Centre for Retail Research. (2021) *Who's Gone Bust in 2021 by Company - Centre for Retail Research*. Centre for Retail Research. [Online] [Accessed on 12/10/2021] https://www.retailresearch.org/whos-gone-bust-retail.html#bycompany

Champely, S. (2020) *pwr: Basic Functions for Power Analysis. Power analysis functions along the lines of Cohen (1988).* [Online] [Accessed on 06/07/2020] https://cran.r-project.org/web/packages/pwr/index.html

Chanda, A. K., Saha, S., Nishi, M. A., Samiullah, M. and Ahmed, C. F. (2015) 'An efficient approach to mine flexible periodic patterns in time series databases.' *Engineering Applications of Artificial Intelligence*, 44 pp. 46-63.

Charnes, A., Cooper, W. W. and Rhodes, E. (1978) 'Measuring the efficiency of decision making units.' *European Journal of Operational Research*, 2(6) pp. 429-444.

Chatfield, C. (2003) *The Analysis of Time Series: An Introduction.* 6th ed., Texts in Statistical Science Series. London: Chapman & Hall/CRC.

Chen, M.-S. and Wang, S.-W. (1999) 'Fuzzy clustering analysis for optimizing fuzzy membershipfunctions.' *Fuzzy Sets and Systems*, 103(3) pp. 239-254.

Chen, Q., Hu, G., Gu, F. and Xiang, P. (2012) 'Learning optimal warping window size of DTW for time series classification.' *In 11th International Conference on Information Science, Signal Processing and their Applications (ISSPA)*. Montreal, QC, pp. 1272-1277.

Cheng, M. M., Luckett, P. F. and Mahama, H. (2007) 'Effect of perceived conflict among multiple performance goals and goal difficulty on task performance.' *Accounting & Finance*, 47(2) pp. 221-242.

Chenhall, R. H., Hall, M. and Smith, D. (2017) 'The expressive role of performance measurement systems: A field study of a mental health development project.' *Accounting, Organizations and Society*, 63 pp. 60-75.

Chiş, M., Banerjee, S. and Hassanien, A. E. (2009) 'Clustering Time Series Data: An Evolutionary Approach.' *In* Abraham, A., Hassanien, A., de Leon, F., de Carvalho, A. P. and Snášel, V. (eds.) *Foundations of Computational, Intelligence Volume 6. Studies in Computational Intelligence*. Berlin, Heidelberg: Springer,

Christaller, W. (1933) *Central Places in Southern Germany. Translation into English by Carlisle W. Baskin in 1966.* (Central Places in Southern Germany) Englewood Cliffs, NJ: Prentice-Hall.

CityCo & ManchesterBID. (2020) *Manchester BID Area*. [Online] [Accessed on 18/06/2019] https://cityco.com/manchester-bid/about-manchester-bid/the-bid-map/

Clarke, I., Bennison, D. and Pal, J. (1997) 'Towards a contemporary perspective of retail location.' *International Journal of Retail & Distribution Management*, 25(2) pp. 59-69.

Cleveland, R. B., Cleveland, W. S. and Terpenning, I. (1990) 'STL: A Seasonal-Trend Decomposition Procedure Based on Loess.' *Journal of Official Statistics*, 6(1) p. 3.

CLG. (2008) 'Models for Sub-Regional Spatial Planning.' [Online] [Accessed on 15/12/2020]

CLG. (2009) *Planning for Town Centres. Practice giudance on need, impact and the sequential period*. Communities and Local Government. [Online] [Accessed on 15/12/2020]
https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/7781/towncentresguide.pdf

CLG. (2012) *National Planning Policy Framework*. Communities and Local Government. [Online] [Accessed on 25/09/2018]
https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/6077/2116950.pdf

Clulow, V. and Reimers, V. (2009) 'How do consumers define retail centre convenience?' *Australasian Marketing Journal (AMJ)*, 17(3) pp. 125-132.

Coca-Stefaniak, J. A. (2013) 'Successful Town Centres - Developing Effective Strategies. Technical Report. Association of Town & City Management, UK.' [Online] [Accessed on 14 August 2014]
http://learningcities2020.org/sites/default/files/downloads/Successful%20town%20centres%20-%20main%20report.pdf

Coca-Stefaniak, J. A. and Bagaeen, S. (2013) 'Strategic Management for Sustainable High Street Recovery.' *Town & Country Planning*, 82(12) pp. 532-537.

Coca-Stefaniak, J. A. and Carroll, S. (2015) 'Traditional or experiential places? Exploring research needs and practitioner challenges in the management of town centres beyond the economic crisis.' *Journal of Urban Regeneration & Renewal*, 9(1) pp. 38-45.

Coca-Stefaniak, J. A., Parker, C. and Rees, P. (2010) 'Localisation as a marketing strategy for small retailers.' *International Journal of Retail & Distribution Management*, 38(9) pp. 677-697.

Coca-Stefaniak, J. A., Parker, C., Quin, S., Rinaldi, R. and Byrom, J. (2009) 'Town centre management models: A European perspective.' *Cities*, 26(2) pp. 74-80.

Cohen, J. (1988) *Statistical power analysis for the behavioral sciences.* 2nd ed., Hillsdale, NJ: Lawrence Erlbaum.

Cohn, M. (2005) *Agile estimating and planning.* London;Upper Saddle River, N.J;: Prentice Hall PTR.

Cole, H. (1966) 'Shopping Assessments at Haydock and Elsewhere, A Review.' *Urban Studies*, 3(2) pp. 147 - 156.

Comber, S., Arribas-Bel, D., Singleton, A. and Dolega, L. (2020) 'Using convolutional autoencoders to extract visual features of leisure and retail environments.' *Landscape and Urban Planning*, 202

Comber, S., Arribas-Bel, D., Singleton, A., Dong, G. and Dolega, L. (2019) 'Building Hierarchies of Retail Centers Using Bayesian Multilevel Models.' *Annals of the American Association of Geographers*, 110(4) pp. 1150-1173.

Cooper, C. H. V., Harvey, I., Orford, S. and Chiaradia, A. J. F. (2019) 'Using multiple hybrid spatial design network analysis to predict longitudinal effect of a major city centre redevelopment on pedestrian flows.' *Transportation*, 48(2) pp. 643-672.

Copeland, A. (2012) 'Seasonality, consumer heterogeneity and price indexes: the case of prepackaged software.' *Journal of Productivity Analysis*, 39(1) pp. 47-59.

Copeland, M. T. (1923) 'Relation of Consumers' Buying Habits to Marketing Methods.' *Harvard Business Review*, 1(3) pp. 282-289.

Cotterill, E., Grail, J., Mitton, C., Ntounis, N., Parker, C., Quin, S., Smith, D., Steadman, C., et al. (2019) *A State-of-the-Art Review of Business Improvement Districts in the UK: Setting the agenda for policy, practice and research.* Manchester Metropolitan University: The BID Foundation.

Cousins, P. D., Lawson, B. and Squire, B. (2008) 'Performance measurement in strategic buyer-supplier relationships.' *International Journal of Operations & Production Management*, 28(3) pp. 238-258.

Cox, J., Thurstain-Goodwin, M. and Tomalin, C. (2000) *Town Centre Vitality & Viability: A Review of the Health Check Methodology.* 17/08/2016, University College London: Centre for Advanced Spatial Analysis (CASA Town Centres).

Craig, S. C., Ghosh, A. and McLafferty, S. L. (1984) 'Models of the Retail Location Process: A Review.' *Journal of Retailing*, 60(1) pp. 5-36.

Crang, M. (2001) 'Rhythms of the City: Temporalised Space and Motion.' *In* May, J. and Thrift, N. (eds.) *Timespace: Geographies of Temporality*. London: Routledge, pp. 187-207.

Cresswell, T. (2015) *Place, an introduction.* 2nd ed., Chichester: Wiley and Sons Ltd.

Cresswell, T. (2020) 'Valuing mobility in a post COVID-19 world.' *Mobilities*, 16(1) pp. 51-65.

Creswell, J. W. (2013) *Qualitative Inquiry & Research Design: Choosing Among Five Approaches.* 3rd ed., London: SAGE Publications Ltd.

Crewe, L. (2000) 'Geographies of retailing and consumption.' *Progress in Human Geography*, 24(2) pp. 275-290.

Crewe, L. (2001) 'The besieged body: geographies of retailing and consumption.' *Progress in Human Geography*, 25(4) pp. 629-640.

Crewe, L. (2003) 'Geographies of retailing and consumption: markets in motion.' *Progress in Human Geography*, 27(3) pp. 352-362.

D'Urso, P., Maharaj, E. A. and Alonso, A. M. (2017) 'Fuzzy clustering of time series using extremes.' *Fuzzy Sets and Systems*, 318 pp. 56-79.

D'Urso, P., De Giovanni, L. and Massari, R. (2018) 'Robust fuzzy clustering of multivariate time trajectories.' *International Journal of Approximate Reasoning*, 99 pp. 12-38.

D’Urso, P. and Massari, R. (2013) 'Fuzzy clustering of human activity patterns.' *Fuzzy Sets and Systems*, 215 pp. 29-54.

D’Urso, P., Massari, R., De Giovanni, L. and Cappelli, C. (2016) 'Exponential distance-based fuzzy clustering for interval-valued data.' *Fuzzy Optimization and Decision Making*, 16(1) pp. 51-70.

Dagum, E. B. (1980) *The X-11-ARIMA Seasonal Adjustment Method: Catalogue No. 12-564E.* Vol. Catalogue No. 12-564E. Ottawa: Statistics Canada.

Dargan, E. (2015) *A Qualitative Evaluation of Grocery Online Solutions for Rural Consumers, Retailers and Producers.* MSc. Manchester Metropolitan University.

Das, G. (2014) 'Store personality and consumer store choice behaviour: an empirical examination.' *Marketing Intelligence & Planning*, 32(3) pp. 375-394.

Davenport, T. H. (2006) 'Competing on analytics.' *Harvard Business Review*, 84(1) pp. 98-107.

Davenport, T. H., Harris, J. G. and Morison, R. (2010) *Analytics at Work: Smarter Decisions, Better Results.* Harvard Business School Press.

Davison Porter, I., Lawlor, D., McInroy, N., Parker, C., Prentice, P., Sparks, L. and Warnaby, G. (2017) 'The World Towns Framework: a call to action.' *Journal of Place Management and Development*, 10(5) pp. 504-520.

Dawson, J. A. (2013) *Retail geography.* Vol. 7. London: Routledge.

DCLG. (2006) *Producing boundaries and statistics for town centres: London Pilot Study Summary Report.* London: Department for Communities and Local Government.

DCLG. (2011) *A plain English guide to the Localism Act*. Department for Communities and Local Government. [Online] [Accessed https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/5959/1896534.pdf

DCLG. (2012) *National Planning Policy Framework*. [Online] [Accessed on 2016/10/08] https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/6077/2116950.pdf

De Beule, M., Van den Poel, D. and Van de Weghe, N. (2014) 'An extended Huff-model for robustly benchmarking and predicting retail network performance.' *Applied Geography*, 46 pp. 80-89.

De Certeau, M. (1984) *The Practice of Everyday Life.* London: University of California Press.

De Geuser, F., Mooraj, S. and Oyon, D. (2009) 'Does the Balanced Scorecard Add Value? Empirical Evidence on its Effect on Performance.' *European Accounting Review*, 18(1) pp. 93-122.

de Kervenoael, R., Hallsworth, A. and Clarke, I. (2006) 'Macro-level change and micro level effects: A twenty-year perspective on changing grocery shopping behaviour in Britain.' *Journal of Retailing and Consumer Services*, 13 pp. 381-392.

De Magalhães, C. (2012) 'Business Improvement Districts and the recession: Implications for public realm governance and management in England.' *Progress in Planning*, 77(4) pp. 143-177.

De Munck, B. (2016) 'Re-assembling Actor-Network Theory and urban history.' *Urban History*, 44(1) pp. 111 - 122.

De Nisco, A. and Warnaby, G. (2013) 'Shopping in downtown: The effect of urban environment on service quality perception and behavioural intentions.' *International Journal of Retail & Distribution Management*, 41(9) pp. 654-670.

De Nisco, A. and Warnaby, G. (2014) 'Urban design and tenant variety influences on consumers' emotions and approach behavior.' *Journal of Business Research*, 67(2) pp. 211-217.

De Nisco, A., Riviezzo, A. and Napolitano, M. R. (2008) 'The role of stakeholders in town centre management: guidelines for identification and analysis.' *Journal of Place Management and Development*, 1(2) pp. 166-176.

De Vos, J., Mokhtarian, P. L., Schwanen, T., Van Acker, V. and Witlox, F. (2015) 'Travel mode choice and travel satisfaction: bridging the gap between decision utility and experienced utility.' *Transportation*, 43(5) pp. 771-796.

Decoene, V. and Bruggeman, W. (2006) 'Strategic alignment and middle-level managers' motivation in a balanced scorecard setting.' *International Journal of Operations & Production Management*, 26(4) pp. 429-448.

Delage, M., Baudet-Michel, S., Fol, S., Buhnik, S., Commenges, H. and Vallée, J. (2020) 'Retail decline in France's small and medium-sized cities over four decades. Evidences from a multi-level analysis.' *Cities*, 02/06/2020, 25 May 2020,

DeLanda, M. (2006) *A New Philosophy of Society. Assemblage Theory and Social Complexity.* London: Continuum.

DeLanda, M. (2016) *Assemblage Theory.* Edinburgh: Edinburgh University Press Ltd.

DeLanda, M. and Harman, G. (2017) *The Rise of Realism.* Cambridge, UK: Polity Press.

Deleuze, G. (1988) *Bergonism.* New York: Zone Books.

Deleuze, G. and Guattari, F. (1988) *A Thousand Plateaus.* London: Bloomsbury Academic.

Deloitte. (2013) *The Deloitte Consumer Review: Reinventing the role of the high street*. Deloitte. [Online] [Accessed on 12/08/2014] http://www.deloitte.com/assets/Dcom-UnitedKingdom/Local%20Assets/Documents/Industries/Consumer%20Business/uk-cb-consumer-review-edition-6.pdf

Demirhan, H. and Renwick, Z. (2018) 'Missing value imputation for short to mid-term horizontal solar irradiance data.' *Applied Energy*, 225 pp. 998-1012.

Dempster, A. P., Laird, N. M. and Rubin, D. B. (1977) 'Maximum Likelihood from Incomplete Data via the EM Algorithm.' *Journal of the Royal Statistical Society. Series B (Methodological)*, 39(1) pp. 1-38.

Deng, H., Runger, G., Tuv, E. and Vladimir, M. (2013) 'A time series forest for classification and feature extraction.' *Information Sciences*, 239 pp. 142-153.

Dennis, C., Marsland, D. and Cockett, T. (2002) 'Central place practice: shopping centre attractiveness measures, hinterland boundaries and the UK retail hierarchy.' *Journal of Retaling and Consumer Services*, 9 pp. 185-199.

Department for Communities and Local Government. (2015) *Business Improvement Districts - Technical Guide for Local Authorities*. London: Department for Communities and Local Government. [Online] [Accessed on 13/05/2020] https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/415990/BIDs_Technical_Guidance.pdf

Dewsbury, J. D. (2003) 'Witnessing space: `knowledge without contemplation'.' *Environment and Planning A*, 35(11) pp. 1907-1932.

Dewsbury, J. D. (2011) 'The Deleuze-Guattarian assemblage: plastic habits.' *Area*, 43(2) pp. 148-153.

Di Caro, L., Frias-Martinez, V. and Frias-Martinez, E. (2010) Analyzing The Role Of Dimension Arrangement For Data Visualization in Radviz. In: M.J., Z., J.X., Y., B., R. and V., P. *Advances in Knowledge Discovery and Data Mining. PAKDD 2010. Lecture Notes in Computer Science.* Vol. 6119. Berlin, Heidelberg: Springer.

Dickinson, R. E. (1932) 'The Distribution and Functions of the Smaller Urban Settlements of East Anglia.' *Geography*, 17(1) pp. 19-31.

Digital High Street Advisory Board. (2015) *The Digital High Street 2020 Report*. [Online] [Accessed on 04/10/2015] http://thegreatbritishhighstreet.co.uk/pdf/Digital_High_Street_Report/The-Digital-High-Street-Report-2020.pdf

Dittmer, J. (2014a) 'Narrating urban assemblages—Chris Ware and Building Stories.' *Social & Cultural Geography*, 15(5) pp. 477-503.

Dittmer, J. (2014b) 'Geopolitical assemblages and complexity.' *Progress in Human Geography*, 38(3) pp. 385-401.

Dobson, J. (2016) 'Rethinking town centre economies: Beyond the 'place or people binary.' *Local Economy*, 31(3) pp. 335-343.

DoE. (1996) *Planning Policy Guidance No. 6: Town Centres and Retail Developments, Revised PPG6.* The Stationery Office (ed.) London: Department of Environment.

Doherty, N. F. and Ellis-Chadwick, F. E. (2006) 'New perspectives in internet retailing: a review and strategic critique of the field.' *International Journal of Retail & Distribution Management*, 34(4/5) pp. 411-428.

Dokumentov, A. and Hyndman, R. J. (2015) 'STR: A Seasonal-Trend Decomposition Procedure Based on Regression. Working Paper 13/15.' Presentation at Monash University, Department of Econometrics and Business Statistics, Dolega, L. and Lord, A. L. (2020) 'Exploring the geography of retail decline: A case study of the Liverpool City Region.' *Cities*, 96

Dolega, L., Pavlis, M. and Singleton, A. (2016) 'Estimating attractiveness, hierarchy and catchment area extents for a national set of retail centre agglomerations.' *Journal of Retailing and Consumer Services*, 28 pp. 78-90.

Dolega, L., Reynolds, J., Singleton, A. and Pavlis, M. (2021) 'Beyond retail: New ways of classifying UK shopping and consumption spaces.' *Environment and Planning B: Urban Analytics and City Science*, 48(1) pp. 132-150.

Donaghy, M., Findlay, A. and Sparkes, L. (2013) 'The evaluation of Business Improvement Districts: Questions and issues from the Scottish experience.' *Local Economy*, 28(5) pp. 471-487.

Dossi, A. and Pateli, L. (2010) 'You Learn From What You Measure: Financial and Non- financial Performance Measures in Multinational Companies.' *Long Range Planning*, 43 pp. 498-526.

Dovey, K. (2012) 'Informal Urbanism and Complex Adaptive Assemblage.' *International Development Planning Review*, 34(4) pp. 349-367.

Dovey, K., Rao, F. and Pafka, E. (2018) 'Agglomeration and assemblage: Deterritorialising urban theory.' *Urban Studies*, 55(2) pp. 263-273.

Drucker, P. F. (2007) *The Practice of Management.* Revised ed., London: Butterworth-Heinemann.

Ducatel, K. J. and Blomley, N. k. (1990) 'Rethinking Retail Capital.' *International Journal of Urban and Regional Research*, 14(2) pp. 207-227.

Duffy, P. and Stojanovic, T. (2017) 'The potential for Assemblage thinking in population geography: Assembling population, space, and place.' *Population, Space and Place*, e2097 pp. 1-18.

Easton, G. (2010) 'Critical realism in case study research.' *Industrial Marketing Management*, 39(1) pp. 118-128.

Edensor, T. (2010) 'Introduction: thinking about rhythm and space.' *In* Edensor, T. (ed.) *Geographies of rhythm: nature, place, mobilities and bodies*. Farnham, UK: Ashgate Publishing,

Edensor, T. and Holloway, J. (2008) 'Rhythmanalysing the Coach Tour: The Ring of Kerry, Ireland.' *Transactions of the Institute of British Geographers, New Series*, 33(4) pp. 483-501.

Elkin, L. (2016) *Flâneuse. Women Walk in the City in Paris, New York, Tokyo, Venice and London.* London: Penguin Random House.

Elms, J., de Kervenoael, R. and Hallsworth, A. (2016) 'Internet or store? An ethnographic study of consumers' internet and store-based grocery shopping practices.' *Journal of Retailing and Consumer Services*, 32 pp. 234-243.

Eppli, M. J. and Benjamin, J. D. (1994) 'The Evolution of Shopping Center Research: A Review and Analysis.' *The Journal of real estate research*, 9(1) pp. 5-32.

Escobar, A. (2001) 'Culture sits in places: reflections on globalism and subaltern strategies of localization.' *Political Geography*, 20(2) pp. 139-174.

Escobar, A. (2007) 'The 'Ontological Turn' in Social Theory. A Commentary on 'Human Geography without Scale',.' *Transactions of the Institute of British Geographers, New Series*, 32(1) pp. 106-111.

Eurostat. (2018) *Handbook on Seasonal Adjustment*. Manuals and Guidelines. Luxembourg: Publications Office of the European Union. [Online] [Accessed on 25/11/2019] https://ec.europa.eu/eurostat/documents/3859598/8939616/KS-GQ-18-001-EN-N.pdf

Everitt, B. S., Landau, S., Leese, M. and Stahl, D. (2011) *Cluster Analysis.* 5th ed., Chichester, UK: John Wiley & Sons Ltd.

Fayyad, U., Piatetsky-Shapiro, G. and Smyth, P. (1996) 'From data mining to knowledge discovery in databases.' *AI Magazine*, 17(3) pp. 37-53.

Featherstone, D. (2011) 'On assemblage and articulation.' *Area*, 42(2) pp. 139-142.

Feil, B., Balasko, B. and Abonyi, J. (2006) 'Visualization of fuzzy clusters by fuzzy Sammon mapping projection: application to the analysis of phase space trajectories.' *Soft Computing*, 11(5) pp. 479-488.

Fent, G., Gosai, J. and Purva, M. (2016) 'A randomized control trial comparing use of a novel electrocardiogram simulator with traditional teaching in the acquisition of electrocardiogram interpretation skill.' *Journal of Electrocardiology*, 49(2), Mar-Apr, 2015/12/29, pp. 112-116.

Fernández-Morales, A. and Cisneros-Martínez, J. D. (2019) 'Seasonal Concentration Decomposition of Cruise Tourism Demand in Southern Europe.' *Journal of Travel Research*, 58(8) pp. 1389-1407.

Ferreira, A. and Otley, D. (2009) 'The design and use of performance management systems: An extended framework for analysis.' *Management Accounting Research*, 20(4) pp. 263-282.

FHSF. (2013) *Future High Streets Forum*. GOV.UK. [Online] [Accessed on 22/03/2021] https://www.gov.uk/government/groups/future-high-streets-forum

Findley, D. F., Monsell, B. C., Bell, W. R., Otto, M. C. and Chen, B.-C. (1998) 'New Capabilities and Methods of the X-12-ARIMA Seasonal-Adjustment Program.' *Journal of Business & Economic Statistics*, 16(2) pp. 127-152.

Folan, P. and Browne, J. (2005) 'A review of performance measurement: Towards performance management.' *Computers in Industry*, 56(7) pp. 663-680.

Foucault, M. (2009) *Security, Territory, Population: Lectures at the Collège de France, 1977-78.* Senellart, M. (ed.) Basingstoke: Palgrave Macmillan.

Franco-Santos, M., Lucianetti, L. and Bourne, M. (2012) 'Contemporary performance measurement systems: A review of their consequences and a framework for research.' *Management Accounting Research*, 23(2) pp. 79-119.

Franco-Santos, M., Bourne, M., Kennerley, M., Micheli, P., Martinez, V., Mason, S., Marr, B., Gray, D., et al. (2007) 'Towards a definition of a business performance measurement system.' *International Journal of Operations & Production Management*, 27(8) pp. 784-801.

Frank, L. D., Sallis, J. F., Saelens, B. E., Leary, L., Cain, K., Conway, T. L. and Hess, P. M. (2010) 'The development of a walkability index: application to the Neighborhood Quality of Life Study.' *Br J Sports Med*, 44(13), Oct, 2009/05/02, pp. 924-933.

Frawley, W. J., Piatetsky-Shapiro, G. and Matheus, C. J. (1992) 'Knowledge Discovery in Databases: An Overview.' *AI Magazine* 13 pp. 57-70.

Frazier, M. (2020) *R color cheatsheet*. [Online] [Accessed on 17/04/2020] https://www.nceas.ucsb.edu/sites/default/files/2020-04/colorPaletteCheatsheet.pdf

Freathy, P. and Calderwood, E. (2013) 'The impact of internet adoption upon the shopping behaviour of island residents.' *Journal of Retailing and Consumer Services*, 20(1) pp. 111-119.

Friedmann, J. (2010) 'Place and Place-Making in Cities: A Global Perspective.' *Planning Theory & Practice*, 11(2) pp. 149-165.

Fryer, K., Antony, J. and Ogden, S. (2009) 'Performance management in the public sector.' *International Journal of Public Sector Management*, 22(6) pp. 478-498.

Fu, T.-c. (2011) 'A review on time series data mining.' *Engineering Applications of Artificial Intelligence*, 24 pp. 164-181.

Fujita, M., Krugman, P. and Venables, A. J. (2001) *The Spatial Economy: Cities, Regions and International Trade.* London: The MIT Press.

Fulcher, B. D. and Jones, N. S. (2014) 'Highly Comparative Feature-Based Time-Series Classification.' *IEEE Transactions on Knowledge and Data Engineering*, 26(12) pp. 3026-3037.

Gale, T. and Botterill, D. (2005) 'A realist agenda for tourist studies, or why destination areas really rise and fall in popularity.' *Tourist Studies*, 5(2) pp. 151-174.

Gallagher, M. and Trendafilov, R. (2018) 'R vs. PYTHON: Ease of use and Numerical Accuracy.' *Journal of Business and Accounting*, 11(1) pp. 117-126.

Gaston, S. (2013) 'Derrida and the Eco-Polemicists.' *PARAGRAPH*, 36(3) pp. 344-360.

Gehl, J. (2010) *Cities for People.* London: Island Press.

Gehl, J. (2011) *Life Between Buildings - Using Public Space.* London: Island Press.

Gehl, J. and Svarre, B. (2013) *How to Study Public Life.* London: Island Press.

Ghosh, A. (1984) 'Parameter nonstationarity in retail choice models.' *Journal of Business Research*, 12(4) pp. 425–436.

Ghosh, A. and McLafferty, S. L. (1982) 'Locating Stores in uncertain environments: A scenario planning approach.' *Journal of Retailing*, 58(4) pp. 5-22.

Giddens, A. (1984) *The Constitution of Society.* Berkeley, CA: Univeristy of California Press.

Giglio, S., Bertacchini, F., Bilotta, E. and Pantano, P. (2019) 'Using social media to identify tourism attractiveness in six Italian cities.' *Tourism Management*, 72 pp. 306-312.

Gimbert, X., Bisbe, J. and Mendoza, X. (2010) 'The Role of Performane Measurement Systems in Strategy Formulation Processes.' *Long Range Planning*, 43 pp. 477-497.

Giorgino, T. (2009) 'Computing and Visualizing Dynamic Time Warping Alignments in R: The dtw Package.' *Journal of Statistical Software*, 31(7) pp. 1-24.

Giorgino, T. (2018) *Package ‘dtw’ - Dynamic Time Warping Algorithms*. [Online] [Accessed on 03/06/2019] https://cran.r-project.org/web/packages/dtw/dtw.pdf

Godener, A. and Söderquist, K. E. (2004) 'Use and impact of performance measurement results in R&D and NPD: an exploratory study.' *R&D Management*, 34(2) pp. 191-219.

Godin, B. (2003) 'The emergence of S&T indicators: why did governments supplement statistics with indicators?' *Research Policy*, 32 pp. 679-691.

González, M. C., Hidalgo, C. A. and Barabási, A.-L. (2008) 'Understanding Individual Human Mobility Patterns.' *Nature*, 453(5) pp. 779-782.

Goodchild, M. F. and Janelle, D. G. (1984) 'The city around the clock: space-time patterns of urban ecological structure.' *Environment and Planning A*, 16(6) pp. 807-820.

Grafton, J., Lillis, A. M. and Widener, S. K. (2010) 'The role of performance measurement and evaluation in building organizational capabilities and performance.' *Accounting, Organizations and Society*, 35(7) pp. 689-706.

Graham, C., Khan, K. and Ilyas, M. (2019) 'Estimating the value of passing trade from pedestrian density.' *Journal of Retailing and Consumer Services*, 46 pp. 103-111.

Grail, J., Mitton, C., Ntounis, N., Parker, C., Quin, S., Steadman, C., Warnaby, G., Cotterill, E., et al. (2019) 'Business improvement districts in the UK: a review and synthesis.' *Journal of Place Management and Development*, 13(1) pp. 73-88.

Greenhough, B. (2011) 'Assembling an island laboratory.' *Area*, 43(2) pp. 134-138.

Gregory, D. (1984) 'Space, Time and Politics in Social Theory: an interview with Anthony Giddens.' *Environment and Planning D: Society and Space*, 2(2) pp. 123-132.

Gregory, D. (2009) *The Dictionary of Human Geography.* 5th ed. ed., Chichester: Wiley-Blackwell.

Grimsey, B. (2013) *The Grimsey Review*. [Online] [Accessed on 30/07/2014] http://www.vanishinghighstreet.com/the-grimsey-review/

Grimsey, B. (2018) 'The Grimsey Review 2.' [Online] [Accessed on 20/07/2020] http://www.vanishinghighstreet.com/wp-content/uploads/2018/07/GrimseyReview2.pdf

Guimarães, P. P. (2013) 'The tools for city centre revitalization in Portugal.' *Journal of Place Management and Development*, 6(1) pp. 52-66.

Guy, C. M. (1994) *The retail development process: location, property and planning.* London: Routledge.

Guy, C. M. (1998) 'Classifications of retail stores and shopping centres: some methodological issues.' *GeoJournal*, 45(4) pp. 255-264.

Habermas, J. (1987) *The Theory of Communicative Action. Volume 2. Lifeworld and System: A Critique of Functionalist Reason.* Boston: Beacon Press.

Hadiloo, S., Mirzaei, S., Hashemi, H. and Beiranvand, B. (2018) 'Comparison between unsupervised and supervised fuzzy clustering method in interactive mode to obtain the best result for extract subtle patterns from seismic facies maps.' *Geopersia*, 8(1) pp. 27-34.

Hafen, R. P., Anderson, D. E., Cleveland, W. S., Maciejewski, R., Ebert, D. S., Abusalah, A., Yakout, M., Ouzzani, M., et al. (2009) 'Syndromic surveillance: STL for modeling, visualizing, and monitoring disease counts.' *BMC Med Inform Decis Mak*, 9, Apr 21, 2009/04/23, p. 21.

Hägerstrand, T. (1970) 'Reflections on "what about people in regional science?".' *Papers of the Regional Science Association*, 66(1) pp. 1-6.

Håkansson, J., Lagin, M. and Wennström, J. (2017) 'Town centre cooperation: changing perception of property owners.' *International Journal of Retail & Distribution Management*, 45(11) pp. 1200-1212.

Haklay, M., O'Sullivan, D. and Thurstain-Goodwin, M. (2001) '``So go downtown'': simulating pedestrian movement in town centres.' *Environment and Planning B: Planning and Design*, 28(3) pp. 343-359.

Halkidi, M., Batistakis, Y. and Vazirgiannis, M. (2001) 'On Clustering Validation Techniques.' *Journal of Intelligent Information Systems*, 17(2:3) pp. 107–145.

Hall, M. (2008) 'The effect of comprehensive performance measurement systems on role clarity, psychological empowerment and managerial performance.' *Accounting, Organizations and Society*, 33(2-3) pp. 141-163.

Hall, P., Marshall, S. and Lowe, M. (2001) 'The Changing Urban Hierarchy in England and Wales, 1913–1998.' *Regional Studies*, 35(9) pp. 775-807.

Hall, S. (2011) 'High street adaptations: ethnicity, independent retail practices, and Localism in London's urban margins.' *Environment and Planning A*, 43(11) pp. 2571-2588.

Hallsworth, A. and Coca-Stefaniak, J. A. (2018) 'National high street retail and town centre policy at a cross roads in England and Wales.' *Cities*, 79 pp. 134-140.

Hallsworth, A., Ntounis, N., Parker, C. and Quin, S. (2015) *Markets Matter - Reviewing the evidence & detecting the market effect*. Manchester Metropolitan University: Institute of Place Management. [Online] [Accessed on 28/12/15] http://www.placemanagement.org/media/19883/markets-matter-final.pdf

Hamel, G. (2009) 'Moon Shots for Management.' *Harvard Business Review*, 87(2) pp. 91-98.

Harman, G. (2008) 'DeLanda's ontology: assemblage and realism.' *Continental Philosophy Review*, 41(3) pp. 367-383.

Harrington, A. (2006) 'Lifeworld.' *Theory, Culture & Society*, Vol 23(2-3) pp. 341-343.

Harrison, G. and Feuerstein, S. (2009) *MySQL Stored Procedure Programming.* Russell, D. (ed.) Cambridge: O'Reilly.

Hart, C., Stachow, G. and Cadogan, J. W. (2013) 'Conceptualising town centre image and the customer experience.' *Journal of Marketing Management*, 29(15-16) pp. 1753-1781.

Hart, C., Stachow, G., Rafiq, M. and Laing, A. (2014) *The Customer Experience of Town Centres.* Leicestershire: Loughborough University.

Hartshorne, R. (1959) *Perspective on the Nature of Geography.* Chicago: Rand McNally for the Association of American Geographers.

Harvey, D. (1990) *The Condition of Postmodernity.* Oxford: Blackwell.

Harvey, D. (1996) *Justice, nature and the geography of difference.* Oxford: Blackwell.

Haslwanter, T. (2016) *An Introduction to Statistics in Python: with Applications in the Life Sciences.* Statistics and Computing. Switzerland: Springer.

Hass-Klau, C. (1993) 'Impact of pedestrianization and traffic calming on retailing. A review of the evidence from Germany and the UK.' *Transport Policy*, 1(1) pp. 21-31.

Hathaway, R. J. and Bezdek, J. C. (2003) 'Visual cluster validity for prototype generator clustering models.' *Pattern Recognition Letters*, 24(9-10) pp. 1563-1569.

Hawkins, C. J. and Lee-Anne, J. R. (2013) 'Festival spaces as third places.' *Journal of Place Management and Development*, 6(3) pp. 192-202.

HCLGC. (2019) *High Streets and Town Centres in 2030. .* HC 1010, UK: House of Commons, Housing, Communities and Local Government Committee.

Heidigger, M. (1971) 'Building Dwelling Thinking.' *In Poetry, language, and thought*. New York: Harper & Row, pp. 145-161.

Herhausen, D., Binder, J., Schoegel, M. and Herrmann, A. (2015) 'Integrating Bricks with Clicks: Retailer-Level and Channel-Level Outcomes of Online–Offline Channel Integration.' *Journal of Retailing*, 91(2) pp. 309-325.

Hernando, A., Hernando, R. and Plastino, A. (2014) 'Space-time correlations in urban sprawl.' *J R Soc Interface*, 11(91), Feb 6, p. 20130930.

Hesselmann, F. and Schendzielorz, C. (2019) 'Evaluations as value-measurement links: Exploring metrics and meanings in science.' *Social Science Information*, 58(2) pp. 282-300.

(2021) *COVID-19 Intelligence and Impact. February 2021 Update.* UK: High Street Task Force. (High Street Task Force Report)

Hill, T., Canniford, R. and Mol, J. (2014) 'Non-representational marketing theory.' *Marketing Theory*, 14(4) pp. 377-394.

Hillier, B., Penn, A., Hanson, J. and Grajewski, J. X. (1993) 'Natural movement: or, configuration and attraction in urban oedestrian movement.' *Environment and Planning B: Planning and Design*, 20(1) pp. 29-66.

Hills, J., Lines, J., Baranauskas, E., Mapp, J. and Bagnall, A. (2013) 'Classification of time series by shapelet transformation.' *Data Mining and Knowledge Discovery*, 28(4) pp. 851-881.

Hinchliffe, S., Kearnes, M. B., Degen, M. and Whatmore, S. (2016) 'Urban Wild Things: A Cosmopolitical Experiment.' *Environment and Planning D: Society and Space*, 23(5) pp. 643-658.

Hoffman, D. L. and Novak, T. P. (2018) 'Consumer and Object Experience in the Internet of Things: An Assemblage Theory Approach.' *Journal of Consumer Research*, 44(6) pp. 1178-1204.

Hoffman, P., Grinstein, G. and Pinkney, D. (1999) 'Dimensional Anchors: A Graphic Primitive for Multidimensional Multivariate Information Visualizations.' *In NPIVM '99: Proceedings of the 1999 workshop on new paradigms in information visualization and manipulation in conjunction with the eighth ACM internation conference on Information and knowledge management*. Kansas City Missouri USA, Association for Computing Machinery, New York, NY, United States, pp. 9-16.

Hogg, S., Medway, D. and Warnaby, G. (2004) 'Town centre management schemes in the UK: Marketing and performance indicators.' *International Journal of Nonprofit and Voluntary Sector Marketing*, 9(4) pp. 309-319.

Hogg, S., Medway, D. and Warnaby, G. (2007) 'Performance Measurement in UK Town Centre Management Schemes and US Business Improvement Districts: Comparisons and UK Implications.' *Environment and Planning A*, 39(6) pp. 1513-1528.

Holten, D. and Van Wijk, J. J. (2010) 'Evaluation of Cluster Identification Performance for Different PCP Variants.' *Computer Graphics Forum*, 29(3) pp. 793-802.

Hood, C. (1991) 'A Public Management For All Seasons?' *Public Administration*, 69 pp. 3-19.

Hoogendoorn, S. P. and Bovy, P. H. L. (2004) 'Pedestrian route-choice and activity scheduling theory and models.' *Transportation Research Part B*, 38 pp. 169-190.

Hossain, M. A. and Cooper, C. H. V. (2021) 'Spatial network analysis as a tool for measuring change in accessibility over time: Limits of transport investment as a driver for UK regional development.' *Growth and Change*,

Hotelling, H. (1929) 'Stability in Competition.' *The Economic Journal*, 39(153) pp. 41-57.

Houghton, M. (1997) 'Performance indicators in town planning: much ado about nothing?' *Local Government Studies*, 23(2) pp. 1-13.

Hoyt, H. (1939) *Structure and Growth of Residential Neighbourhoods in American Cities.* Washington DC: Federal Housing Administration.

Hoyt, L. and Gopal-Agge, D. (2007) 'The Business Improvement District Model: A Balanced Review of Contemporary Debates.' *Geography Compass*, 1(4) pp. 946-958.

HSTF. (2020) 'COVID-19 Recovery Framework.' *High Streets Task Force*. [Online] [Accessed on 02/01/2021] https://www.highstreetstaskforce.org.uk/covid-19/covid-19-recovery-framework/

Huff, D. L. (1964) 'Defining and Estimating a Trading Area.' *Journal of Marketing*, 28(3) pp. 34-38.

Hyndman, R. and Khandakar, Y. (2008) 'Automatic time series forecasting: the forecast package for R.' *Journal of Statistical Software*, 26(3) pp. 1-22.

Hyndman, R. and Athanasopoulos, G. (2018) Forecasting: principles and practice. (25/11/2019) 2nd ed. Melbourne, Australia: OTexts.

Hyndman, R., Athanasopoulos G, Bergmeir C, Caceres G, Chhay L, O'Hara-Wild M, Petropoulos F, Razbash, et al. (2019a) *forecast: Forecasting functions for time series and linear models (R package version 8.6)*. [Online] [Accessed on 03/06/2019] URL: http://pkg.robjhyndman.com/forecast

Hyndman, R., Athanasopoulos, G., Bergmeir, C., Caceres, G., Chhay, L., O'Hara-Wild, M., Petropoulos, F., Razbash, S., et al. (2019b) *Package 'forecast' - Forecasting Functions for Time Series and Linear Models*. [Online] [Accessed on 03/06/2019] https://CRAN.R-project.org/package=forecast

Information Week India. (2019) 'Python Beats R and SAS in Analytics Tool Survey.' *Information Week India.* 2019/09/03/.

Ingold, T. (2007) *Lines.* Abingdon, Oxon: Routledge Classics.

Institute of Place Management. (2021) *Building Capacity for Placemaking: High Streets Task Force*. [Online] [Accessed on 22/02/2021] https://www.placemanagement.org/research/high-streets-task-force/

Ittner, C. D. and Larcker, D. F. (2003) 'Coming Up Short on Nonfinancial Performance Measurement.' *Harvard Business Review*, 81(11) pp. 88-95.

Izakian, H., Pedrycz, W. and Jamal, I. (2015) 'Fuzzy clustering of time series data using dynamic time warping distance.' *Engineering Applications of Artificial Intelligence*, 39 pp. 235-244.

Jackson, C. (2001) 'A Model of Spatial Patterns across Local Retail Property Markets in Great Britain.' *Urban Studies*, 38(9) pp. 1445-1471.

Jackson, V. P. and Stoel, L. (2011) 'A qualitative examination of decoupling, recoupling and organizational survival of rural retailers.' *Qualitative Market Research: An International Journal*, 14(4) pp. 410-428.

Jacobs, J. (1961) *The death and life of great American cities.* New York: Vintage.

Jagosh, J. (2020) 'Retroductive theorizing in Pawson and Tilley's applied scientific realism.' *Journal of Critical Realism*, 19(2) pp. 121-130.

Jeong, Y.-S., Jeong, M. K. and Omitaomu, O. A. (2011) 'Weighted dynamic time warping for time series classification.' *Pattern Recognition*, 44(9) pp. 2231-2240.

Johnson, H. T. and Kaplan, R. S. (1987) *Relevance Lost - The Rise and Fall of Management Accounting.* Boston, MA: Harvard Business School Press.

Johnston, R., Harris, R., Jones, K., Manley, D., Wang, W. W. and Wolf, L. (2018) 'Quantitative methods I: The world we have lost – or where we started from.' *Progress in Human Geography*, 43(6) pp. 1133-1142.

Jones, C. (2020) 'Reframing the intra-urban retail hierarchy.' *Cities*, 2020/11/26/, p. 103037.

Kabacoff, R. I. (2015) *R in Action: Data Analysis and Graphics in R.* 2nd ed., Shelter Island, NY 11964: Manning Publications Co.

Kahle, D. and Wickham, H. (2013) 'ggmap: Spatial Visualization with ggplot2.' *The R Journal*, 5(1) pp. 144-161.

Kahneman, D. and Thaler, R. H. (2006) 'Anomalies: Utility Maximization and Experienced Utility.' *The Journal of Economic Perspectives*, 20(1) pp. 221-234.

Kahneman, D., Wakker, P. P. and Sarin, R. (1977) 'Back to Bentham? Explorations of Experienced Utility.' *The Quarterly Journal of Economics*, 112(2) pp. 375-405.

Kang, Y., Fukahori, K. and Kubota, Y. (2018) 'Evaluation of the influence of roadside non-walking spaces on the pedestrian environment of a Japanese urban street.' *Sustainable Cities and Society*, 43 pp. 21-31.

Kaplan, R. S. and Norton, D. P. (1992) 'The balanced scorecard: measures that drive performance.' *Harvard Business Review*, 70(1) pp. 71-79.

Kaplan, R. S. and Norton, D. P. (1993) 'Putting the Balanced Scorecard to Work.' *Harvard Business Review*, 65(5) pp. 132-142.

Kärrholm, M. (2008) 'The Territorialisation of a Pedestrian Precinct in Malmö: Materialities in the Commercialisation of Public Space.' *Urban Studies*, 45(9) pp. 1903-1924.

Kärrholm, M. (2009) 'To the rhythm of shopping—on synchronisation in urban landscapes of consumption.' *Social & Cultural Geography*, 10(4) pp. 421-440.

Kärrholm, M. (2012) *Retailising space: architecture, retail and the territorialisation of public space.* London: Ashgate Publishing.

Kärrholm, M. (2016) 'The temporality of territorial production – the case of Stortorget, Malmö.' *Social & Cultural Geography*, 18(5) pp. 683-705.

Kärrholm, M. and Wirdelöv, J. (2019) 'The Neighbourhood in Pieces: The Fragmentation of Local Public Space in a Swedish Housing Area.' *International Journal of Urban and Regional Research*, 43(5) pp. 870-887.

Kate, R. J. (2015) 'Using dynamic time warping distances as features for improved time series classification.' *Data Mining and Knowledge Discovery*, 30(2) pp. 283-312.

Kaufman, L. and Rousseeuw, P. J. (2005) *Finding groups in data: an introduction to cluster analysis.* Chichester;Hoboken, N.J;: Wiley.

Kelling, S., Hochachka, W. M., Fink, D., Riedewald, M., Caruana, R., Ballard, G. and Hooker, G. (2009) 'Data-intensive Science: A New Paradigm for Biodiversity Studies.' *BioScience*, 59(7) pp. 613-620.

Kelsey, T. and Kenny, M. (2021) *Townscapes: 7. The Value of Social Infrastructure.* Policies Report Series. University of Cambridge: Bennett Institute for Public Policy.

Keogh, E. and Kasetty, S. (2003) 'On the Need for Time Series Data Mining Benchmarks: A Survey and Empirical Demonstration.' *Data Mining and Knowledge Discovery*, 7(4) pp. 349-371.

Keogh, E. and Lin, J. (2004) 'Clustering of time-series subsequences is meaningless: implications for previous and future research.' *Knowledge and Information Systems*, 8(2) pp. 154-177.

Kerr, W. R. and Kominers, S. D. (2015) 'Agglomerative Forces and Cluster Shapes.' *Review of Economics and Statistics*, 97(4) pp. 877-899.

Khoo-Lattimore, C., Prayag, G. and Disegna, M. (2019) 'Me, My Girls, and the Ideal Hotel: Segmenting Motivations of the Girlfriend Getaway Market Using Fuzzy C-Medoids for Fuzzy Data.' *Journal of Travel Research*, 58(5) pp. 774-792.

Killick, R. and Eckley, I. (2014) 'changepoint: An R Package for Changepoint Analysis.' *Journal of Statistical Software*, 58(3) pp. 1-19.

Kim, S., Park, S. and Lee, J. S. (2014) 'Meso- or micro-scale? Environmental factors influencing pedestrian satisfaction.' *Transportation Research Part D: Transport and Environment*, 30 pp. 10-20.

Kimball, R. and Ross, M. (2013) *The Data Warehouse Toolkit: The Definitive Guide to Dimensional Modeling.* 3rd ed., Indianapolis, IN 46256, USA: John Wiley & Sons Inc.

Kinkaid, E. (2019) 'Assemblage as ethos: Conceptual genealogies and political problems.' *Area*, pp. 1-8. [Online] [Accessed on 05/12/2019] https://doi.org/10.1111/area.12600

Kirkup, M. (1999) 'Electronic footfall monitoring: experiences among UK clothing multiples.' *International Journal of Retail & Distribution Management*, 27(4) pp. 166-173.

Kitchin, R. (2014a) 'Big Data, new epistemologies and paradigm shifts.' *Big Data & Society*, 1(1) pp. 1-12.

Kitchin, R. (2014b) 'The Reframing of Science, Social Science and Humanities Research.' *In The Data Revolution: Big Data, Open Data, Data Infrastructures & Their Consequences*. London: SAGE Publications Ltd, pp. 128-148.

Kitchin, R., Lauriault, T. P. and McArdle, G. (2015) 'Knowing and governing cities through urban indicators, city benchmarking and real-time dashboards.' *Regional Studies, Regional Science*, 2(1) pp. 6-28.

Kolehmainen, K. (2010) 'Dynamic Strategic Performance Measurement Systems: Balancing Empowerment and Alignment.' *Long Range Planning*, 43 pp. 527-554.

Koufteros, X., Verghese, A. and Lucianetti, L. (2014) 'The effect of performance measurement systems on firm performance: A cross-sectional and a longitudinal study.' *Journal of Operations Management*, 32(6) pp. 313-336.

Krishnapuram, R., Joshi, A., Nasraoui, O. and Yi, L. (2001) 'Low-Complexity Fuzzy Relational Clustering Algorithms for Web Mining.' *IEEE Transactions on Fuzzy Systems*, 9(4) pp. 595-607.

Kroll, A. (2011) 'On Choosing the Fuzziness Parameter for Identifying TS Models with Multidimensional Membership Functions.' *Journal of Artificial Intelligence and Soft Computing Research*, 4(1) pp. 283-300.

Kruskal, J. B. and Liberman, M. (1983) 'The symmetric time-warp problem: From continuous to discrete.' *In* Sankoff, D. and Kruskal, J. B. (eds.) *Time Warps, String Edits, and Macromolecules: The Theory and Practice of Sequence Comparison*. London: Addison-Wesley Publishing Company, Inc, pp. 125-161.

Kwan, M.-P. (2002) 'Feminist Visualization: Re-envisioning GIS as a Method in Feminist Geographic Research.' *Annals of the Association of American Geographers*, 92(4) pp. 645-661.

Kwan, M.-P. (2018) 'The Limits of the Neighborhood Effect: Contextual Uncertainties in Geographic, Environmental Health, and Social Science Research.' *Annals of the American Association of Geographers*, 108(6) pp. 1482-1490.

Kyriakidis, P. C., Miller, N. L. and Kim, J. (2004) 'A spatial time series framework for simulating daily precipitation at regional scales.' *Journal of Hydrology*, 297(1-4) pp. 236-255.

Lamont, M. (2012) 'Toward a Comparative Sociology of Valuation and Evaluation.' *Annual Review of Sociology*, 38(1) pp. 201-221.

Latham, A. and McCormack, D. (2004) 'Moving cities: rethinking the materialities of urban geographies.' *Progress in Human Geography*, 28(6) pp. 701-724.

Latour, B. (2005) *Reassembling the Social.* Oxford: Oxford University Press.

Law, J. (2009) 'Actor-Network Theory and Material Semiotics.' *In* Turner, B. (ed.) *The New Blackwell Companion to Social Theory*. Oxford: Blackwell, pp. 141-158.

Lazer, D., Pentland, A., Adamic, L., Aral, S., Barabási, A.-L. s., Brewer, D., Christakis, N., Contractor, N., et al. (2009) 'Computational Social Science.' *Science, New Series*, 323(5915) pp. 721-723.

Le Feuvre, M., Medway, D., Warnaby, G., Ward, K. and Goatman, A. (2016) 'Understanding stakeholder interactions in urban partnerships.' *Cities*, 52 pp. 55-65.

Lefebvre, H. (1991) *The Production of Space (English translation by Donald Nicholson-Smith from Production de l'espace, Anthropos, 1984 2nd Edition).* Oxford: Blackwell Publishing.

Lefebvre, H. (1992) *Éléments de rythmanalyse.* Paris: Éditions Syllepse.

Lefebvre, H. (2004) *Rhythmananalysis: Space, Time and Everyday Life (English translation by Stuart Elden and Gerald Moore from Elements de rythmanalyse by Editions Syllepse, paris, 1992).* London: Bloomsbury Academic.

Leffingwell, D. (2011) *Agile software requirements: lean requirements practices for teams, programs, and the enterprise.* London;Boston, Mass;: Addison-Wesley.

Lei, Y., Bezdek, J. C., Chan, J., Vinh, N. X., Romano, S. and Bailey, J. (2017) 'Extending Information-Theoretic Validity Indices for Fuzzy Clustering.' *IEEE Transactions on Fuzzy Systems*, 25(4) pp. 1013-1018.

Lenntorp, B. (1974) *Transporter i dygnsprogrammet.* Stockholm: Statens Offentliga Utredningar, 1974:2, Allmänna Förlaget.

Lepot, M., Aubin, J.-B. and Clemens, F. (2017) 'Interpolation in Time Series: An Introductive Overview of Existing Methods, Their Performance Criteria and Uncertainty Assessment.' *Water*, 9(10)

Lewicka, M. (2011) 'Place attachment: How far have we come in the last 40 years?' *Journal of Environmental Psychology*, 31(3) pp. 207-230.

Lin, J., Khade, R. and Li, Y. (2012) 'Rotation-invariant similarity in time series using bag-of-patterns representation.' *Journal of Intelligent Information Systems*, 39(2) pp. 287-315.

Lin, J., Keogh, E., Wei, L. and Lonardi, S. (2007) 'Experiencing SAX: a novel symbolic representation of time series.' *Data Mining and Knowledge Discovery*, 15(2) pp. 107-144.

Lines, J. and Bagnall, A. (2014) 'Time series classification with ensembles of elastic distance measures.' *Data Mining and Knowledge Discovery*, 29(3) pp. 565-592.

Lipe, M. G. and Salterio, S. E. (2000) 'The Balanced Scorecard: Judgmental Effects of Common and Unique Performance Measures.' *The Accounting Review*, 75(3) pp. 283-298.

Little, R. J. A. and Rubin, D. B. (2020) *Statistics with Missing Data.* 3rd ed., Hoboken, NJ, USA: Wiley & Sons Inc.

Liu, Y., Kang, C., Gao, S., Xiao, Y. and Tian, Y. (2012) 'Understanding intra-urban trip patterns from taxi trajectory data.' *Journal of Geographical Systems*, 14(4) pp. 463-483.

Łuczak, M. (2016) 'Hierarchical clustering of time series data with parametric derivative dynamic time warping.' *Expert Systems with Applications*, 62 pp. 116-130.

Lugomer, K. and Longley, P. (2018) 'Towards a Comprehensive Temporal Classification of Footfall Patterns in the Cities of Great Britain.' *In 10th International Conference on Geographic Information Science.* Vol. 114. Dagstuhl, Winter, S., Griffin, A. and Sester, M. (eds.)Wadern, pp. 43:41-43:46. [Accessed on 31/08/2020] http://drops.dagstuhl.de/opus/volltexte/2018/9371

Lumpkin, J. R., Hawes, J. M. and Darden, W. R. (1986) 'Shopping Patterns of the Rural Consumer: Exploring the Relationship between Shopping Orientations and Outshopping.' *Journal of Business Research*, 14(1) pp. 63-81.

Lyon, D. (2016) 'Doing Audio-Visual Montage to Explore Time and Space: The Everyday Rhythms of Billingsgate Fish Market.' *Sociological Research Online*, 21(3) p. 12.

MacFarlane, K. (2017) 'A thousand CEOs: Relational thought, processual space, and Deleuzian ontology in human geography and strategic management.' *Progress in Human Geography*, 41(3) pp. 299-320.

MacQueen, J. (1967) *Some methods for classification and analysis of multivariate observations.* Berkeley, Calif., 1967. University of California Press.

Mahama, H. (2006) 'Management control systems, cooperation and performance in strategic supply relationships: A survey in the mines.' *Management Accounting Research*, 17(3) pp. 315-339.

Malina, M. A. and Selto, F. H. (2001) 'Communicating and Controlling Strategy: An Empirical Study of the Effectiveness of the Balanced Scorecard.' *Journal of Management Accounting Research*, 13(1) pp. 47-90.

Manchester Christmas Markets. (2017) *The one stop place for all your Manchester Christmas Markets information...* christmasmarketsmanchester.co.uk. [Online] [Accessed on 25/04/2021] https://christmasmarketsmanchester.co.uk/about-the-markets

Manchester City Council. (2020a) *New Cathedral Street*. [Online] [Accessed on 18/06/2020] https://www.manchester.gov.uk/directory_record/166437/new_catherdral_street/category/1225/view_all_spaces

Manchester City Council. (2020b) *Exchange Square*. [Online] [Accessed on 18/06/2020] https://www.manchester.gov.uk/directory_record/162279/exchange_square/category/1225/view_all_spaces

Mandelbrot, B. (1967) 'How Long Is the Coast of Britain? Statistical Self-Similarity and Fractional Dimension.' *Science*, 156(3775) pp. 636-638.

Manley, E. and Dennett, A. (2018) 'New Forms of Data for Understanding Urban Activity in Developing Countries.' *Applied Spatial Analysis and Policy*, 12(1) pp. 45-70.

Manning, E. (2009) *Relationscapes.* London: The MIT Press.

Marston, S., Jones III, J. P. and Woodward, K. (2005) 'Human Geography without Scale.' *Transactions of the Institute of British Geographers*, 30(4) pp. 416-432.

Mårtensson, S. (1974) *Drag i hushållens levnadsvillkor.* Stockholm: Statens Offentliga Utredningar, 1974:2, Allmänna Förlaget.

Martin, R. and Sunley, P. (2015) 'On the notion of regional economic resilience: conceptualization and explanation.' *Journal of Economic Geography*, 15(1) pp. 1-42.

Martínez, F., Frías, M. P., Pérez, M. D. and Rivera, A. J. (2017) 'A methodology for applying k-nearest neighbor to time series forecasting.' *Artificial Intelligence Review*, 52(3) pp. 2019-2037.

Martínez Plumé, J., Marténez Durá, J., Cirilo Gimeno, R., Soriano García, F. and García Celda, A. (2019) 'Evaluation of the Use of a City Center through the Use of Bluetooth Sensors Network.' *Sustainability*, 11(4)

Maskell, B. (1992) 'Performance measurement for world class manufacturing.' *Corporate Controller (COP)*, (January-February) pp. 44-48.

Massey, D. (1995) *Spatial Divisions of Labour. Social Structures and the Geography of Production.* 2nd ed., London: Macmillan Press Ltd.

Massey, D. (2005) *For Space.* London: Sage Publications Ltd.

Massumi, B. (1996) 'Becoming Deleuzian.' *Environment and Planning D: Society and Space*, 14(4) pp. 395-406.

Masud, M. A., Huang, J. Z., Wei, C., Wang, J., Khan, I. and Zhong, M. (2018) 'I-nice: A new approach for identifying the number of clusters and initial cluster centres.' *Information Sciences*, 466 pp. 129-151.

McCleary, R. and Hay, R. A. J. (1980) *Applied Time Series Analysis for the Social Sciences.* 1st ed., Beverly Hills, California: Sage Publications Inc.

McCormack, D. P. (2013) *Experience and Experiment in Affective Spaces. Refrains for Moving Bodies.* London: Duke University Press.

McCormack, D. P. (2016) 'Diagramming Practice and Performance.' *Environment and Planning D: Society and Space*, 23(1) pp. 119-147.

McCormack, D. P. (2017) 'The circumstances of post-phenomenological life worlds.' *Transactions of the Institute of British Geographers*, 42(1) pp. 2-13.

McFarlane, C. (2011) 'The City as Assemblage: Dwelling and Urban Space.' *Environment and Planning D: Society and Space*, 29(4) pp. 649-671.

McFarlane, C. and Anderson, B. (2011) 'Thinking with assemblage.' *Area*, 43(2) pp. 162-164.

McKinney, W. (2012) *Python for Data Analysis.* Steele, J. and Blanchette, M. (eds.) Farnham, Hampshire: O'Reilly Media Inc.

McLeod, A. I., Yu, H. and Mahdi, E. (2012) 'Time Series Analysis with R.' *In Handbook of Statistics*. Vol. 30. Elsevier B.V., pp. 661-712.

Medway, D., Alexander, A., Bennison, D. and Warnaby, G. (1999) 'Retailers' financial support for town centre management.' *International Journal of Retail & Distribution Management*, 27(6) pp. 246-255.

Medway, D., Warnaby, G., Bennison, D. and Alexander, A. (2000) 'Reasons for retailers' involvement in town centre management.' *International Journal of Retail & Distribution Management*, 28(8) pp. 368-378.

Meerow, S., Newell, J. P. and Stults, M. (2016) 'Defining urban resilience: A review.' *Landscape and Urban Planning*, 147 pp. 38-49.

Mehta, V. (2007) 'Lively Streets.' *Journal of Planning Education and Research*, 27(2) pp. 165-187.

Mehta, V. (2013) *The Street. A Quintessential Social Public Space.* Abingdon, Oxon: Routledge.

Melnyk, S. A., Bititci, U., Platts, K., Tobias, J. and Andersen, B. (2014) 'Is performance measurement and management fit for the future?' *Management Accounting Research*, 25(2) pp. 173-186.

Merriman, P. (2012) 'Human geography without time-space.' *Transactions of the Institute of British Geographers*, 37(1) pp. 13-27.

Meserole, W. H. (1935) 'The Qualitative Character of Pedestrian Traffic.' *American Marketing Journal*, 2(3) pp. 157-162.

Ministry of Housing, C. L. G. (2021) *Supporting Housing Delivery and Public Service Infrastructure.* London: (MHCLG Report)

Micheli, P. and Mari, L. (2014) 'The theory and practice of performance measurement.' *Management Accounting Research*, 25(2) pp. 147-156.

Miller, H. J. (2010) 'The Data Avalanche Is Here. Shouldn’t We Be Digging?' *Journal of Regional Science*, 50(1) pp. 181-201.

Milligan, G. W. and Copper, M. C. (1988) 'A study of standardization of variables in cluster analysis.' *Journal of Classification*, 5(2) pp. 181-204.

Millington, S. and Ntounis, N. (2017) 'Repositioning the high street: evidence and reflection from the UK.' *Journal of Place Management and Development*, 10(4) pp. 364-379.

Millington, S., Ntounis, N., Parker, C. and Quin, S. (2015) *Multifunctional Centres: a sustainable role for town and city centres*. Institute of Place Management, Manchester Metropolitan University. [Online] [Accessed on 03/10/2016] http://www.placemanagement.org/media/56154/Multifunctional-Centres.zip

Mintzberg, H. and Waters, J. A. (1985) 'Of Strategies, Deliberate and Emergent.' *Strategic Management Journal*, 6(3) pp. 257-272.

Monheim, R. (1998) 'Methodological aspects of surveying the volume, structure, activities and perceptions of city centre visitors.' *GeoJournal*, 45(4) pp. 273-287.

Moritz, S. and Bartz-Beielstein, T. (2017) 'ImputeTS: Time Series Missing Value Imputation in R.' *The R Journal*, 9(1) pp. 207-218.

Moritz, S., Sardá, A., Bartz-Beielstein, T., Zaefferer, M. and Stork, J. r. (2015) 'Comparison of different Methods for Univariate Time Series Imputation in R.' [Online] [Accessed on 19/11/2019] https://arxiv.org/pdf/1510.03924.pdf

Moxham, C. (2013) 'Measuring up: examining the potential for voluntary sector performance measurement to improve public service delivery.' *Public Money & Management*, 33(3) pp. 193-200.

Müller, M. (2015) 'Assemblages and Actor-networks: Rethinking Socio-material Power, Politics and Space.' *Geography Compass*, 9(1) pp. 27-41.

Müller, M. and Schurr, C. (2016) 'Assemblage thinking and actor-network theory: conjunctions, disjunctions, cross-fertilisations.' *Transactions of the Institute of British Geographers*, 41(3) pp. 217-229.

Mumford, C., Parker, C., Ntounis, N. and Dargan, E. (2017) *A clustering study to verify four distinct monthly footfall signatures: a classification for UK retail centres*. School of Computer Science & Informatics, Cardiff University Institute of Place Management, Manchester Metropolitan University: [Online] [Accessed on 12/04/2017] https://ipm-members.mkmapps.com/media/83469/MonthlySignatureClustering.pdf

Mumford, C., Parker, C., Ntounis, N. and Dargan, E. (2021) 'Footfall signatures and volumes: Towards a classification of UK centres.' *Environment and Planning B: Urban Analytics and City Science*, 48(6) pp. 1495-1510.

Mundy, J. (2010) 'Creating dynamic tensions through a balanced use of management control systems.' *Accounting, Organizations and Society*, 35(5) pp. 499-523.

Murcio, R., Soundararaj, B. and Lugomer, K. (2018) 'Movements in Cities: Footfall and its Spatio-Temporal Distribution.' *In* Longley, P., Cheshire, J. and Singleton, A. (eds.) *Consumer Data Research*. London: UCL Press, pp. 84-95.

Neely, A. (2002) *The Performance Prism: The scorecard for Measuring and Managing Stakeholder Relationships.* London: Financial Times/Prentice Hall.

Neely, A. (2005) 'The evolution of performance measurement research.' *International Journal of Operations & Production Management*, 25(12) pp. 1264-1277.

Neely, A., Gregory, M. and Platts, K. (1995) 'Performance measurement system design: A literature review and research agenda.' *International Journal of Operations and Production Management*, 15(4) pp. 80-116.

Nemeškal, J., Ouředníček, M. and Pospíšilová, L. (2020) 'Temporality of urban space: daily rhythms of a typical week day in the Prague metropolitan area.' *Journal of Maps*, 16(1) pp. 30-39.

Netto, V. M., Soares, M. P. and Paschoalino, R. (2015) 'Segregated Networks in the City.' *International Journal of Urban and Regional Research*, 39(6) pp. 1084-1102.

Netto, V. M., Meirelles, J. V., Pinheiro, M. and Lorea, H. (2018) 'A temporal geography of encounters.' *Cybergeo*, 05 February 2018,

Nevin, J. R. and Houston, M. J. (1980) 'Image as a Component of Attraction to Intraurban Shopping Areas.' *Journal of Retailing*, 56(1) pp. 77-93.

Newing, A., Clarke, G. and Clarke, M. (2013) 'Identifying seasonal variations in store-level visitor grocery demand.' *International Journal of Retail & Distribution Management*, 41(6) pp. 477-492.

Newing, A., Clarke, G. P. and Clarke, M. (2015) 'Developing and Applying a Disaggregated Retail Location Model with Extended Retail Demand Estimations.' *Geographical Analysis*, 47(3) pp. 219-239.

NPPF. (2019) *National Planning Policy Framework*. Ministry of Housing, Communities and Local Government. [Online] [Accessed on 15/12/2020]

Ntounis, N. (2018) *Place Management through Different Lenses.* PhD. Manchester Metropolitan University, UK. [Accessed on 01/10/2018]

Ntounis, N. and Parker, C. (2017) 'Engaged scholarship on the High Street: the case of HSUK2020.' *Journal of Place Management and Development*, 10(4) pp. 349-363.

Ntounis, N. and Kavaratzis, M. (2017) 'Re-branding the High Street: the place branding process and reflections from three UK towns.' *Journal of Place Management and Development*, 10(4) pp. 392-403.

Ntounis, N., Medway, D. and Parker, C. (2020) 'Managing Places.' *In* Edensor, T., Kalandides, A. and Kothari, U. (eds.) *The Routledge Handbook of Place*. Oxon, UK: Routledge,

Ntounis, N., Mumford, C., Lorono-Leturiondo, M., Parker, C. and Still, K. (2020) 'How safe is it to shop? Estimating the amount of space needed to safely social distance in various retail environments.' *Saf Sci*, 132, Dec, 2020/09/22, p. 104985.

O'Kelly, M. E. (2009) 'Applied Retail Location Models Using Spatial Interaction Tools.' pp. 420-442.

O'Dell, T. (2009) 'My Soul for a Seat. Commuting and the Routines of Mobility.' *In* Shove, E., Trentmann, F. and Wilk, R. R. (eds.) *Time, Consumption and Everyday life*. London: Bloomsbury Academic, pp. 85-98.

Ollman, B. (2003) *Dance of the Dialetic. Steps in Marx's Method.* Chicago: University of Illinois Press.

Osman, R. and Mulíček, O. (2017) 'Urban chronopolis: Ensemble of rhythmized dislocated places.' *Geoforum*, 85 pp. 46-57.

Otley, D. (1999) 'Performance management: a framework for management control systems research.' *Management Accounting Research*, 10(4) pp. 363-382.

Otsuka, N. and Reeve, A. (2007) 'Town Centre Management and Regeneration: The Experience in Four English Cities.' *Journal of Urban Design*, 12(3) pp. 435-459.

OU. (2007) *Time Series: M249 practical modern statistics.* Milton Keynes: The Open University.

Ozbay, K., Bartin, B., Yang, H., Walla, R. and Williams, R. (2010) *Automatic Pedestrian Counter*. Rutgers University. [Online] [Accessed on 09/10/15] http://www.nj.gov/transportation/refdata/research/reports/FHWA-NJ-2010-001.pdf

Page, S. J. and Hardyman, R. (1996) 'Place marketing and town centre management: A new tool for urban revitalization.' *Cities*, 13(3), 6//, pp. 153-164.

Paiva, D., Cachinho, H., Barata-Salgueiro, T. and Amílcar, A. (2017) 'A Criação De Geoetnografias Como Metodologia Para O Estudo Dos Ritmos Urbanos. Uma Aplicação No Chiado, Lisboa.' *Revista Electrónica de Geografía y Ciencias Sociales Universitat de Barcelona*, XXI(569) p. 29.

Pal, J. and Sanders, E. (1997) 'Measuring the effectiveness of town centre management schemes: an exploratory framework.' *International Journal of Retail & Distribution Management*, 25(2) pp. 70-77.

Papalexandris, A., Ioannou, G. and Prastacos, G. P. (2004) 'Implementing the Balanced Scorecard in Greece: a Software Firm’s Experience.' *Long Range Planning*, 37(4) pp. 351-366.

Parastar, H. and Bazrafshan, A. (2016) 'Fuzzy C-means clustering for chromatographic fingerprints analysis: A gas chromatography-mass spectrometry case study.' *J Chromatogr A*, 1438, Mar 18, 2016/02/27, pp. 236-243.

Parker, C. and Ntounis, N. (2015) The Past, Present and Future of the UK High Street as a Horizontal Marketing Channel. Working Paper, Institute of Place Management.

Parker, C., Ntounis, N. and Dargan, E. (2016) 'Radical Marketing and the UK High Street: Towards a new Typology of Towns.' *In Radical Marketing.* Vol. . Newcastle Business School,

Parker, C., Ntounis, N., Quin, S. and Grime, I. (2014) 'High Street research agenda: identifying High Street research priorities.' *Journal of Place Management and Development*, 7(2) pp. 176-184.

Parker, C., Ntounis, N., Millington, S., Quin, S. and Castillo-Villar, F. R. (2017) 'Improving the vitality and viability of the UK High Street by 2020.' *Journal of Place Management and Development*, 10(4) pp. 310-348.

Parkes, D. and Thrift, N. (1980) *Times, Spaces, and Places. A Chronogeographic Perspective.* Chichester: John Wiley & Sons.

Parlin, C. C. (1914) *Merchandising of Textiles.* Boston: Curtis Publishing Co.

Parlin, C. C. and Youker, H. S. (1913) *Encyclopedia of Cities.* Philadelphia, PA: Curtis Publishing Company.

Pavlis, M., Dolega, L. and Singleton, A. (2018) 'A Modified DBSCAN Clustering Method to Estimate Retail Center Extent.' *Geographical Analysis*, 50(2) pp. 141-161.

Pavlov, A. and Bourne, M. (2011) 'Explaining the effects of performance measurement on performance.' *International Journal of Operations & Production Management*, 31(1) pp. 101-122.

Peck, J. (2017) 'Transatlantic city, part 1: Conjunctural urbanism.' *Urban Studies*, 54(1) pp. 4-30.

Peck, J. and Tickell, A. (1995) 'The social regulation of uneven development: ‘regulatory deficit’, England’s South East, and the collapse of Thatcherism.' *Environment and Planning A*, 27(1) pp. 15-40.

Pedrycz, W. (2005) 'Interpretation of clusters in the framework of shadowed sets.' *Pattern Recognition Letters*, 26(15) pp. 2439-2449.

Peel, D. (2003) 'Town Centre Management: Multi-stakeholder Evaluation. Increasing the Sensitivity of Paradigm Choice.' *Planning Theory & Practice*, 4(2) pp. 147-164.

Peel, D. and Parker, C. (2017) 'Planning and governance issues in the restructuring of the high street.' *Journal of Place Management and Development*, 10(4) pp. 404-418.

Peel, D., Lloyd, G. and Lord, A. (2009) 'Business Improvement Districts and the Discourse of Contractualism.' *European Planning Studies*, 17(3) pp. 401-422.

Percival, D. B. and Walden, A. T. (2000) *Wavelet Methods for Time Series Analysis.* Cambridge Series in Statistical and Probabilistic Mathematics. New York: Cambridge University Press.

Perla, R. J., Provost, L. P. and Murray, S. K. (2011) 'The run chart: A simple analytical tool for learning from variation in healthcare processes.' *BMJ Quality and Safety*, 20(1) pp. 46-51.

Persson, O. and Ellegård, K. (2012) 'Torsten Hägerstrand in the Citation Time Web.' *The Professional Geographer*, 64(2) pp. 250-261.

Phan, T.-T.-H., Poisson Caillault, É., Lefebvre, A. and Bigand, A. (2017) 'Dynamic time warping-based imputation for univariate time series data.' *Pattern Recognition Letters*,

Philp, S., Dolega, L., Singleton, A. and Green, M. (2021) 'Archetypes of Footfall Context: Quantifying Temporal Variations in Retail Footfall in relation to Micro-Location Characteristics.' *Applied Spatial Analysis and Policy*, 28 July 2021,

Pierce, J. and Martin, D. G. (2015) 'Placing Lefebvre.' *Antipode*, 47(5) pp. 1279-1299.

Pink, S. (2007) 'Sensing Cittàslow: Slow Living and the Constitution of the Sensory City.' *Senses & Society*, 2(1) pp. 59-78.

Portas, M. (2011) *The Portas Review - an independent review into the future of our high streets*. Department for Business, Innovation and Skills. [Online] [Accessed on 02/07/2014] https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/6292/2081646.pdf

Powe, N. A. and Shaw, T. (2004) 'Exploring the current and future role of market towns in servicing their hinterlands: a case study of Alnwick in the North East of England.' *Journal of Rural Studies*, 20(4) pp. 405-418.

Powe, N. A. and Hart, T. (2009) 'Competing for the custom of small town residents: exploring the challenges and potential.' *International Journal of Retail & Distribution Management*, 37(9) pp. 732-747.

Pred, A. (1977) 'The Choreography of Existence: Comments on Hägerstrand's Time-Geography and Its Usefulness.' *Economic Geography*, 53(2) pp. 207-221.

R Core Team. (2019) *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing. [Online] [Accessed on 22/12/2019] https://www.R-project.org/

R Core Team. (2020) *Scale - Scaling and Centering of Matrix-Like Objects*. [Online] [Accessed on 30/06/2020] https://www.rdocumentation.org/packages/base/versions/3.6.2/topics/scale

Radnor, Z. J., Martinez, V. and Barnes, D. (2007) 'Historical analysis of performance measurement and management in operations management.' *International Journal of Productivity and Performance Management*, 56(5/6) pp. 384-396.

Rakthanmanon, T., Campana, B., Mueen, A., Batista, G., Westover, B., Zhu, Q., Zakaria, J. and Keogh, E. (2013) *Addressing Big Data Time Series: Mining Trillions of Time Series Subsequences Under Dynamic Time Warping.* Article 10, ACM, New York: ACM Transactions on Knowledge Discovery from Data, Vol. 7, No. 3, Article 10.

Rapoport, A. (1987) 'Pedestrian Street Use: Culture and Perception.' *In* Moudon, A. V. (ed.) *Public Streets for Public Use*. New York: Van Norstrand Reinhold, pp. 80-94.

Rasheed, F. and Alhajj, R. (2014) 'A Framework for Periodic Outlier Pattern Detection in Time-Series Sequences.' *IEEE Transactions on Cybernetics*, 44(5) pp. 569-582.

Ratanamahatana, C. A. and Keogh, E. (2005) *Three Myths about Dynamic Time Warping Data Mining.* Newport Beach, CA: SIAM - Society for Industrial and Applied Mathematics.

Ravenscroft, N. (2000) 'The Vitality and Viability of Town Centres.' *Urban Studies*, 37(13) pp. 2533-2549.

Read, D. (2007) 'Experienced utility: Utility theory from Jeremy Bentham to Daniel Kahneman.' *Thinking & Reasoning*, 13(1) pp. 45-61.

Reilly, W. J. (1931) *The Law of Retail Gravitation.* New York: Knickerbocker Press.

Reimers, V. (2014) 'A consumer definition of store convenience (finally).' *International Journal of Retail & Distribution Management*, 42(4) pp. 315-333.

Reimers, V. and Clulow, V. (2009) 'Retail centres: it's time to make them convenient.' *International Journal of Retail & Distribution Management*, 37(7) pp. 541-562.

Relph, E. (1976) *Place and Placelessness.* London: Pion Ltd.

Retail Week. (2012) 'Government launches Portas Plus plans to rescue failing high streets.' [Online] Journal, Electronic. [Accessed on 23/12/2017] https://www.retail-week.com/government-launches-portas-plus-plans-to-rescue-failing-high-streets/5035273.article?authent=1

Reuters. (2020) *Exclusive: IKEA's shopping malls arm Ingka Centres plans U.S. entry in major play*. Reuters. [Online] [Accessed on 25/04/2021] https://www.reuters.com/article/us-ikea-ingka-centres-exclusive-idUSKBN22Q2MF

Reynolds, J. and Schiller, R. (1992) 'A new classification of shopping centres in Great Britain using multiple branch numbers.' *Journal of Property Research*, 9(2) pp. 122-160.

Rhys, H. (2020) *Machine Learning with R, the tidyverse and mlr.* Shelter Island, NY: Manning.

Richard, P. J., Devinney, T. M., Yip, G. S. and Johnson, G. (2009) 'Measuring Organizational Performance: Towards Methodological Best Practice.' *Journal of Management*, 35(3) pp. 718-804.

Richards, G. (2010) 'Increasing the Attractiveness of Places Through Cultural Resources.' *Tourism Culture & Communication*, 10(1) pp. 47-58.

Ridgway, V. F. (1956) 'Dysfunctional Consequences of Performance Measurements.' *Administrative Science Quarterly*, 1(2) pp. 240-247.

Rigby, D. (2007) 'Evolution in economic geography?' *In* Tickell, A., Sheppard, E. and Peck, J. (eds.) *Politics and practice in economic geography*. London: SAGE Publications Ltd, pp. 176-186.

Riviezzo, A., de Nisco, A. and Rosaria Napolitano, M. (2009) 'Importance-performance analysis as a tool in evaluating town centre management effectiveness.' *International Journal of Retail & Distribution Management*, 37(9) pp. 748-764.

RMBC. (2020) *Rotherham Town Centre Markets - Rotherham Metropolitan Borough Council*. Rotherham Metropolitan Borough Council. [Online] [Accessed on 23/06/2020] https://www.rotherham.gov.uk/town-centres/rotherham-town-centre/3

Rojo, J., Rivero, R., Romero-Morte, J., Fernandez-Gonzalez, F. and Perez-Badia, R. (2017) 'Modeling pollen time series using seasonal-trend decomposition procedure based on LOESS smoothing.' *International Journal of Biometeorology*, 61(2), Feb, 2016/08/06, pp. 335-348.

Romesburg, H. C. (1984) *Cluster Analysis for Researchers.* North Carolina, US: Lulu Press.

Roper, S. and Parker, C. (2013) 'Doing well by doing good: A quantitative investigation of the litter effect.' *Journal of Business Research*, 66(11) pp. 2262-2268.

Rose, G. (1993) *Feminism and Geography. The Limits of Geographical Knowledge.* Minneapolis: University of Minneapolis Press.

Rose, M. (2006) 'Gathering ‘Dreams of Presence’: A Project for the Cultural Landscape.' *Environment and Planning D: Society and Space*, 24(4) pp. 537-554.

Rosenbloom, B. (1976) 'The Trade Area Mix and Retailing Mix: A Retail Strategy Matrix.' *Journal of Marketing*, 40(4) pp. 58-66.

Rousseeuw, P. J. (1987) 'Silhouettes: A graphical aid to the interpretation and validation of cluster analysis.' *Journal of Computational and Applied Mathematics*, 20 pp. 53-65.

Roy, J. R. and Thill, J.-C. (2004) 'Spatial interaction modelling.' *Papers in Regional Science*, 83 pp. 339-361.

RStudio and Inc. (2017) *htmltools: Tools for HTML (R package version 0.3.6)*. [Online] [Accessed on 03/02/2018] https://CRAN.R-project.org/package=htmltools

RStudio Team. (2018) *RStudio: Integrated Development Environment for R*. Boston, MA: RStudio, Inc. [Online] [Accessed on 04/02/2018] http://www.rstudio.com/

RTC. (2020) *Rotherham Town Centre - Markets*. [Online] [Accessed on 23/06/2020] http://www.rotherhamtowncentre.co.uk/enjoying/rotherham-markets/1

Saenz, V. B., Hatch, D., Bukoski, B. E., Kim, S., Lee, K.-h. and Valdez, P. (2011) 'Community College Student Engagement Patterns: A Typology Revealed through Exploratory Cluster Analysis.' *In* John, G. (ed.) *SAGE Secondary Data Analysis*. London: SAGE Publications Ltd,

Sanchez-Vazquez, M. J., Nielen, M., Gunn, G. J. and Lewis, F. I. (2012) 'Using seasonal-trend decomposition based on loess (STL) to explore temporal patterns of pneumonic lesions in finishing pigs slaughtered in England, 2005-2011.' *Prev Vet Med*, 104(1-2), Apr 1, 2011/12/14, pp. 65-73.

Sandford, M. (2014) *Business Improvement Districts.* House of Commons Library.

Sardá-Espinosa, A. (2018) *Comparing Time-Series Clustering Algorithms in R Using the dtwclust Package*. [Online] [Accessed on 04/02/2018] https://cran.r-project.org/web/packages/dtwclust/vignettes/dtwclust.pdf

Sardá-Espinosa, A. (2019) *Package ‘dtwclust’ - Time Series Clustering Along with Optimizations for the Dynamic Time Warping Distance*. [Online] [Accessed on 03/06/2019] https://cran.r-project.org/package=dtwclust

Sassen, S. (2006) *Territory, Authority, Rights: From Medieval to Global Assemblages.* Princeton NJ: Princeton University Press.

Sato-Ilic, M. and Ilic, P. (2016) 'Visualization of Fuzzy Clustering Result in Metric Space.' *Procedia Computer Science*, 96 pp. 1666-1675.

Sax, C. and Eddelbuettel, D. (2018) 'Seasonal Adjustment by X-13ARIMA-SEATS in R.' *Journal of Statistical Software*, 87(11) pp. 1-17.

Sayer, A. (2000) *Realism and Social Science.* London: SAGE Publications Ltd.

Schatzki, T. (2009) 'Timespace and the Organisation of Social Life.' *In* Shove, E., Trentmann, F. and Wilk, R. R. (eds.) *Time, Consumption and Everyday life*. London: Bloomsbury Academic, pp. 35-48.

Schiller, R. (1988) 'Retail Decentralization. A Property View.' *The Geographical Journal*, 154(1) pp. 17-19.

Schiller, R. (1994) 'Vitality and Viability: Challenge to the Town Centre.' *International Journal of Retail & Distribution Management*, 22(6) pp. 46-50.

Schirmer, P. M. and Axhausen, K. W. (2015) 'A Multiscale Classification of Urban Morphology.' *The Journal of Transport and Land Use*, 9(1) pp. 101-130.

Schmid, C., Karaman, O., Hanakata, N. C., Kallenberger, P., Kockelkorn, A., Sawyer, L., Streule, M. and Wong, K. P. (2017) 'Towards a new vocabulary of urbanisation processes: A comparative approach.' *Urban Studies*, 55(1) pp. 19-52.

Schwarzkopf, S. (2016) 'In search of the consumer. The history of market research from 1890 to 1960.' *In* Jones, D. G. B. and Tadajewski, M. (eds.) *The Routledge Companion to Marketing History*. London: Routledge, Taylor and Francis Group, pp. 61-83.

Scott, A. J. and Storper, M. (2015) 'The Nature of Cities: The Scope and Limits of Urban Theory.' *International Journal of Urban and Regional Research*, 39(1) pp. 1-15.

Seamon, D. (1979) *A Geography of the Lifeworld: Movement, Rest and Encounter.* London: Croom Helm.

Seamon, D. (1980) 'Body-Subject, Time-Space Routines, and Place Ballets.' *In* Buttimer, A. and Seamon, D. (eds.) *Human Experience of Space & Place*. London: Croom Helm Ltd, pp. 148-165.

Seamon, D. (2015) *Lifeworld, Place, and Phenomenology: Holistic and Dialectical Perspectives*. [Online] [Accessed on 10/10/2016] https://www.academia.edu/9508643/Lifeworld_Place_and_Phenomenology_Holistic_and_Dialectical_Perspectives_forthcoming_2018_

Seamon, D. (2018) *Life Takes Place. Phenomenology, Lifeworlds and Place Making.* London: Routledge.

Seamon, D. and Nordin, C. (1980) 'Marketplace as Place Ballet: The Example of Varberg.' *Landscape*, 24(3) pp. 35-41.

Seaton, A. V. (1996) 'Hay on Wye, the mouse that roared: book towns and rural tourism.' *Tourism Management*, 17(5), 8//, pp. 379-382.

Seigworth, G. J. (2000) 'Banality for Cultural Studies.' *Cultural Studies*, 14(2) pp. 227-268.

Sharko, J. and Grinstein, G. (2009) 'Visualizing Fuzzy Clusters Using RadViz.' *In 2009 13th International Conference Information Visualisation*. NW Washington, DC, US, IEEE Computer Society, pp. 307-316.

Shilon, M. and Shamir, R. (2016) 'Becoming an airline passenger: Body, luggage, and documents.' *Subjectivity*, 9(3) pp. 246-270.

Shim, S. and Eastlick, M. A. (1998) 'The Hierarchial influence of Personal Values on Mall Shopping Attitute and Behavior.' *Journal of Retailing*, 74(1) pp. 139-160.

Shove, E. (2009) 'Everyday Practice and the Production and Consumption of Time.' *In* Shove, E., Trentmann, F. and Wilk, R. R. (eds.) *Time, Consumption and Everyday life*. London: Bloomsbury Academic, pp. 17-34.

Shove, E. and Southerton, D. (2000) 'Defrosting the freezer: From novelty to convenience. A Narrative of Normalization.' *Journal of Material Culture*, 5(3) pp. 301-319.

Shove, E., Trentmann, F. and Wilk, R. (2009) *Time, Consumption and Everyday life.* Shove, E., Trentmann, F. and Wilk, R. R. (eds.) London: Bloomsbury Academic.

Simons, R. (1995a) 'Control in an Age of Empowerment.' *Harvard Business Review*, 67(2) pp. 80-88.

Simons, R. (1995b). Levers of Control: How Managers Use Innovative Control Systems to Drive Strategic Renewal. *Harvard Business School Press*.

Simonsen, K. (2012) 'In quest of a new humanism: Embodiment, experience and phenomenology as critical geography.' *Progress in Human Geography*, 37(1) pp. 10-26.

Simpson, P. (2008) 'Chronic everyday life: rhythmanalysing street performance1.' *Social & Cultural Geography*, 9(7) pp. 807-829.

Simpson, P. (2011) 'Street Performance and the City: Public Space, Sociality, and Intervening in the Everyday.' *Space and Culture*, 14(4) pp. 415-430.

Simpson, P. (2012) 'Apprehending everyday rhythms: rhythmanalysis, time-lapse photography, and the space-times of street performance.' *Cultural Geographies*, 19(4) pp. 423-445.

Simpson, P. (2017) 'Spacing the subject: Thinking subjectivity after non-representational theory.' *Geography Compass*, 11(12)

Singh, R., Das, D., Jana, R. K. and Tiwari, A. K. (2018) 'A wavelet analysis for exploring the relationship between economic policy uncertainty and tourist footfalls in the USA.' *Current Issues in Tourism*, pp. 1-8.

Singleton, A. and Arribas-Bel, D. (2019) 'Geographic Data Science.' *Geographical Analysis*, 53(1) pp. 61-75.

Singleton, A. D. and Spielman, S. E. (2013) 'The Past, Present, and Future of Geodemographic Research in the United States and United Kingdom.' *The Professional Geographer*, 66(4) pp. 558-567.

Singleton, A. D., Dolega, L., Riddlesden, D. and Longley, P. A. (2016) 'Measuring the spatial vulnerability of retail centres to online consumption through a framework of e-resilience.' *Geoforum*, 69 pp. 5-18.

Smailes, A. E. (1944) 'The Urban Hierarchy in England and Wales.' *Journal of the Geographical Association*, 29(2) pp. 41-51.

Smith, M. and Bititci, U. S. (2017) 'Interplay between performance measurement and management, employee engagement and performance.' *International Journal of Operations & Production Management*, 37(9) pp. 1207-1228.

Smith, R. H. T. (1965) 'Method and Purpose in Functional Town Classification.' *Annals of the Association of American Geographers*, 55(3) pp. 539-548.

Smith, R. J. and Hall, T. (2018) 'Everyday territories: homelessness, outreach work and city space.' *The British Journal of Sociology*, 69(2), Jun, 2017/07/19, pp. 372-390.

Soja, E. W. (1986) 'Taking Los Angeles apart: some fragments of a critical human geography.' *Environment and Planning D: Society and Space*, 4 pp. 255-272.

Solnit, R. (2001) *Wanderlust. A History of Walking.* London: Granta Publications.

Soomro, K., Bhutta, M. N. M., Khan, Z. and Tahir, M. A. (2019) 'Smart city big data analytics: An advanced review.' *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 9(5)

Southerton, D. (2009) 'Re-ordering Temporal Rhythms. Coordinating Daily Practices in the UK in 1937 and 2000.' *In* Shove, E., Trentmann, F. and Wilk, R. R. (eds.) Trentmann, F. *Time, Consumption and Everyday Life*. London: Bloomsbury Publishing Ltd, https://www.dawsonera.com:443/abstract/9781847885937

Sparks, L. (1996) 'The Census of Distribution: 25 years in the dark.' *Area*, 28(1) pp. 89-95.

Speckbacher, G., Bischof, J. and Pfeiffer, T. (2003) 'A descriptive analysis on the implementation of Balanced Scorecards in German-speaking countries.' *Management Accounting Research*, 14(4) pp. 361-388.

Spiggle, S. and Sewall, M. A. (1987) 'A Choice Sets Model of Retail Selection.' *Journal of Marketing*, 51(2) pp. 97-111.

Springboard. (2015) *Springboard High Street Technology*. [Online] [Accessed on 13/12/15] http://www.spring-board.info/mediaLibrary/images/english/76934.pdf

Springboard. (2020) *Footfall Benchmark Statistics*. [Online] [Accessed on 05/10/2020] https://www.spring-board.info/benchmarks

Stewart, K. (2007) *Ordinary Affects.* London: Duke University Press.

Stineman, R. W. A. (1980) 'A Consistently Well Behaved Method of Interpolation.' *Creative Computing*, 6(7) pp. 54-57.

Storper, M. and Scott, A. J. (2016) 'Current debates in urban theory: A critical assessment.' *Urban Studies*, 53(6) pp. 1114-1136.

Sulis, P. and Manley, E. (2018) 'Exploring Similarities and Variations of Human Mobility Patterns in the City of London.' *In 3rd International Conference on Smart Data and Smart Cities.* Vol. Volume XLII-4/W11. Delft, The Netherlands, 4–5 October 2018.The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, pp. 51-58.

Sulis, P., Manley, E., Zhong, C. and Batty, M. (2018) 'Using mobility data as proxy for measuring urban vitality.' *Journal of Spatial Information Science*, 16 pp. 137-162.

Sun, Z. (2021) 'A rhythmanalysis approach to understanding the vending-walking forms and everyday use of urban street space in Yuncheng, China.' *Urban Studies*, 30/05/2021, 26 March 2021,

Taylor, P. J. and Parkes, D. N. (1975) 'A Kantian view of the city: a factorial-ecology experiment in space and time.' *Environment and Planning A*, 7(6) pp. 671-688.

Teller, C. (2008) 'Shopping streets versus shopping malls - determinants of agglomeration format attractiveness from the consumers' point of view.' *The International Review of Retail, Distribution and Consumer Research*, 18(4) pp. 381-403.

Teller, C. and Reutterer. (2008) 'The evolving concept of retail attractiveness: What makes retail agglomerations attractive when customers shop at them?' *Journal of Retailing and Consumer Services*, 15 pp. 127-143.

Teller, C. and Elms, J. R. (2012) 'Urban place marketing and retail agglomeration customers.' *Journal of Marketing Management*, 28(5-6) pp. 546-567.

Tessier, S. and Otley, D. (2012) 'A conceptual development of Simons' Levers of Control framework.' *Management Accounting Research*, 23(3) pp. 171-185.

The Journal (Newcastle). (2012) 'Cash boost to revamp the region's high streets.' *The Journal (Newcastle, England).* 2012/10/23/. p. 5.

Theodoridis, C. and Kayas, O. G. (2017) 'Place Management decision-making under uncertainty: Evidence from the UK and Ireland.' *In 4th Corfu Symposium on Managing & Marketing Places*. Corfu, Greece, 24-27 April 2017.Institute of Place Management, Manchester Metropolitan University, Theodoridis, C., Ntounis, N. and Pal, J. (2017) 'How to reinvent the High Street: evidence from the HS2020.' *Journal of Place Management and Development*, 10(4) pp. 380-391.

Theodoridis, S. and Koutroumbas, K. (2009) *Pattern Recognition.* 4th ed., London: Academic Press.

Theodorou, V., Abelló, A., Lehner, W. and Thiele, M. (2016) 'Quality measures for ETL processes: from goals to implementation.' *Concurrency and Computation: Practice and Experience*, 28(15) pp. 3969-3993.

Thompson, D. L. (1967) 'Consumer Convenience and Retail Area Structure.' *Journal of Marketing Research*, 4(1) pp. 37-44.

Thornton, S. J., Bradshaw, R. P. and McCullagh, M. J. (1991) 'Pedestrian flows and retail turnover.' *British Food Journal*, 93(9) pp. 23-28.

Thorpe, D. (1968) 'The Main Shopping Centres of Great Britain in 1961: Their Locational and Structural Characteristics.' *Urban Studies*, 5(2) pp. 165-206.

Thrift, N. (1999) 'The Place of Complexity.' *Theory, Culture & Society*, 16(3) pp. 31-69.

Thrift, N. (2000) 'Afterwords.' *Environment and Planning D: Society and Space*, 18(2) pp. 213-255.

Thrift, N. (2004) 'Movement-space: The changing domain of thinking resulting from the development of new kinds of spatial awareness.' *Economy and Society*, 33(4) pp. 582-604.

Thrift, N. (2008) *Non-Representational Theory: Space, Politics, Affect.* London: Routledge.

Thrift, N. (2011) 'Lifeworld Inc—and what to do about it.' *Environment and Planning D: Society and Space*, 29(1) pp. 5-26.

Thrift, N. (2014) 'The ‘sentient’ city and what it may portend.' *Big Data & Society*, 1(1) pp. 205395171453224–205395171453224.

Thrift, N. and Pred, A. (1981) 'Time-geography: a new beginning.' *Progress in Human Geography*, 5(2) pp. 277-286.

Thurstain-Goodwin, M. and Unwin, D. (2000) 'Defining and Delineating the Central Areas of Towns for Statistical Monitoring Using Continuous Surface Representations.' *Transactions in GIS*, 4(4) pp. 305-317.

Timmermans, H. J. P., Van der Hagen, X. and Borgers, A. (1992) 'Transportation systems, retail environments and pedestrian trip chaining behaviour. Modelling issues and applications.' *Transportation Research Part B*, 268(1) pp. 45-59.

Tomalin, C. (1997) 'Town Centre Health Checks: Some Developments from Practice.' *Planning Practice & Research*, 12(4) pp. 383-392.

Traunmueller, M. W., Johnson, N., Malik, A. and Kontokosta, C. E. (2018) 'Digital footprints: Using WiFi probe and locational data to analyze human mobility trajectories in cities.' *Computers, Environment and Urban Systems*, 72 pp. 4-12.

Trentmann, F. (2009) 'Disruption is Normal. Blackouts, Breakdowns and the Elasticity of Everyday Life.' *In* Shove, E., Trentmann, F. and Wilk, R. R. (eds.) *Time, Consumption and Everyday life*. London: Bloomsbury Academic, pp. 67-84.

Tuan, Y. (1974) *Topophilia: a study of environmental perception, attitudes, and values.* Englewood Cliffs, N.J;London;: Prentice-Hall.

Tuan, Y. (1977) *Space and Place. The Perspective of Experience.* Minneapolis: University of Minnesota Press.

Tukey, J. W. (1977) *Exploratory data analysis.* London: Addison-Wesley.

Ukko, J., Tenhunen, J. and Rantanen, H. (2007) 'Performance measurement impacts on management and leadership: Perspectives of management and employees.' *International Journal of Production Economics*, 110(1-2) pp. 39-51.

URBED. (1994) *Vital and Viable Town Centres: Meeting the Challenge.* London: HMSO.

URBED. (1997) *Town centre partnerships: a survey of good practice and report of an action research project.* London: The Stationery Office.

Van De Ven, A. H. and Johnson, P. E. (2006) 'Knowledge for Theory and Practice.' *Academy of Management*, 31(4) pp. 802-821.

Van Dooren, W., Bouckaert, G. and Halligan, J. (2015) *Performance management in the public sector.* 2nd ed., London: Routledge.

Van Leeuwen, E. S. (2010) 'The effects of future retail developments on the local economy: Combining micro and macro approaches.' *Papers in Regional Science*, 89(4) pp. 691-711.

Verbesselt, J., Hyndman, R., Zeileis, A. and Culvenor, D. (2010a) 'Phenological change detection while accounting for abrupt and gradual trends in satellite image time series.' *Remote Sensing of Environment*, 114(12) pp. 2970-2980.

Verbesselt, J., Hyndman, R., Newnham, G. and Culvenor, D. (2010b) 'Detecting trend and seasonal changes in satellite image time series.' *Remote Sensing of Environment*, 114(1) pp. 106-115.

Verhoef, E. and Nijkamp, P. (2008) 'Urban Environmental Externalities, Agglomeration Forces, and the Technological ‘Deus ex Machina’.' *Environment and Planning A: Economy and Space*, 40(4) pp. 928-947.

Verhoef, P., Neslin, S. A. and Vroomen, B. (2007) 'Multichannel customer management: Understanding the research-shopper phenomenon.' *International Journal of Research in Marketing*, 24(2) pp. 129-148.

Verhoef, P., Kannan, P. K. and Inman, J. J. (2015) 'From Multi-Channel Retailing to Omni-Channel Retailing.' *Journal of Retailing*, 91(2) pp. 174-181.

Verhoef, P., Lemon, K. N., Parasuraman, A., Roggeveen, A., Tsiros, M. and Schlesinger, L. A. (2009) 'Customer Experience Creation: Determinants, Dynamics and Management Strategies.' *Journal of Retailing*, 85(1) pp. 31-41.

VisitManchester.com. (2020) *Market Street*. [Online] [Accessed on 18/06/2020] https://www.visitmanchester.com/things-to-see-and-do/market-street-p275041

Voigt, S., Kemper, T., Riedlinger, T., Kiefl, R., Scholte, K. and Mehl, H. (2007) 'Satellite Image Analysis for Disaster and Crisis-Management Support.' *IEEE Transactions on Geoscience and Remote Sensing*, 45(6) pp. 1520-1528.

von Thünen, J. H. (1826) *Der Isolierte Staat in Beziehung auf Landschaft und Nationalokonomie (English translation by C.M. Wartenburg, von Thünen's Isolated State, Oxford: Pergamon Press, 1966).* Hamburg.

Waddington, T. B. P., Clarke, G. P., Clarke, M. and Newing, A. (2017) 'Open all hours: spatiotemporal fluctuations in U.K. grocery store sales and catchment area demand.' *The International Review of Retail, Distribution and Consumer Research*, 28(1) pp. 1-26.

Wallace, J. M. and Hobbs, P. V. (1977) *Atmospheric Science: An Introductory Survey.* London: Academic Press Inc.

Wang, R. J.-H., Malthouse, E. C. and Krishnamurthi, L. (2015) 'On the Go: How Mobile Shopping Affects Customer Purchase Behavior.' *Journal of Retailing*, 91(2) pp. 217-234.

Wang, W. and Zhang, Y. (2007) 'On fuzzy cluster validity indices.' *Fuzzy Sets and Systems*, 158(19) pp. 2095-2117.

Wang, X., Wirth, A. and Wang, L. (2007) 'Structure-Based Statistical Features and Multivariate Time Series Clustering.' *In Seventh IEEE International Conference on Data Mining (ICDM 2007)* pp. 351-360.

Wang, X., Smith, K. A., Hyndman, R. and Alahakoon, D. (2004) 'A Scalable Method for Time Series Clustering.' Presentation at Monash University, Victoria, Australia, School of Business Systems and Department of Econometrics and Business Statistics,

Wang, Y. (2014) *Fuzzy Clustering Models for Gene Expression Data Analysis.* Ph.D.

Ward, D. B. (2010) *A New Brand of Business: Charles Coolidge Parlin, Curtis Publishing Company and the Origins of Market Research.* Philadelphia, PA: Temple University Press.

Ward, K. (2007) 'Business Improvement Districts: Policy origins, Mobile Policies and Urban Liveability.' *Geography Compass*, 1(3) pp. 657-672.

Warnaby, G. (2009) 'Look up! Retailing, historic architecture and city centre distinctiveness.' *Cities*, 26(5) pp. 287-292.

Warnaby, G. (2019) 'Of time and the city: curating urban fragments for the purposes of place marketing.' *Journal of Place Management and Development*, 12(2) pp. 181-196.

Warnaby, G. and Man Yip, K. (2005) 'Promotional planning in UK regional shopping centres: an exploratory study.' *Marketing Intelligence & Planning*, 23(1) pp. 43-57.

Warnaby, G. and Parker, C. (2017) 'Mobility, marketing, and the experience of the city.' *In* Campelo, A. (ed.) *Handbook on Place Branding and Marketing*. Cheltenham and Northampton MA: Edward Elgar, pp. 203-218.

Warnaby, G., Alexander, A. and Medway, D. (1998) 'Town centre management in the UK: A review, synthesis and research agenda.' *The International Review of Retail, Distribution and Consumer Research*, 8(1) pp. 15-31.

Warren Liao, T. (2005) 'Clustering of time series data—a survey.' *Pattern Recognition*, 38(11) pp. 1857-1874.

Wayland, J. P., Simpson, L. D. and Kemmerer, B. E. (2003) *Rural Retailing: Understanding the Multi-Channel Outshopper.* Houston, Texas, Tate, U. S. (ed.): College of Business, University of North Texas - Association of Collegiate Marketing educators.

Wayner, P. (2017, 2017/04/06). Python vs. R: The battle for data scientist mind share. *InfoWorld.com*.

Weber, A. (1909) *Über den Standort der Industrien. Erster Teil: Reine Theorie des Standorts [Theory of the location of industries].* Tübingen: Mohr.

Weltevreden, J. (2007) 'Substitution or complementarity? How the Internet changes city centre shopping.' *Journal of Retailing and Consumer Services*, 14(3) pp. 192-207.

Weltevreden, J. (2014) 'The digital challenge for the high street: insights from Europe.' *In* Wrigley, N. and Brookes, E. (eds.) Council, E. S. R. *Evolving High Streets: Resilience & Reinvention, Perspectives from Social Science*. University of Southampton: ESRC, pp. 32-35. http://www.riben.org.uk/Cluster_publications_&_media/Opinion_Pieces_Southampton_Nov_2014.pdf

Weltevreden, J. and Von Rietbergen, T. (2007) 'E-Shopping versus City Centre Shopping: The Role of Perceived City Centre Attractiveness.' *Tijdschrift voor Economische en Sociale Geografie*, 98(1) pp. 68-85.

Weltevreden, J. and van Rietbergen, T. (2009) 'The Implications of E-Shopping for in-Store Shopping at Various Shopping Locations in the Netherlands.' *Environment and Planning B: Planning and Design*, 36(2) pp. 279-299.

Whatmore, S. (2002) *Hybrid Geographies: Natures Cultures Spaces.* London: Sage.

Whitehead, T., Simmonds, D. and Preston, J. (2006) 'The effect of urban quality improvements on economic activity.' *Journal of Environmental Management*, 80(1), Jul, pp. 1-12.

Wickham, H. (2016) *ggplot2: Elegant Graphics for Data Analysis.* 2nd ed., Use R! Switzerland: Springer Nature.

Wickham, H., François, R. and Henry, L. (2020) *Tidyverse*. [Online] [Accessed on 07/12/2020] https://dplyr.tidyverse.org/index.html

Wickham, H., François, R., Henry, L. and Müller, K. (2019) *dplyr: A Grammar of Data Manipulation (R package version 0.8.0.1)*. [Online] [Accessed on 07/12/2020] https://CRAN.R-project.org/package=dplyr

Wilson, A. (2010) 'Entropy in Urban and Regional Modelling: Retrospect and Prospect.' *Geographical Analysis*, 42 pp. 384-394.

Wolf, L. J., Fox, S., Harris, R., Johnston, R., Jones, K., Manley, D., Tranos, E. and Wang, W. W. (2020) 'Quantitative geography III: Future challenges and challenging futures.' *Progress in Human Geography*, 45(3) pp. 596-608.

Wrigley, N. (1983) 'Quantitative method: on data and diagnostics.' *Progress in Human Geography*, 7(4) pp. 567-577.

Wrigley, N. and Lowe, M. (1996) *Retailing, Consumption and Capital: Towards the new retail geography.* Harlow, England: Longman Group Ltd.

Wrigley, N. and Dolega, L. (2011) 'Resilience, fragility, and adaptation: new evidence on the performance of UK high streets during global economic crisis and its policy implications.' *Environment and Planning A*, 43(10) pp. 2337-2363.

Wrigley, N. and Lambiri, D. (2014) *High Street Performance and Evolution - A brief guide to the evidence*. [Online] [Accessed on 18/11/2014] http://eprints.soton.ac.uk/367614/

Wrigley, N. and Lowe, M. (2014) *Reading Retail: A geographical perspective on retailing and consumption spaces.* London: Routledge.

Wrigley, N. and Brookes, E. (2014) *Evolving High Streets: Resilience & Reinvention, Perspectives from Social Science*. University of Southampton: ESRC. [Online] [Accessed on 21/11/2015] http://www.riben.org.uk/Cluster_publications_&_media/Opinion_Pieces_Southampton_Nov_2014.pdf

Wrigley, N. and Lambiri, D. (2015) *British High Streets: from Crisis to Recovery? A comprehensive view of the evidence*. University of Southampton: Economic & Social Research Council. [Online] [Accessed on 06/11/2015] https://eprints.soton.ac.uk/375492/

Wrigley, N., Cudworth, K. and Li, J. (2012) *The Impact of Small-Format In-Centre Foodstores on Small Towns*. [Online] [Accessed on 18/10/2015] http://www.riben.org.uk/Current_&_recently_completed_projects/Small_Foodstores_Exec_Summary.pdf

Wu, C.-E., Yang, W.-Y., Ting, H.-C. and Wang, J.-S. (2017) 'Traffic pattern modeling, trajectory classification and vehicle tracking within urban intersections.' *In 2017 International Smart Cities Conference (ISC2)* IEEE, pp. 1-6.

Wunderlich, F. M. (2008) 'Walking and Rhythmicity: Sensing Urban Space.' *Journal of Urban Design*, 13(1) pp. 125-139.

Wunderlich, F. M. (2013) 'Place-Temporality and Urban Place-Rhythms in Urban Analysis and Design: An Aesthetic Akin to Music.' *Journal of Urban Design*, 18(3) pp. 383-408.

Wunderlich, F. M. (2014) 'Place-temporality and rhythmicity: A new aesthetic and methodological foundation for urban design theory and practice.' *In* Carmona, M. (ed.) *Explorations in urban design: An urban design research primer.* Farnham: Ashgate, pp. 59-73.

Wylie, J. (2009) 'Landscape, Absence and the Geographies of Love.' *Transactions of the Institute of British Geographers, New Series*, 34(3) pp. 275-289.

Xie, Y. (2019) *knitr: A General-Purpose Package for Dynamic Report Generation in R. R package version 1.22*. [Online] [Accessed on 06/06/2019]

Xie, Y., Allaire, J. J. and Grolemund, G. (2018) R Markdown: The Definitive Guide. (07/12/2018): Chapman and Hall/CRC.

Ye, L. and Keogh, E. (2010) 'Time series shapelets: a novel technique that allows accurate, interpretable and fast classification.' *Data Mining and Knowledge Discovery*, 22(1-2) pp. 149-182.

Yim Yiu, C. (2011) 'The impact of a pedestrianisation scheme on retail rent: an empirical test in Hong Kong.' *Journal of Place Management and Development*, 4(3) pp. 231-242.

Zeileis, A., Hornik, K. and Murrell, P. (2009) 'Escaping RGBland: Selecting colors for statistical graphics.' *Computational Statistics & Data Analysis*, 53(9) pp. 3259-3270.

Zhao, Y., Luo, F., Chen, M., Wang, Y., Xia, J., Zhou, F., Wang, Y., Chen, Y., et al. (2018) 'Evaluating Multi-Dimensional Visualizations for Understanding Fuzzy Clusters.' *IEEE Transactions on Visualization and Computer Graphics*, 25(1), Aug 20, 2018/08/24, pp. 12-21.

Zhou, F., Chen, M., Wang, Z., Luo, F., Luo, X., Huang, W., Chen, Y. and Zhao, Y. (2017) 'A radviz-based visualization for understanding fuzzy clustering results.' *In Proceedings of the 10th International Symposium on Visual Information Communication and Interaction - VINCI '17*. Bangkok, Thailand, pp. 9-15.

Zhou, F., Bai, B., Wu, Y., Chen, M., Zhong, Z., Zhu, R., Chen, Y. and Zhao, Y. (2019) 'FuzzyRadar: visualization for understanding fuzzy clusters.' *Journal of Visualization*, 22(5) pp. 913-926.

Zhou, J., Liang , Z., Liu, Y., Guo, H., He, D. and Zhao, L. (2015) 'Six-decade temporal change and seasonal decomposition of climate variables in Lake Dianchi watershed (China): stable trend or abrupt shift?' *Theoretical and Applied Climatology*, 119(1-2) pp. 181-191.

Zhu, X. and Guo, D. (2017) 'Urban event detection with big data of taxi OD trips: A time series decomposition approach.' *Transactions in GIS*, 21(3) pp. 560-574.