Oxford Bulletin of Economics and Statistics

ORIGINAL ARTICLE OPEN ACCESS

Seasonal Temperatures and Economic Growth in the United Kingdom

Lotanna E. Emediegwu[1] | Veronica Vienne[2] | Jubril Animashaun[3]

[1]Finance and Economics, Manchester Metropolitan University, Manchester, UK, | [2]University of Huddersfield, Huddersfield, UK, | [3]University of Manchester, Manchester, UK,

Correspondence: Lotanna E. Emediegwu (l.emediegwu@mmu.ac.uk)

Received: 26 January 2024 | **Revised:** 13 March 2025 | **Accepted:** 14 March 2025

Keywords: GDP | seasonality | spatial econometrics | temperature | UK

ABSTRACT

We study the effect of seasonal temperature on economic growth using spatiotemporal econometric techniques and council-level data for the United Kingdom (UK). We find that higher temperatures during summer reduce economic growth, whereas milder winters raise output growth. These effects are amplified in wealthy local councils on the Southern axis of the UK. Also, we find that local economic growth is related to growth in neighbouring councils. The results are robust to several sensitivity analyses. They are persistent and not driven by unobservable factors related to regional economic conditions. Our findings provide new insights into the consequences of future warming in advanced economies.

JEL Classification: Q54, O44, C33, R12

1 | Introduction

One of the key manifestations of climate change is the increase in global temperatures, which has far-reaching consequences for natural systems, society and human well-being. Specific attention has been justifiably paid to the effect of climate change on economic outcomes in developing economies [1]. Understandably, because of the vulnerability of these regions to climatic shocks due to the agriculture-dependent structure of their economies, poverty, credit constraints, dearth of adaptive technology, reduced investment, lower labour productivity, poorer human health, and the *rain-fed* nature of agricultural production [2, 3]. While several works, for example [4], have also considered the impact of weather shocks on developed economies, most overlook an important climatological aspect – seasonality. Seasonal weather fluctuations can significantly impact economic growth in various sectors, particularly those sensitive to weather conditions, such as agriculture, tourism and energy. For example, unfavourable weather conditions during peak seasons can significantly impact tourism revenue, as travellers may alter or cancel their plans, leading to decreased economic activity in the sector. Understanding the effects of these fluctuations is essential for policymakers, businesses and individuals to plan and manage their activities effectively. For instance, the increase in wildfire incidence in the US during summer months has generated renewed interest in research investigating the causes, effects and mitigation measures of such weather-induced natural disasters.[1] The Biden-Harris Administration, for example, announced on 31 July 2023, a nearly $11 million investment for current wildland fire research priorities [5].

Previous studies that focused on developed economies also neglect significant spatial spillovers, which could bias the true estimate of the impact of weather fluctuations on economic growth. For example, spatial correlations occur due to incidental commonalities or geographical characteristics [6–8]. This study attempts to account for these potential spatial influences while analysing the effect of weather shocks on economic growth.

In this research, we look at the effect of seasonal temperature on economic output growth in an advanced economy context. Our empirical analysis focuses on the United Kingdom, a developed economy with temperate weather and distinct seasons. Understanding how temperature impacts economic performance at the subnational level is crucial for effective policy formulation and sustainable development strategies; hence, we conduct our analysis at the council level. We employ spatiotemporal econometric techniques, developed by Baltagi et al. [9], to account for spatial spillovers that capture the effects in one geographic location due to economic activities in the neighbourhood. Specifically, our empirical strategy includes spatial and temporal lags of the dependent variable with errors clustered at the council level to account for potential spatial correlation of the outcome variable and idiosyncratic shocks, respectively.[2]

Our results show that higher temperatures during summer and autumn reduce the annual gross domestic product (GDP) growth rate, whereas higher temperatures during winter increase GDP growth. Specifically, we find that a 1°C increase in temperature during the summer (autumn) season results in a 2.44% (1.55%) drop in economic growth, whereas a similar change in temperature during winter months is associated with a 1.15% increase in economic growth. These coefficients are larger than those estimated with a non-spatial model. Also, we find that councils surrounded by productive neighbours experience more economic growth. Analogous to the US study by Colacito et al. [12], we document that the impact of temperature is stronger in councils in the southern end of the UK, where temperatures are relatively higher than in the northern regions. Similar to the mechanisms driving climate impact in developing economies [13–15], we provide evidence that the temperature impact is driven by an income effect, as we find that productive councils are more impacted by temperature changes than the rest. We also document evidence showing the influence of the London region (the most productive region of the UK in terms of GDP generation) as a major bearer of the temperature effect. Our analysis of the potential channels explaining the results shows that they can be due to a decline in agricultural productivity, a decline in economic activities in the South of the UK and a comparatively larger disruption of economic activity through the reduction in the mean and median electricity consumption during summer than in other seasons.

Our work can be fitted into two branches of literature. First, this paper contributes to the growing debate on the economic impacts of global warming. We push this literature further by employing a more disaggregated approach, utilising subnational economic output data, similar to Greßer et al. [16], and isolating the weather components in each location by season. Our study aims to uncover some of the complex ways temperature impacts economic growth in developed economies. It further stresses the importance of disaggregating weather data into seasons to better understand the extent of the economic consequences of increasing global temperatures.

Secondly, our study relates to a new wave of recent empirical studies [3, 11, 17, 18] that outlines the importance of identifying the signature of past or neighbour's economic activities. To avoid misrepresenting what appears a transient effect as a persistent response, it is important to account for potential *ripple/delayed effects* with respect to both space and time. Standard panel data models fail to capture these effects because they model a contemporaneous relationship with units of observations assumed to be spatially independent [19]. Therefore, we capture spatial dependence using spatial panel data models.[3, 4]

The rest of the paper is structured as follows. We describe the data and specify the estimation model in the next section. Results are presented and discussed in Section 3. Finally, Section 4 concludes the paper with important policy implications.

2 | Data Description and Methodology

2.1 | Data Source and Description

Economic Growth Data

We use annual estimates of the balanced UK subnational GDP as a measure of economic growth from 1998 until 2020. The dataset, published by the Office of National Statistics (ONS), contains data for all local authority districts, London boroughs, unitary authorities, and Scottish council areas.[5] Overall, the dataset consists of 374 subnational units (henceforth, local councils) spanning the four nations of the UK (England, Northern Ireland, Scotland and Wales). The use of subnational data for estimating environmental impacts has been shown to be superior to national data in several studies; see [4, 22, 23]. Spatial averaging or aggregation over a sparse area can attenuate significant nonlinearities due to Jensen's inequality. Figure 1 shows the existence of spatial heterogeneity in economic growth among UK local councils—making our assessment of spatial interactions relevant.

Weather Data

Annual weather data mask the influence of seasonality on economic outcomes, as it assumes a homogeneous damage distribution across the year. Several studies, for example, [24, 25], have found that the impact of weather on economic outcomes, like agriculture, differs by season – especially in developed economies where there is heterogeneity in weather distributions across seasons, as exemplified in our case (see Figure 2). Hence, we construct seasonal weather measures to capture the effect of seasonality on the UK's economic growth. We carry out this task by averaging weather measures along seasonal lines: December–January–February (winter), March–April–May (spring), June–July–August (summer), and September–October–November (autumn).[6] We use the University of East Anglia's Climate Research Unit CRU TS v4.05 to construct council-level population-weighted weather information (refer to Appendix B for more details on data construction). Our population weights are from the Year 2000 population count extracted from the Gridded Population of the World (GPWv4) dataset at 0.5° × 0.5° resolution (approx. 56 km × 56 km across the equator) [26].

We present the descriptive statistics of the main variables used in the study in Table 1. As expected, temperature is highest during summer and lowest during winter. Figure 2 reveals the

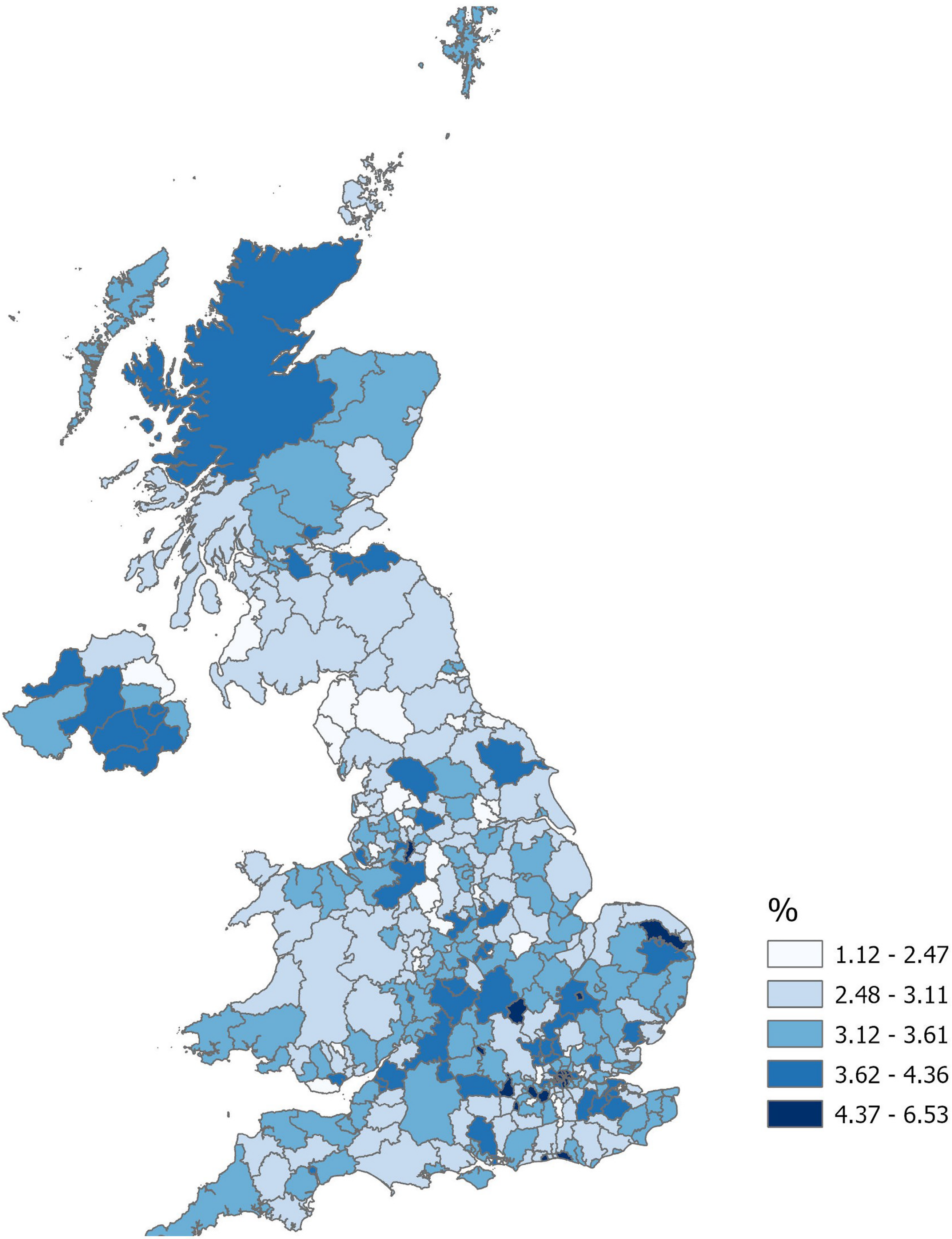

FIGURE 1 | Spatial distribution of the average GDP growth (1998–2020). Each polygon represents a local council's average GDP growth for the period under consideration. The darker the shade, the higher the average GDP growth over time. [Colour figure can be viewed at wileyonlinelibrary.com]

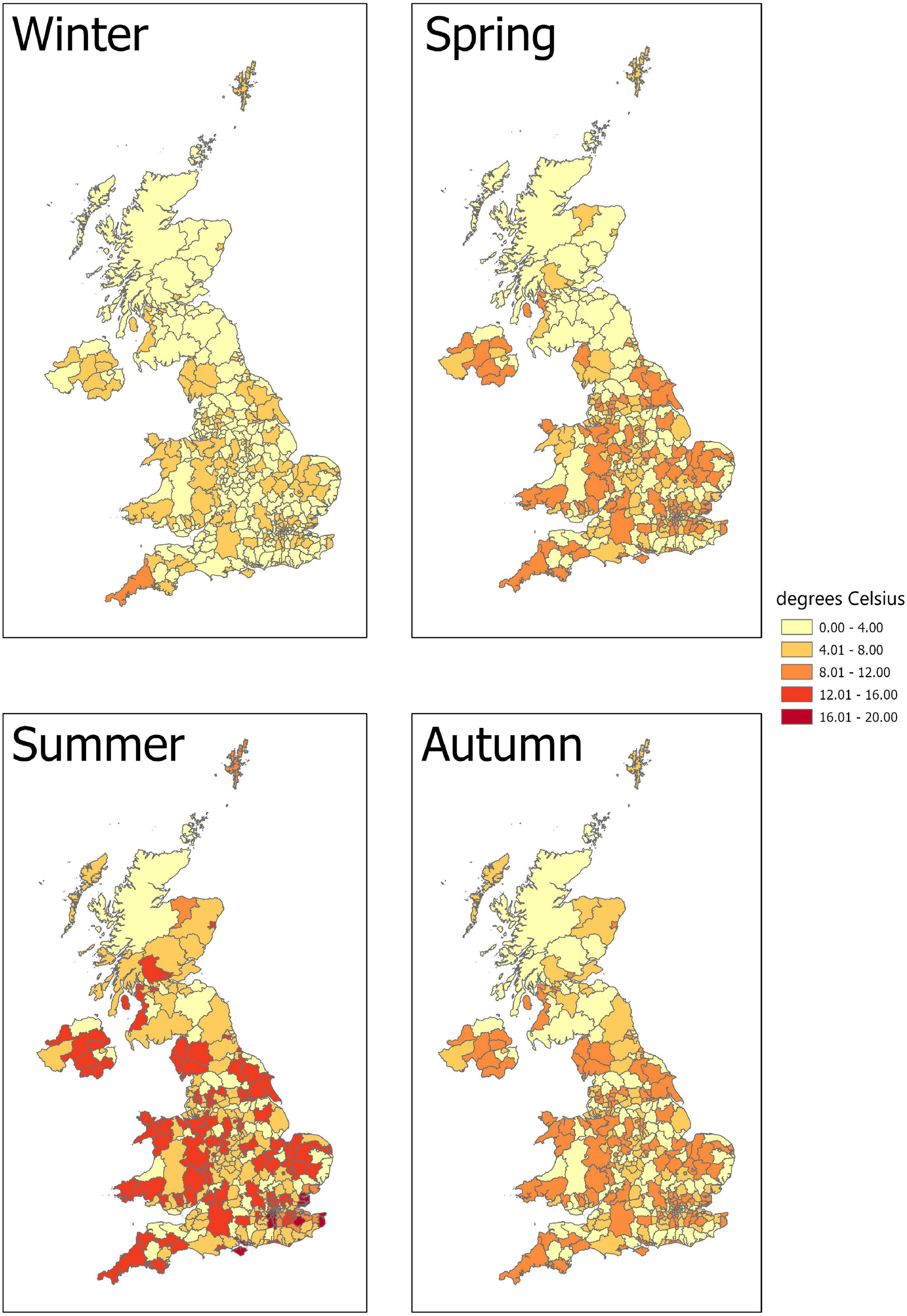

FIGURE 2 | Spatial distribution of the average seasonal temperature in the UK (1998–2020). Each polygon represents a local council's average seasonal temperature for the period under consideration. The darker the shade, the higher the average seasonal temperature over time. [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 1 | Summary statistics.

Variables	Mean	SD
GDP growth (%)	3.22	3.66
T_{winter} (°C)	3.14	1.78
T_{spring} (°C)	5.85	2.95
T_{summer} (°C)	10.24	5.04
T_{autumn} (°C)	6.99	3.50
Observations	8,228	

Note: SD denotes standard deviation. Weather entries are population-adjusted.

spatial variation in temperature in the UK, with the southern regions being relatively hotter across all seasons than their northern counterparts. We use this dichotomy to investigate potential mechanisms driving the impact of weather changes on economic growth. The observed spatial (and temporal) variations are the basis for using seasonal weather shocks to predict changes in economic growth within the UK.

2.2 | Empirical Strategy

We begin with a simple reduced form model:

$$g_t = X_t \beta + \rho + v_r t + \varepsilon_t \quad (1)$$

where the dependent variable, g_t is an $N \times 1$ vector of council-level GDP growth rates (%) at time t; X_t is an $N \times K$ matrix of the independent variables, where $K = 16$. The matrix includes the average temperature by season, total rainfall by season, as well as their squared terms, to capture potential nonlinearities. We do not add other controls to avoid the bad control scenario [27, 28]. ρ is an $N \times 1$ vector of council-level fixed effects to control for council-specific time-invariant factors of economic growth (e.g., distance to an international airport), and $v_r t$ are region-specific trends that account for time-changing determinants of economic growth that are common within a region (e.g., the impact of the war in Ukraine).[7] We include a complete set of council-level fixed effects and region-specific linear time trends to ensure that the derived estimates come from seasonal weather variations.[8] Finally, ε_t represents the error terms clustered at the council level. As a robustness check, we also employed alternative methods for correcting standard errors, including Conley corrections, clustering by weather stations and bootstrapping, applied to the non-spatial model (Table E4).[9]

Spatial interactions in economic growth may arise from cross-sectional dependence due to potential sectoral and regional economic integrations among neighbouring councils (see Figure 1). Similarly, past economic outcomes can influence contemporaneous outcomes. To account for these potential spatial and temporal spillovers, we estimate a modified version of Equation (1):

$$g_t = g_{t-1}\alpha + W g_t \gamma + X_t \beta + \rho + v_r t + \varepsilon_t \quad (2)$$

where g_{t-1} is the time-lagged dependent variable (which makes the model dynamic), W is a row-normalised $N \times N$ matrix of the spatial weights describing the spatial arrangement of the N units. $W g_t$ represents spatially autocorrelated outcomes and γ is the spatial autoregressive (SAR) coefficient; other variables are as defined in Equation (1).[10] The (non)existence of spatial spillovers in Equation (2) can be ascertained from the (non)significance of $\hat{\gamma}$. Equation (2), also known as spatial autoregressive (SAR) model, can be analysed as either a dynamic model, as represented in Equation (2), or as a static model, by constraining $\alpha = 0$. We present results for both forms. We do not include the spatial lags of temperature because we believe that including them is unnecessary due to temperature's inherent spatial autocorrelation—neighbouring regions' temperatures are highly correlated. Localized impacts of temperature shocks are more relevant, where local factors dominate. Also, from an econometric perspective, adding spatial lags of multiple covariates can introduce multicollinearity and redundancy without improving the model. To support this point, we show in the Appendix (Table E2) that the effect of adding the lags of seasonal temperature is small and insignificant, even at a 10% significance level.

We construct W based on queen contiguity, where two units are considered neighbours if they share common boundaries. In such a case, they are assigned the value *1*. Otherwise, they are non-neighbours and are assigned a zero in the weight matrix (refer to the Appendix, Section C, for a detailed discussion on spatial weights). Since we do not know what the true W is, we use other spatial weight matrices to check for the robustness of the results. A correctly specified model should not see significant variation in results using alternative weight matrices [31].

The lagged dependent variable in Equation (2) introduces endogeneity and incidental parameter problems, such as the classic Nickel bias, into the model. Specifically, the issue of endogeneity arises when the spatial lag variable (Wg) is correlated with the error term, which can lead to biased estimates if the standard OLS is used. To overcome these econometric concerns, we implement the bias-corrected quasi–maximum likelihood (QML) using the *xsmle* package in Stata developed by Belotti et al. [32] to estimate the attendant equation.[11] This approach addresses the endogeneity issue by incorporating the spatial structure of the data directly into the likelihood function.[12] Ord [34] demonstrates this structural transformation by modelling the spatial dependence in the error term through a spatial autoregressive process.[13] By doing so, QML ensures that the interdependence of observations across space is taken into account, allowing for consistent estimation of the parameters. Besides, this technique has been applied in numerous studies, for example, [11, 37, 38], where it has been shown to effectively address spatial endogeneity.

3 | Empirical Results

3.1 | Main Results

Table 2 reports the results of estimating the non-spatial model (Equation 1) in column 1 and the spatial models (Equation 2) in columns 2 and 3. Column 1 shows that while a 1°C increase in the average summer temperature is associated with a decreased economic growth, the same temperature increase in winter leads to an increase in economic growth. This finding is consistent with the notion that temperature affects aggregate economic growth in rich countries when the relationship is analysed more

TABLE 2 | Model comparisons for impact on GDP growth rate.

Outcome variable: GDP growth rate	Non-spatial (1)	SAR (2)	Dynamic SAR (3)
T_{winter}	1.128*** (0.180)	1.473*** (0.242)	1.152*** (0.267)
T_{spring}	−0.837** (0.383)	0.142 (0.454)	0.506 (0.456)
T_{summer}	−1.148** (0.551)	−1.867*** (0.625)	−2.443*** (0.676)
T_{autumn}	−1.172*** (0.345)	−1.437*** (0.420)	−1.553*** (0.407)
α			0.028 (0.019)
γ		0.407*** (0.012)	0.412*** (0.012)
Log likelihood		−19, 740	−19, 810
R^2/R_w^2	0.37	0.22	0.22
Observations	8,206	8,206	7,833

Note: Spatial weight matrix is a queen matrix. The annual average GDP growth rate for the period under consideration is 3.22%. The months comprising each season are discussed in-text. All specifications contain precipitation controls, quadratic terms of the seasonal weather measures, council-level fixed effects and region-specific linear trends. Standard errors in parentheses are clustered at the council level.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

granularly across seasons [12]. For example, the average temperature is relatively low in winter, but deviations from the mean could still be within a comfortable range that allows efficient heat exchange with the environment, provoking a less costly behavioural, physiological and psychological mitigation than in summer.

On the other hand, summer is associated with heat, and above-mean temperatures could hurt consumer demand and labour productivity by increasing health-related work absenteeism [12, 39]. Moreover, prior research show evidence that heat waves are harmful to business and result in lower industry earnings in summer [40]. They also reduce time allocation for work at the higher end of the distribution [41] and diminish human capital accumulation and learning outcomes [42]. Therefore, acclimatisation and short-run adaptation to higher temperatures in winter might be lower than in summer.

To account for relevant spatial spillovers, column 2 reports the results of estimating Equation (2) with the spatial lag of the dependent variable while excluding the time lag component (static SAR model). Lastly, column 3 includes both spatial and temporal lags of the dependent variable (dynamic SAR model). The estimation results in columns 2 and 3 are largely similar, except for the winter temperature, where the positive and statistically significant coefficient closely resembles the estimate from the non-spatial model. More specifically, the spatial lag specification suggests that the impact of temperature changes in autumn and summer is not confined to the local area but extends to neighbouring regions, indicating the presence of significant spatial dependencies. In other words, there are widespread distributional consequences both within and between councils [43].

The similar magnitude of the winter temperature coefficient across both models suggests that the impact of winter temperature is primarily localised and does not exhibit substantial spatial spillovers, unlike the autumn and summer scenarios where the estimated effects are larger in the spatial model compared to those in the non-spatial model. This dichotomy could be due to several factors, such as the nature of winter weather patterns, which might affect regions uniformly, or the possibility that winter-related activities are less interdependent between neighbouring areas. Hence, activities and interactions that might lead to spatial spillovers, such as farming and tourism, are reduced in winter, leading to more localised effects of temperature shocks. We note, however, that this similarity does not translate to the absence of spillover effects, but it is a sign of reduced dependence. Table 3 shows that the indirect effects from changes in winter temperatures are significant but less than those from summer and autumn temperature fluctuations. Lastly, our preferred estimates are those in column 3 because their dynamic nature permits the computation of long-run effects, as presented in the subsequent tables (see Section D in the Appendix for details of how long-run effects of a dynamic model are computed).

While the coefficients of seasonal temperatures in column 1 denote semi-elasticity, the same cannot be inferred from the other columns with spatial components, as the marginal effect of seasonal temperature on economic growth may vary across local councils due to spatial interactions. Consequently, we report the semi-elasticities controlling for spatial interactions in Table 3 as direct, indirect and total impacts, with the marginal effects averaged over all local councils. The interpretation of direct and indirect effects of temperature changes is crucial for understanding spatial dependencies and spillover effects, as well as for crafting localised versus regional policy responses. Direct effects capture the immediate impact of seasonal temperature changes on a council's economic growth without accounting for intrinsic spatial dependencies. Indirect effects, on the other hand, capture the spillover impacts on neighbouring councils, mediated through spatial interactions (weights), reflecting how seasonal temperature-induced changes propagate through regional networks.[14] This interpretation means that temperature changes in one council can affect adjacent councils' outcomes due to economic linkages, migration or environmental diffusion processes.[15] Our results in Table 3 show that the estimates of the direct and indirect effects associated with temperature shocks are significant across winter, summer and autumn seasons. We report that although the estimates of the indirect effects are less than those of the direct effects, they are not negligible and, hence, cannot be ignored. Therefore, we conclude that the impacts of summer, autumn and winter temperature fluctuations on

TABLE 3 | Marginal effects of seasonal weather fluctuations on economic growth.

Panel A	Long-run direct effects		Long-run indirect effects		Long-run total effects	
	SAR	Dynamic SAR	SAR	Dynamic SAR	SAR	Dynamic SAR
T_{winter}	0.914*** (0.153)	0.730*** (0.171)	0.558*** (0.090)	0.480*** (0.110)	1.473*** (0.242)	1.211*** (0.280)
T_{spring}	0.088 (0.281)	0.320 (0.289)	0.054 (0.172)	0.211 (0.190)	0.142 (0.454)	0.532 (0.479)
T_{summer}	−1.157*** (0.385)	−1.546*** (0.426)	−0.709*** (0.241)	−1.021*** (0.288)	−1.867*** (0.625)	−2.568*** (0.711)
T_{autumn}	−0.891*** (0.260)	−0.983*** (0.258)	−0.545*** (0.161)	−0.648*** (0.171)	−1.437*** (0.420)	−1.632*** (0.428)

Panel B	Short-run direct effects (Dynamic SAR)	Short-run indirect effects (Dynamic SAR)	Short-run total effects (Dynamic SAR)
T_{winter}	0.707*** (0.166)	0.444*** (0.102)	1.152*** (0.267)
T_{spring}	0.310 (0.280)	0.195 (0.176)	0.506 (0.456)
T_{summer}	−1.498*** (0.412)	−0.945*** (0.266)	−2.443*** (0.676)
T_{autumn}	−0.953*** (0.250)	−0.600*** (0.158)	−1.553*** (0.407)

Note: Spatial weight matrix is a queen matrix. The months comprising each season are discussed in-text. All specifications contain precipitation controls, quadratic terms of the seasonal weather measures, council-level fixed effects and region-specific linear trend. Marginal effects are computed at the average values of seasonal temperatures. Standard errors in parentheses are clustered at the council level.

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

economic growth are not entirely local. The indirect effect from winter temperature is smaller compared to that of the other two seasons, which is unsurprising given the nature of the season that restricts economic activities (e.g., agriculture, tourism) and spatial transmissions.

Table 3 further distinguishes between short-run marginal effects for the static models and both short-run and long-run marginal effects for the dynamic models. In line with Belotti et al. [32], we compare the long-run effects in the static models (Panel A) with the short-run effects in the dynamic models (Panel B). The results in both panels of Table 3 are consistently similar, with winter temperatures positively related to economic growth, while summer and autumn temperatures negatively affect economic growth in the UK. The long-run results agree with the findings of Kahn et al. [44], who, using a stochastic growth model, find that any deviation from the historical norm has a detrimental effect on economic activity in the future.

Focusing on the short-run total effects in panel B, a 1°C increase in temperature during winter months is associated with a 1.15% increase in economic growth.[16] Conversely, a similar marginal change in temperature during summer (autumn) season results in a 2.44% (1.55%) drop in economic growth. These coefficients are larger than those from the non-spatial model in column 1, Table 2. It is important to note that for subsequent analysis, we will focus on short-run total effects and not distinguish between direct and indirect effects for brevity. The positive γ coefficient indicates spatial interactions in economic growth arising from cross-sectional dependence, which is due to potential sectoral and regional economic integration among neighbouring councils. Finally, the coefficient of the lagged dependent variable, α, is positively signed but not statistically significant, possibly due to the lack of more extended time series observations.

3.2 | Robustness Results

This subsection highlights the results of several sensitivity tests to ascertain the robustness of estimates from Equation (2). The robustness checks follow our preferred specification, the dynamic SAR model.

Since the true W is unknown, we follow the convention by using other spatial weight matrices to check the robustness of our results. While we reserve an elaborate discussion on spatial weight matrices to Section C of the Appendix, it is important to know that the weight matrices used here are constructed using the same principle of contiguity as the baseline queen matrix but with different definitions of contiguity. For queen and rook matrices, we define contiguity using border lines. Distance-based matrices, such as the inverse-distances matrix, define neighbourhoods as entities within a given circumference (e.g., 50 km) from a centroid point. Similarly, we can define neighbours as the k closest spatial entities to unit i-known as *k-nearest neighbour* (k-NN), where k is a positive integer.

We re-estimate our preferred model using other forms of contiguity-based spatial weights: minmax, spectra normalised and unnormalised queen matrices, as well as rook matrix. Figure 3 shows that the total impact estimates using different contiguity-based spatial weight matrices are qualitatively similar to the baseline results using a row-normalised queen matrix. Similar results showing the direct and indirect estimates can be found in Figure E1 of the Appendix.

The tendency for economically contiguous councils to be concentrated in specific geographic regions, as well as the possibility that they might share similar climate conditions, underscores the need for understanding spatial dynamics, that is, the

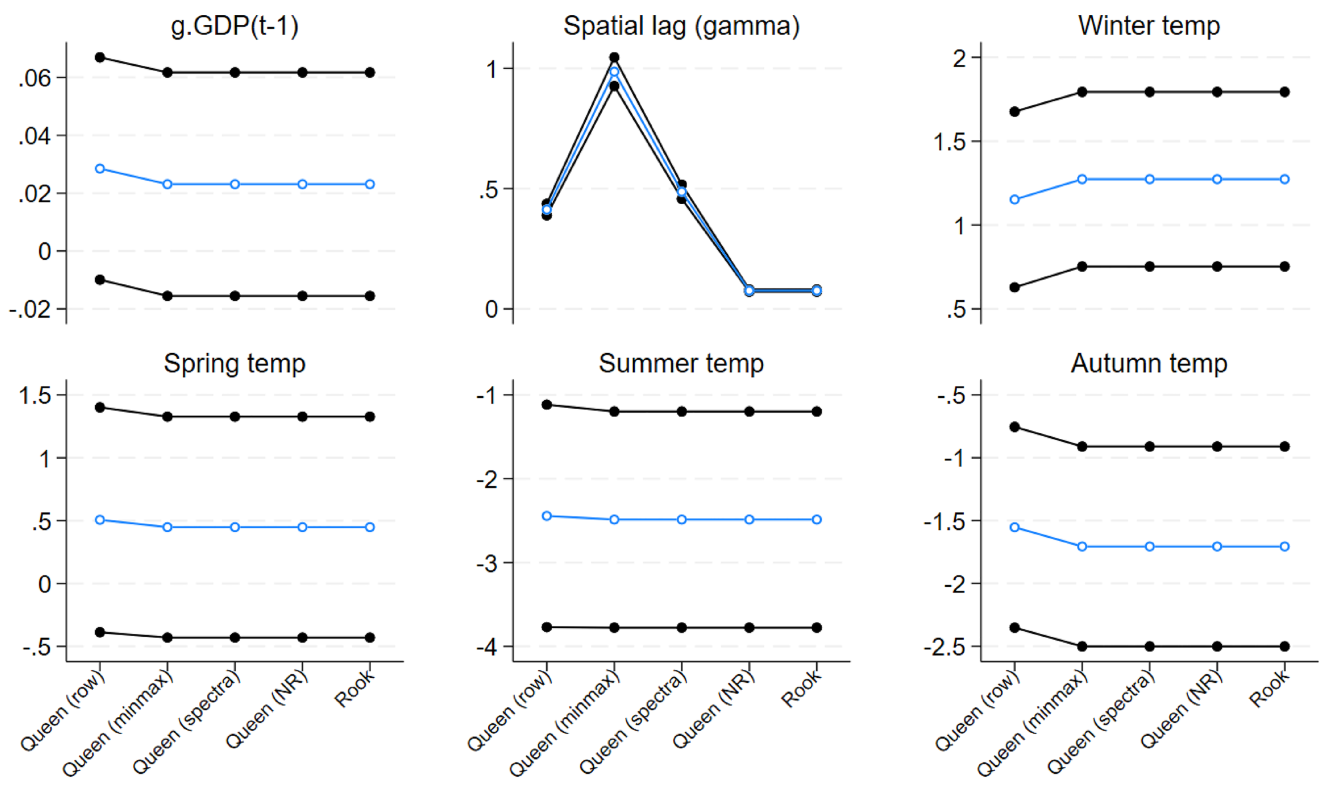

FIGURE 3 | Spatial weight matrices test (contiguity-based). The blue dots correspond to the coefficients for Equation (2) estimated using various spatial weight matrices. Black dots are confidence intervals at 95%. The matrices are briefly explained in-text and broadly described in the Appendix, Section C. The estimates presented here are short-run total impacts. [Colour figure can be viewed at wileyonlinelibrary.com]

separation of the local effect from those due to spatial spillovers from economically contiguous councils. More specifically, by spatial dynamics, we consider contingently linked councils with some economic interdependence that generates economic spillovers over neighbouring councils. Theoretically, many of the spatial spillovers we envisaged arise from economic linkages, interdependence and economic interactions among analogous councils [45].

We empirically investigate two categories: distance-based spatial weights and weights based on networks, to explain potential spatial interactions between analogous councils.[17] The inverse distance spatial weight matrix assigns weights to pairs of locations based on the inverse of the distance between them, meaning closer locations have higher weights and more influence on each other. Values are assigned by calculating $w_{ij} = \frac{1}{d_{ij}}$, where w_{ij} is the weight between locations i and j and d_{ij} is the Euclidean distance between the location centroids. Figure 4 shows a distance decay as the scope of contiguity based on distance expands. This interpretation aligns with the use of *k-nearest neighbour* (k-NN) as spatial weights, as illustrated in Figure E7 in the Appendix.

In addition, we test the stability of our baseline results using migration-based spatial weights as an alternative weight matrix. Migration flows were chosen because they capture not only physical proximity but also economic interactions between councils, aligning with findings from economic geography literature [48]. Moreover, migration has been shown to be a significant driver of regional economic disparities, affecting labour mobility, capital flows and resource allocation in developed economies [49–51]. Using cross-border flow data from the Office of National Statistics (ONS), we construct out-migration flows between councils, weighted by the volume of migration.[18] Higher weights are assigned to council pairs with greater migration flows, reflecting stronger economic ties, while lower weights are assigned to those with fewer migrations. Figure 5 shows that the migration-based matrix produced results consistent with the queen contiguity matrix.

Also, we re-examine our baseline equation using spatial weights to account for regional commonalities. To create this special spatial weight matrix, we group the councils within the UK into their regions. We proceed by assigning the value 1 to councils within the same region and 0 to others. Figure 6 shows that using the re-specified weights produces larger estimates for impacts from summer and autumn temperature changes than the baseline (which uses a queen matrix). Overall, our findings consistently indicate that expanding the neighbourhood scope amplifies the influence of seasonal temperatures.

Next, we present our estimates using alternative weather data. We obtain historical weather data from the ERA5 reanalysis product published by the European Centre for Medium-Range Weather Forecasts (ECMWF), which provides daily gridded weather variables at $0.25^{\circ} \times 0.25^{\circ}$ resolution.[19] The results presented in Table 4 confirm that our findings are robust to the choice of a different source of weather data. We also present the marginal effects in Table E3 of the Appendix estimated with ERA5 data, which are analogous to those obtained from the CRU data.

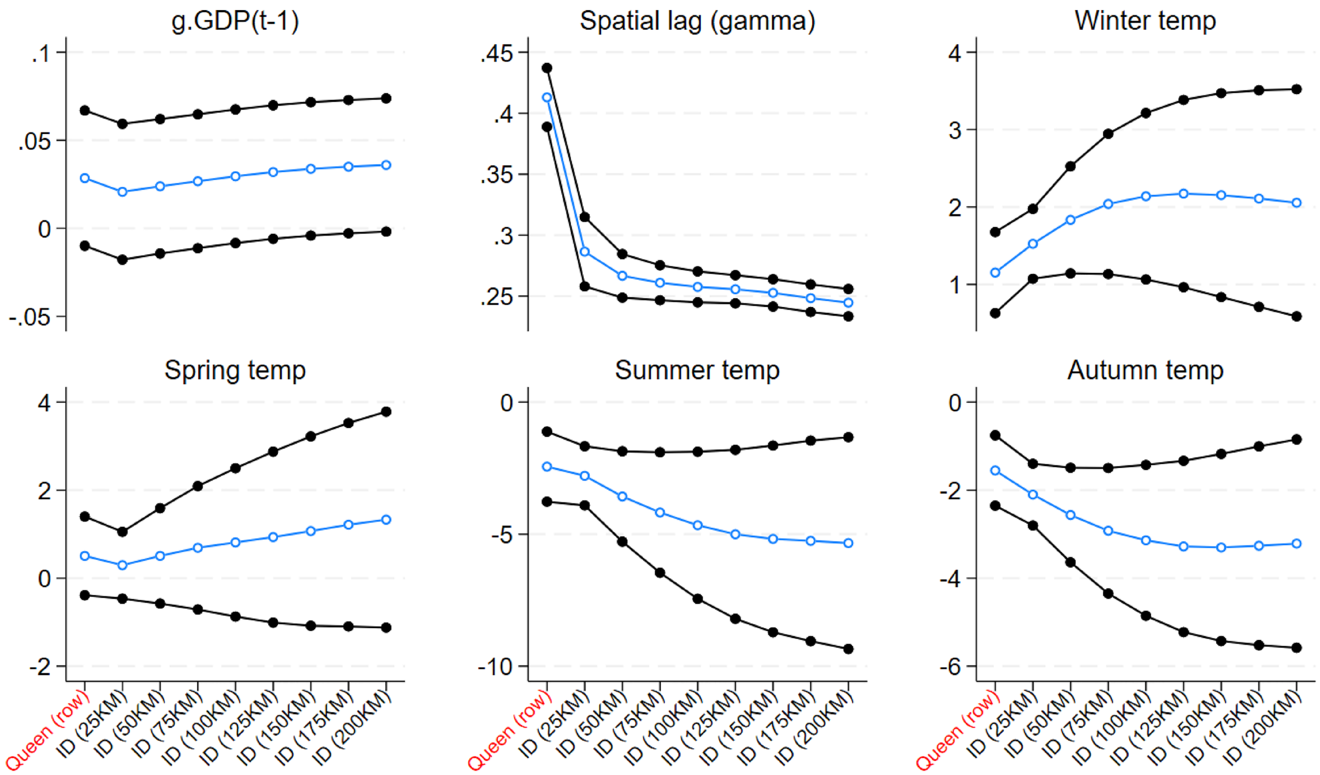

FIGURE 4 | Spatial weight matrices test (distance-based). The blue dots correspond to the coefficients for Equation (2) estimated using various spatial weight matrices. Black dots are confidence intervals at 95%. The matrices are briefly explained in-text and broadly described in the Appendix, Section C. The estimates presented here are short-run total impacts. [Colour figure can be viewed at wileyonlinelibrary.com]

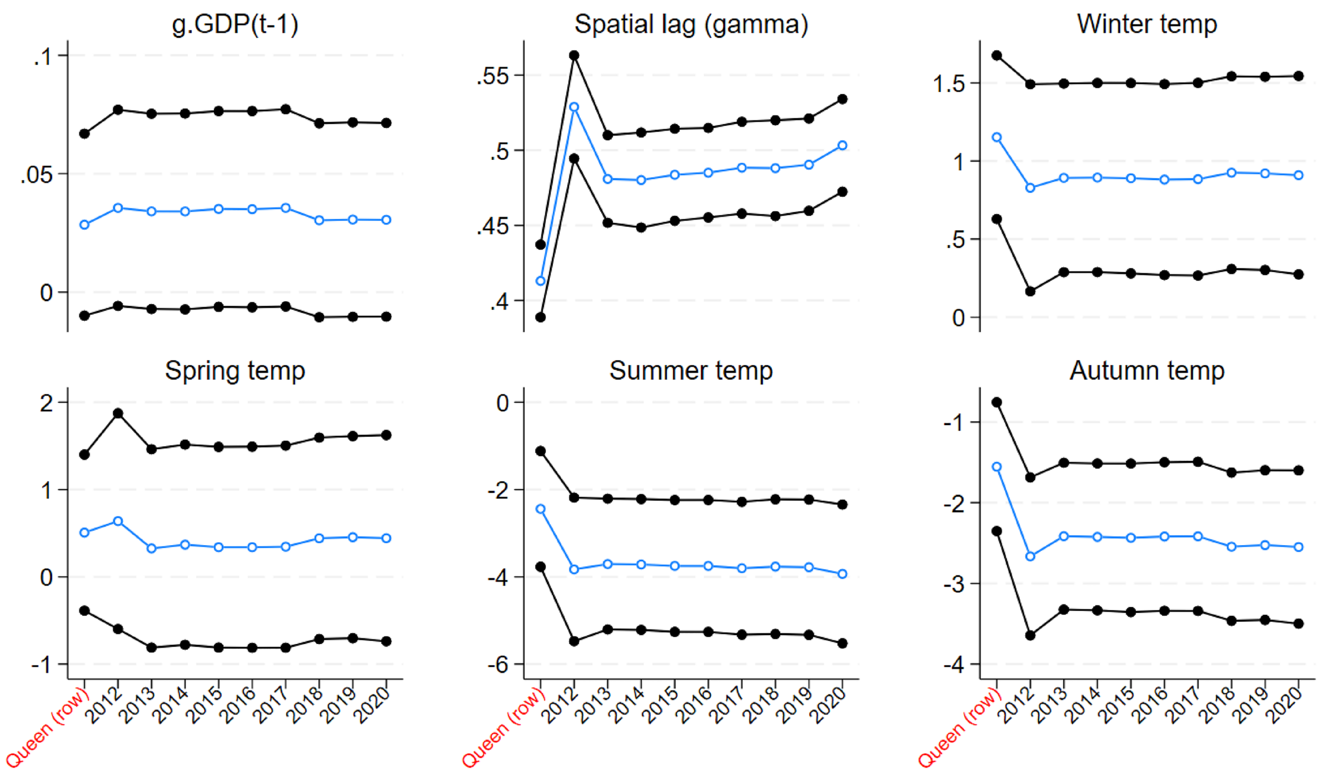

FIGURE 5 | Spatial weight matrices test (migration-based). The blue dots correspond to the coefficients for Equation (2) estimated using spatial weight matrices constructed from internal migration between 2012 and 2020. Black dots are confidence intervals at 95%. The estimates presented here are short-run total impacts. [Colour figure can be viewed at wileyonlinelibrary.com]

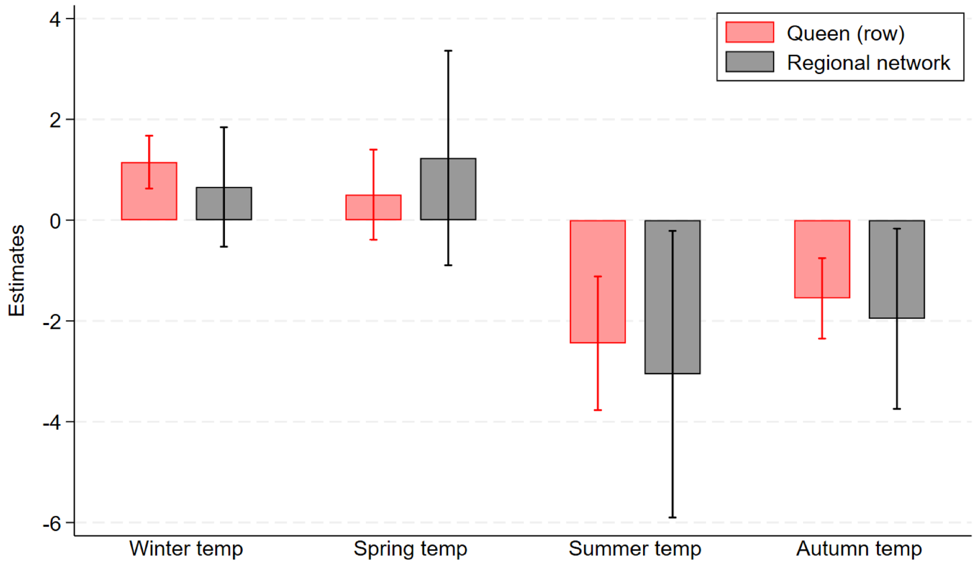

FIGURE 6 | Spatial weight matrices test (regional network).The bars correspond to the coefficients for Equation (2) estimated using the queen matrix (red bars) and regional network matrix (black bars). The spikes are confidence intervals at 95%. The matrices are briefly explained in-text and broadly described in the Appendix, Section C. The estimates presented here are short-run total impacts. [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 4 | Weather measure alternatives and GDP growth rate.

Outcome variable: GDP growth rate	**Source of weather measure**	
	CRU	**ERA5**
T_{winter}	1.152*** (0.267)	0.973*** (0.217)
T_{spring}	0.506 (0.456)	0.395 (0.444)
T_{summer}	−2.443*** (0.676)	−1.845*** (0.637)
T_{autumn}	−1.553*** (0.407)	−1.263*** (0.392)
α	0.028 (0.019)	0.026 (0.019)
γ	0.412*** (0.012)	0.415*** (0.012)
Log likelihood	−19, 810	−19, 810
R^2_w	0.22	0.22
Observations	7,833	7,833

Note: Spatial weight matrix is a queen matrix. The months comprising each season are discussed in-text. All specifications contain precipitation controls, quadratic terms of the seasonal weather measures, council-level fixed effects and region-specific linear trend. Standard errors in parentheses are clustered at the council level.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 5 shows the results of modifying the functional form of the outcome variable. Substituting the outcome variable with the growth rate of GDP per capita to measure the effect on personal income and welfare yields similar results to those of the baseline. Also, using logarithmic form rather than growth rate does not affect the significance and sign of the primary results, with the exception of α, which becomes significant.[20] Further, to test for a placebo effect, we re-estimated the baseline model, incorporating one to three lags of seasonal temperatures. Additionally, we included leads of seasonal temperatures up to 3 years ahead in the original model specifications. The results in Figure E5 in the Appendix show no significant estimates for either the lags or leads, providing evidence against any spurious correlation. The results of these several checks confirm that our findings are stable and devoid of large deviations.

3.3 | Investigating Mechanisms

To address the adverse impact of temperature shocks on economic growth, it is crucial to identify the economic sectors that are most vulnerable to seasonal weather fluctuations [12].[21] We use a non-spatial model (Equation 1) for these analyses because some of the strong econometric requirements associated with the use spatial models, such as a balanced panel and absence of islands, are not met. In any case, the findings should be similar because the baseline results for both models are qualitatively similar (see Table 2). We rely on Rosés and Wolf [52], who provide subnational GDP share of three sectors – agriculture, industry and services.[22] Our findings highlight that warmer summers lead to a notable decline in the growth rate of agriculture share of GDP, as shown in Figure 7. On the other hand, the effects on the industrial and services sectors' output remain comparatively limited. We note, however, that these findings should be interpreted with caution due to the high aggregation level of sectoral GDP data and limited temporal coverage, which includes wide gaps between the available data periods.

High temperatures might exacerbate heat and drought event frequencies during summer, negatively affecting agricultural sectoral output [53]. Indeed, the seminal contribution of Dell et al. [54] offers some supportive evidence of the negative impact of high temperature on economic output through a decline in agricultural productivity. Further, evidence of agricultural yield variations is more observed during extremely hot and dry summers in contrast to extremely cold and wet conditions [55]. Output in the agricultural sector could favour inter-sectoral spillovers, at least to some extent, given the robust intersectoral linkages between

TABLE 5 | Alternative outcomes.

	Outcome variable			
	GDP		GDP per capita	
	Growth rate	Log form	Growth rate	Log form
T_{winter}	1.152***	0.013***	1.126***	0.014***
T_{spring}	0.506	0.002	0.527	0.001
T_{summer}	−2.443***	−0.024***	−2.443***	−0.024***
T_{autumn}	−1.553***	−0.018***	−1.693***	−0.019***
α	0.028	0.949***	0.044**	0.943***
γ	0.412***	0.096***	0.404***	0.099***
Log likelihood	−19, 810	15,970	−19, 870	15,953
R_w^2	0.22	0.97	0.22	0.96
Observations	7,833	7,833	7,833	7,833

Note: Spatial weight matrix is a queen matrix. The months comprising each season are discussed in-text. All specifications contain precipitation controls, quadratic terms of the seasonal weather measures, council-level fixed effects, and region-specific linear trend. Errors were clustered at the council level.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

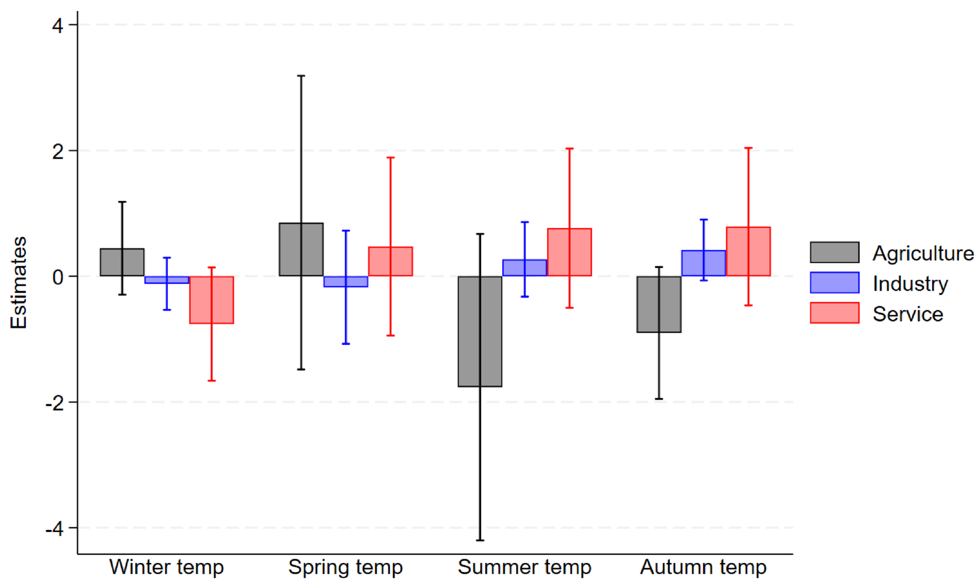

FIGURE 7 | Sectoral analysis. The bars correspond to the coefficients for the non-spatial form of Equation (2) estimated using the following economic sectors as respective outcome variables: agriculture (black bars), industry (blue bars) and service (red bars). The spikes are confidence intervals at 95%. [Colour figure can be viewed at wileyonlinelibrary.com]

the agricultural and labour demand and supply and employment in other productive economic sectors. By the same token, a decline in the agricultural sector might lower aggregate output through the negative spillovers on other productive sectors.

Additionally, we conduct regional- and income-based analyses to examine whether there are particular areas in the United Kingdom where the impacts of seasonal temperature fluctuations are more remarkable. First, we divide the councils into North and South partitions based on their locations on the map. We classify councils within the London, South East, East of England and South West regions as "South", while other regions, including Scotland, Northern Ireland and Wales, are classified as "North". Focusing on what happens during temperature changes in summer and winter seasons, Figure 8 shows that while temperature fluctuations impact both North and South similarly, the impact is more noticeable in the South of the UK than in the North. Councils in the South tend to slightly benefit more from a warmer winter than those in the North. However, the economy in the South with higher seasonal temperatures (see Figure 2) suffers greater damage than the North from high summer temperature.[23] This large differential shows that the source of the economic impact of summer temperature shocks is the South, while the winter temperature impacts on the UK economy appear to be equally driven by economic activities in both the North and South. This finding is consistent with the fact that there is a much lower standard deviation in winter temperature than in summer, as shown in Table 1.[24] Figure E2 of the Appendix also shows that most effects observed from the South originate from London. This burden of impact is not unexpected given the central role of London in the

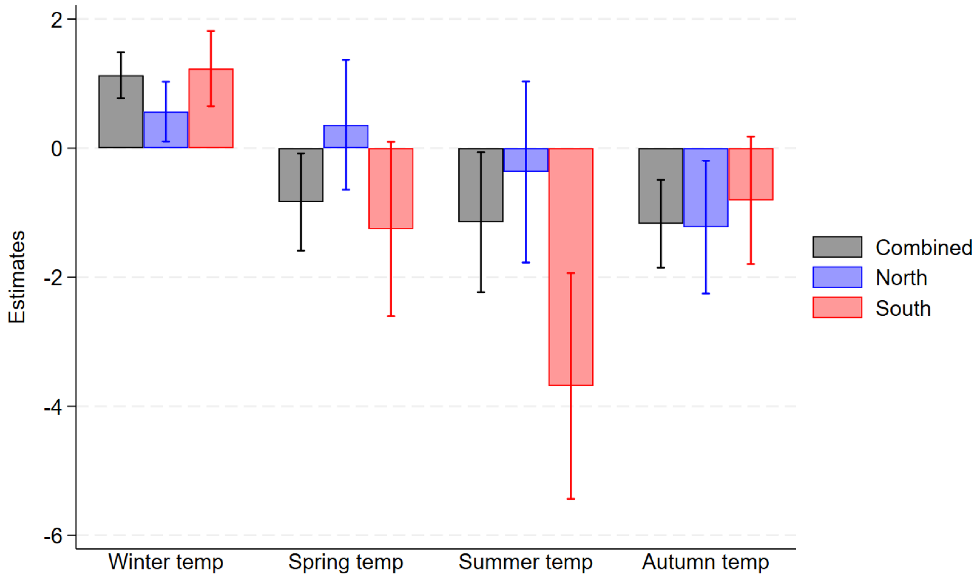

FIGURE 8 | Zonal analysis (the North/South divide). The bars correspond to the coefficients for the non-spatial form of Equation (2) estimated for the entire sample (black bars), northern councils (blue bars) and southern councils (red bars). The spikes are confidence intervals at 95%. The procedure for classifying councils into North and South is explained in-text. [Colour figure can be viewed at wileyonlinelibrary.com]

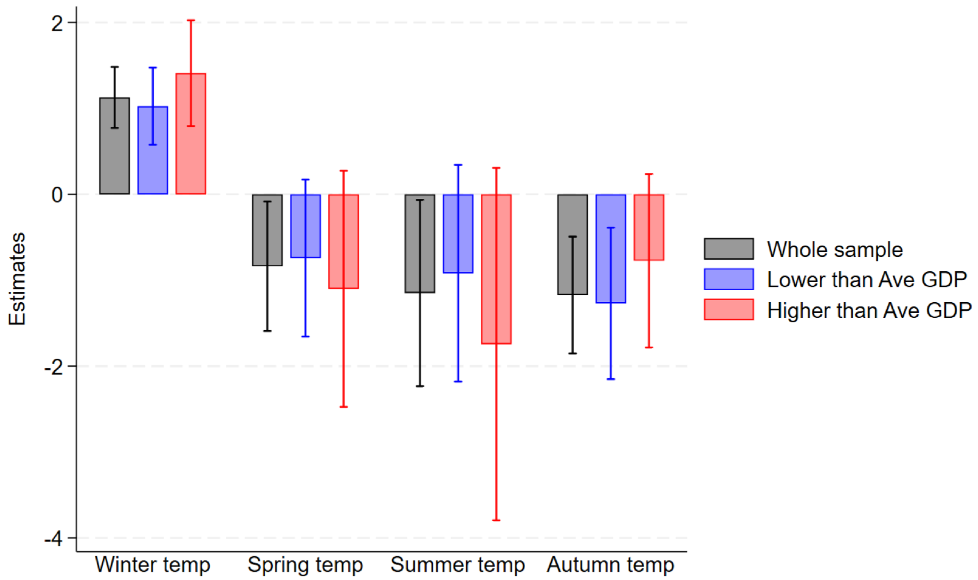

FIGURE 9 | Effects by income classification. The bars correspond to the coefficients for the non-spatial form of Equation (2) estimated for the entire sample (black bars), low-income councils (blue bars) and high-income councils (red bars). The spikes are confidence intervals at 95%. The procedure for classifying councils into low and high income is explained in-text. [Colour figure can be viewed at wileyonlinelibrary.com]

UK's socio-political and economic life. For example, over 53% of financial service output in the UK comes from London [56].[25]

We further investigate the source of the effect of temperature shocks on economic growth in the UK by analysing Equation (1) by income group. We divide the councils into two groups based on their average GDP size with respect to the UK's average GDP for the period under consideration. We define a council as "high income" if its average GDP is above the national mean, and those lower we define as "low income".[26] We also provide evidence in the Appendix Section (Figure E3) that the results are broadly similar if we redefine the income classification to vary with time, where a council is defined as "high income" in year *t* if its average GDP is above the national mean; otherwise, it is classified as "low income". The results displayed in Figure 9 show that high-income councils are more affected by an increase in winter and summer temperatures than low-income councils.[27] High-income councils are almost twice as likely to experience economic losses from a 1°C summer temperature increase than their low-income counterparts. This margin widens when we redefine income class to vary with time, as seen in Figure E3 of the Appendix. However, this difference does not appear to be statistically significant. A possible reason for the insignificant difference is that the margin between the high- and low-income councils could be blurred, especially around the borders between high- and low-income councils. We overcome this challenge by dividing the region's income levels into quantiles. The results in Figure 10 corroborate our findings that high-income councils – especially the top 25% of the wealthiest councils – are the most impacted by changes in summer temperature. Regionalising the impact of environmental factors is essential to help inform appropriate formulation and implementation of policies. We find that southern, high-income local councils are more vulnerable to the effects of hot summers than other councils (see Figure E6 in Appendix). Hence, appropriate region-specific mitigation and adaptation measures, such as grants for air-conditioners, could be helpful in minimising economic losses associated with such events.

We further investigate the role of electricity consumption in explaining economic growth, given its direct and indirect links to economic expansion [57] and the influence of temperature on energy demand [58]. Specifically, we model how temperature changes impact electricity demand, providing additional evidence for the relationship between seasonal temperature fluctuations and economic growth. Electricity consumption often serves as a proxy for economic complexity, reflecting the substantial demand associated with sustained industrial and technological advancement [59–61]. Using electricity data from the UK Department for Energy Security and Net Zero, we test this relationship by reanalysing the baseline model with the natural logarithm of the average electricity consumption in kilowatt hours (kWh). Table 6 shows that the declines in mean and median electricity consumption for both domestic and

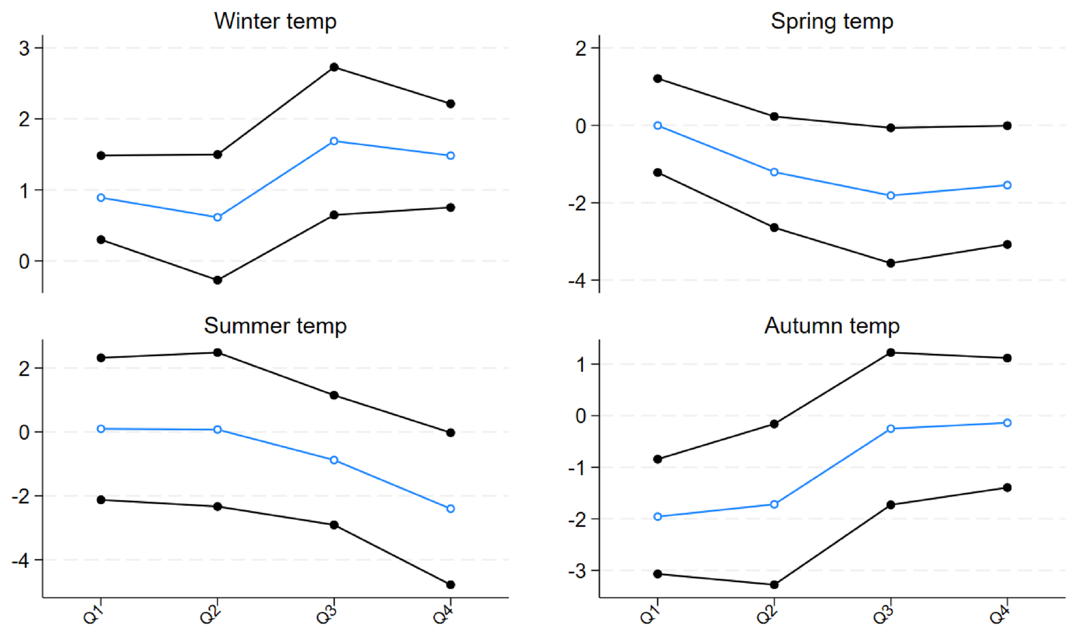

FIGURE 10 | Effects by income quantiles. The blue dots correspond to the coefficients for the non-spatial form of Equation (2) estimated by income quantiles from the lowest income quantile (Q1) to the highest (Q4). The black dots represent confidence intervals at 95%. [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 6 | Impact on seasonal weather fluctuations on electricity consumption in the UK.

	Mean consumption		**Median consumption**	
	Domestic	**Non-domestic**	**Domestic**	**Non-domestic**
T_{winter}	−0.032*** (0.002)	−0.015** (0.007)	−0.016*** (0.003)	−0.070*** (0.013)
T_{spring}	−0.018*** (0.003)	−0.052*** (0.009)	−0.059*** (0.003)	0.010 (0.007)
T_{summer}	−0.105*** (0.006)	−0.079*** (0.021)	−0.133*** (0.007)	−0.350*** (0.020)
T_{autumn}	1.262*** (0.006)	0.041*** (0.014)	0.052*** (0.005)	0.082*** (0.017)
Observations	5,555		3,124	
Period	2005–2020		2012–2020	

Note: Outcome variable is the log of electricity consumption in kilowatt hours (kWh). The months comprising each season are discussed in-text. All specifications contain precipitation controls, quadratic terms of the seasonal weather measures and fixed effects. Standard errors in parentheses are clustered at the council level.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

non-domestic uses during summer are more pronounced than those in winter.

4 | Conclusion and Policy Implications

This paper examines the effect of seasonal temperature on economic output growth in the United Kingdom using spatiotemporal econometric techniques. We find a statistically significant relationship between seasonal temperature and economic growth. Warmer temperatures during summer and autumn are related to a reduced output growth rate, whereas a temperature increase in winter months is associated with higher economic growth rate. Specifically, we find that a 1°C increase in temperature during summer (autumn) seasons results in a 2.44% (1.55%) drop in economic growth, whereas a similar change in temperature during winter is associated with about a 1.15% increase in economic growth. Overall, more affluent councils in the South of the UK are more affected by warmer temperatures: they are both positively affected by milder winters and negatively affected by hotter summers. One limitation of this paper is that our method does not account for the inter-annual trade-offs that economic agents make, which may offset or amplify the contemporaneous estimates presented here. Thus, we note that what we estimate are short-run changes in economic activities that may not reflect long-run responses to climate change (e.g., changing occupations, migration patterns, shifts in agricultural practices, infrastructural adaptations, long-term investments in climate resilience, amongst others).[28]

Our results provide some plausible context that answers the questions of "where" and "for whom" climate-related shocks economically matter. If wealthy economies and regions have low costs of adapting to shocks, a related question that opens new avenues of research arises: why do they find it difficult to mitigate climate risks with lower costs, or to decouple productive activities away from environment-sensitive activities? One hypothesis is that the high marginal costs of adapting economic activities to changing climatic conditions in economically advanced regions can alter incentives to invest in climate-mitigating technologies if such technologies are season-specific and practically not useful in the production process during other seasons [63].

We can think of two scenarios in which higher summer temperatures increase the marginal costs of climate adaptation. The first scenario relates to economic complexity [64]. Regions with competitive advantages in producing goods and services tend to have highly complex economies. These economies rely on year-round, interconnected supply and demand chains, many of which depend on networks of integrated subnational units [65]. Attuning production activities to reflect seasonal temperature specificities might increase marginal costs if they raise the overall variable production costs without necessarily increasing economic output or demand. The second scenario relates to the high sensitivity of agricultural production to climate stress. Agricultural production requires a low spatial density of human and physical capital [63], which can potentially increase the marginal cost of adapting agricultural production to changing climatic conditions [66], as we observe in the case of higher winter temperatures.

Concerning the channels, we are able to show that the adverse impact of higher temperatures on economic output is realised through (1) a decline in agricultural productivity, (2) a decline in economic activities in the South of the UK, characterised by having competitive advantages in several high complexity activities and among high-income neighbourhoods, and (3) a comparatively larger disruption of economic activity through the reduction in the mean and median electricity consumption during summer than in other seasons.

Our analysis of the contemporary United Kingdom context shows that, despite its high-income levels and potential for adopting adaptation technologies, economic growth might be exacerbated by warmer temperatures in advanced economies [66]. The results contributes to previous studies that find that mild winters positively impact output growth and hot summers have lasting adverse effects on output growth in advanced economies [12, 40, 42, 67]. The results that hotter summers depress economic output are consistent with the narrative that climate-related shocks have significant macroeconomic effects over the business cycle in advanced regions [68]. This conclusion is similar to studies in low-income countries, where there is evidence that the disruptive effect of hotter temperatures is more pronounced on agricultural productivity [2, 69, 70].

This study highlights the need for continued research on the relationship between weather shocks and economic growth in advanced economies with temperate climates, and the importance of developing adaptive strategies to ensure continued economic prosperity in the face of climate change. Economic systems could adapt to the changing climate by proactively investing in adaptation measures. For example, coastal protection can potentially reduce the risk of climate-related damages, as well as redouble its efforts to reduce greenhouse gas emissions by at least 68 per cent by 2030, as pledged by the then Prime Minister Rishi Sunak at the COP27 summit in Egypt [71]. Fulfilling such lofty goals would ensure that the UK is resilient to the challenges of a warming world.

Acknowledgments

We appreciate the three anonymous reviewers and the editor for their constructive comments.

Endnotes

[1] The National Interagency Fire Center puts the total number of fires between 1 January 2023 and 31 August 2023 in the US at 39,299, with over two million acres of land destroyed, making an average of 51.08 acres destroyed per fire. Notably, most of these fire incidents occurred during summer seasons (see full report in https://www.nifc.gov/fire-information/nfn).

[2] Studies using a similar technique find that estimates from spatial models differ from their non-spatial counterparts; see [3, 10, 11].

[3] According to Elhorst [20], spatial panels refer to georeferenced point data over time of geographical units or (although less common) economic agents.

[4] Dell et al. [21] argue that neglecting potential spillovers in a standard panel analysis could bias the resulting estimates; hence, controlling for such spillovers could be of *first-order* importance.

[5] The dataset can be assessed via https://www.ons.gov.uk/economy/grossdomesticproductgdp/datasets/regionalgrossdomesticproductlocalauthorities.

[6] These are standard monthly classifications for the four seasons in the UK according to the UK Met Office (see, https://www.metoffice.gov.uk/weather/learn-about/met-office-for-schools/other-content/other-resources/our-seasons).

[7] England has nine regions, while Scotland, Northern Ireland and Wales are considered as regions by the ONS.

[8] Most of our results are robust to the substitution of specific linear time trend with region-by-year fixed effects, as shown in Table E5 in the Appendix.

[9] The spatial mechanism shaping the model's structure relies heavily on the panel design, making it impractical to cluster by spatial areas that differ from the unit of observation—in this case, the council level. Forcing the model to deviate from this structure, as tested in our robustness check, introduces a convexity issue where the gradient matrices become non-positive. This leads to the exclusion of spatial effects, yielding estimates that capture only non-spatial variation.

[10] Equation (2) is based on spatial panels, a class of models built on the achievement of traditional panel models [29] and spatial interaction models [30].

[11] The package relies on bias correction in Yu et al. [33] to eliminate the incidental parameter problem accompanying dynamic fixed effects models with short T.

[12] Interested readers can consult Yu et al. [33] for a detailed derivation of the likelihood of models with a spatially lagged dependent variable.

[13] Ord [34] seminal work focused on maximum likelihood estimation, laying the foundation for subsequent advancements. Building on this, Lee [35] and Elhorst [36] extend the econometric framework to accommodate QML estimation, broadening its applicability and robustness.

[14] We remind readers that neighbours in the case of the queen matrix are defined as those sharing boundaries with a council. Hence, the indirect effects do not capture spillovers from noncontiguous councils.

[15] In addition to the queen spatial matrix used as our baseline, we construct other spatial weight matrices in the robustness section to test these potential mechanisms.

[16] The total impact is the sum of the direct and indirect effects. It represents the overall impact of a change in seasonal temperatures on economic growth, considering both local and spillover impacts.

[17] As outlined in Corrado and Fingleton [46], Ullah [47], spatial weight matrices can be created to reflect spatial interactions based on economic (or regional market) networks.

[18] Data for migration flows between English and Welsh local authorities, Scotland and Northern Ireland can be accessed via https://www.ons.gov.uk/peoplepopulationandcommunity.

[19] See https://cds.climate.copernicus.eu for a complete description of the dataset.

[20] We treat the significance of α with scepticism given that, unlike growth rate, it inherits the non-stationarity properties of observed GDP.

[21] Section A.1 in the Appendix presents a fuller description of how seasonal weather fluctuations could influence various sectoral components of the economy.

[22] We appreciate the editor for signposting us to this dataset.

[23] The difference between summer temperature impact for North and South is significant at 1% level (F-Stat=8.54), while it is significant at the 10% level for winter temperatures (F-Stat=2.19).

[24] We also present the spatial distribution of the difference in mean summer and winter temperatures across regions in the UK for the period under consideration in Figure E8 in the Appendix.

[25] Further, we show that the results are not influenced by the type of weather data in Figure E4 in the Appendix where we used ERA5 data with similar findings for winter and summer temperature effects.

[26] We also tried several income thresholds, such as comparison with median income, and obtained similar results, which can be made available on request.

[27] The reader could think that it is possible that most high-income areas including London are located in the South, making it difficult to distinguish between the two mechanisms—income and location. However, we show that both mechanisms are not strongly correlated as shown in Table E1 in the Appendix. For example, the correlation between GDP growth in high-income areas and councils in the South is 0.38.

[28] This problem is omnipresent in empirical works that use panel data in analysing the response to environmental impacts, for example, [54, 62].

References

1. S. Acevedo, M. Mrkaic, N. Novta, M. Poplawski-Ribeiro, E. Pugacheva, and P. Topalova, "The Effects of Weather Shocks on Economic Activity: How Can Low-Income Countries Cope," *World Economic Outlook:* Seeking Sustainable Growth—Short-Term Recovery, Long-Term Challenges (International Monetary Fund, 2017), 117–184.

2. S. Acevedo, M. Mrkaic, N. Novta, E. Pugacheva, and P. Topalova, "The Effects of Weather Shocks on Economic Activity: What Are the Channels of Impact?" *Journal of Macroeconomics* 65 (2020): 103207.

3. L. E. Emediegwu, A. Wossink, and A. Hall, "The Impacts of Climate Change on Agriculture in Sub-Saharan Africa: A Spatial Panel Data Approach," *World Development* 158 (2022): 105967.

4. D. Du, X. Zhao, and R. Huang, "The Impact of Climate Change on Developed Economies," *Economics Letters* 153 (2017): 43–46.

5. USDA, "Biden-Harris Administration to Invest Nearly $11 Million in Wildland Fire Science Research and Knowledge Exchange, As Part of Investing in America Agenda," 2023.

6. J. C. Driscoll and A. Kraay, *Spatial correlations in panel data* (World Bank Publications, 1995).

7. X. Tian and M. Zhang, "Research on Spatial Correlations and Influencing Factors of Logistics Industry Development Level," *Sustainability* 11, no. 5 (2019): 1356.

8. P. S. Ward, R. J. Florax, and A. Flores-Lagunes, "Climate Change and Agricultural Productivity in Sub-Saharan Africa: A Spatial Sample Selection Model," *European Review of Agricultural Economics* 41, no. 2 (2014): 199–226.

9. B. H. Baltagi, B. Fingleton, and A. Pirotte, "Estimating and Forecasting With a Dynamic Spatial Panel Data Model," *Oxford Bulletin of Economics and Statistics* 76, no. 1 (2014): 112–138.

10. D. da Firmino Costa Silva, J. P. Elhorst, and R. d. M. Silveira Neto, "Urban and Rural Population Growth in a Spatial Panel of Municipalities," *Regional Studies* 51, no. 6 (2017): 894–908.

11. M. Harari and E. L. Ferrara, "Conflict, Climate, and Cells: A Disaggregated Analysis," *Review of Economics and Statistics* 100, no. 4 (2018): 594–608.

12. R. Colacito, B. Hoffmann, and T. Phan, "Temperature and Growth: A Panel Analysis of the United States," *Journal of Money, Credit and Banking* 51, no. 2–3 (2019): 313–368.

13. L. E. Emediegwu, "Assessing the Asymmetric Effect of Global Climate Anomalies on Food Prices: Evidence From Local Prices," *Environmental and Resource Economics* 87 (2024): 2743–2772.

14. G. Felbermayr, J. Gröschl, M. Sanders, V. Schippers, and T. Steinwachs, "The Economic Impact of Weather Anomalies," *World Development* 151 (2022): 105745.

15. M. Sandhani, A. Pattanayak, and K. Kavi Kumar, “Weather Shocks and Economic Growth in India,” *Journal of Environmental Economics and Policy* 12, no. 2 (2023): 97–123.

16. C. Greßer, D. Meierrieks, and D. Stadelmann, “The Link Between Regional Temperature and Regional Incomes: Econometric Evidence With Sub-National Data,” *Economic Policy* 36, no. 107 (2021): 523–550.

17. V. Boucher, M. Rendall, P. Ushchev, and Y. Zenou, “Toward a General Theory of Peer Effects,” *Econometrica* 92, no. 2 (2024): 543–565.

18. N. M. Fortin, T. Lemieux, and N. Lloyd, “Labor Market Institutions and the Distribution of Wages: The Role of Spillover Effects,” *Journal of Labor Economics* 39, no. S2 (2021): S369–S412.

19. B. H. Baltagi, *Spatial Panels* (Chapman and HallTaylor and Francis Group, 2011).

20. J. P. Elhorst, “Specification and Estimation of Spatial Panel Data Models,” *International Regional Science Review* 26, no. 3 (2003): 244–268.

21. M. Dell, B. F. Jones, and B. A. Olken, “What Do We Learn From the Weather? The New Climate-Economy Literature,” *Journal of Economic Literature* 52, no. 3 (2014): 740–798.

22. S. Chen and B. Gong, “Response and Adaptation of Agriculture to Climate Change: Evidence From China,” *Journal of Development Economics* 148 (2021): 102557.

23. M. Kalkuhl and L. Wenz, “The Impact of Climate Conditions on Economic Production. Evidence From a Global Panel of Regions,” *Journal of Environmental Economics and Management* 103 (2020): 102360.

24. M. Bozzola, E. Massetti, R. Mendelsohn, and F. Capitanio, “A Ricardian Analysis of the Impact of Climate Change on Italian Agriculture,” *European Review of Agricultural Economics* 45, no. 1 (2018): 57–79.

25. R. Mendelsohn, W. D. Nordhaus, and D. Shaw, “The Impact of Global Warming on Agriculture: A Ricardian Analysis,” *American Economic Review* 84 (1994): 753–771.

26. CIESIN, “Gridded Population of the World, Version 4 (GPWv4): Population Count, Revision 11,” 2018.

27. J. D. Angrist and J.-S. Pischke, *Mostly Harmless Econometrics: An Empiricist’s Companion* (Princeton University Press, 2008).

28. O. Oyekola, L. E. Emediegwu, and J. O. Animashaun, “Commodity Windfalls, Political Regimes, and Environmental Quality,” *Energy Economics* 138 (2024): 107813.

29. B. H. Baltagi, *Econometric Analysis of Panel Data* (John Wiley & Sons, 2001).

30. L. Anselin, “Spatial Externalities, Spatial Multipliers, and Spatial Econometrics,” *International Regional Science Review* 26, no. 2 (2003): 153–166.

31. J. P. LeSage and R. K. Pace, *Introduction to Spatial Econometrics*Statistics, Textbooks and Monographs (CRC Press, 2009).

32. F. Belotti, G. Hughes, and A. P. Mortari, “Spatial Panel-Data Models Using Stata,” *Stata Journal* 17, no. 1 (2017): 139–180.

33. J. Yu, R. De Jong, and L.-f. Lee, “Quasi-Maximum Likelihood Estimators for Spatial Dynamic Panel Data With Fixed Effects When Both n and t Are Large,” *Journal of Econometrics* 146, no. 1 (2008): 118–134.

34. K. Ord, “Estimation Methods for Models of Spatial Interaction,” *Journal of the American Statistical Association* 70, no. 349 (1975): 120–126.

35. L.-F. Lee, “Asymptotic Distributions of Quasi-Maximum Likelihood Estimators for Spatial Autoregressive Models,” *Econometrica* 72, no. 6 (2004): 1899–1925.

36. J. P. Elhorst, *Spatial Econometrics: From Cross-Sectional Data to Spatial Panel* (Springer, 2014).

37. P. Elhorst, G. Piras, and G. Arbia, “Growth and Convergence in a Multiregional Model With Space–Time Dynamics,” *Geographical Analysis* 42, no. 3 (2010): 338–355.

38. G. Huang, J. Zhang, J. Yu, and X. Shi, “Impact of Transportation Infrastructure on Industrial Pollution in Chinese Cities: A Spatial Econometric Analysis,” *Energy Economics* 92 (2020): 104973.

39. S. Sahu, M. Sett, and T. Kjellstrom, “Heat Exposure, Cardiovascular Stress and Work Productivity in Rice Harvesters in India: Implications for a Climate Change Future,” *Industrial Health* 51, no. 4 (2013): 424–431.

40. J. M. Addoum, D. T. Ng, and A. Ortiz-Bobea, “Temperature Shocks and Industry Earnings News,” *Journal of Financial Economics* 150, no. 1 (2023): 1–45.

41. J. Graff Zivin and M. Neidell, “Temperature and the Allocation of Time: Implications for Climate Change,” *Journal of Labor Economics* 32, no. 1 (2014): 1–26.

42. R. J. Park, J. Goodman, M. Hurwitz, and J. Smith, “Heat and Learning,” *American Economic Journal: Economic Policy* 12, no. 2 (2020): 306–339.

43. S. Dasgupta, F. Bosello, E. De Cian, and M. Mistry, “Global Temperature Effects on Economic Activity and Equity: A Spatial Analysis,” *European Institute on Economics and the Environment* Working Paper 22-1 (2022).

44. M. E. Kahn, K. Mohaddes, R. N. Ng, M. H. Pesaran, M. Raissi, and J.-C. Yang, “Long-Term Macroeconomic Effects of Climate Change: A Cross-Country Analysis,” *Energy Economics* 104 (2021): 105624.

45. S. Mohapatra, L. Wen, B. Sharp, and D. Sahoo, “Unveiling the Spatial Dynamics of Climate Impact on Rice Yield in India,” *Economic Analysis and Policy* 83 (2024): 922–945.

46. L. Corrado and B. Fingleton, “Where Is the Economics in Spatial Econometrics?,” *Journal of Regional Science* 52, no. 2 (2012): 210–239.

47. A. Ullah, *Handbook of Applied Economic Statistics* (CRC Press, 1998).

48. A. Faggian and P. McCann, “Human Capital, Graduate Migration and Innovation in British Regions,” *Cambridge Journal of Economics* 33, no. 2 (2009): 317–333.

49. C. Cattaneo, M. Beine, C. J. Fröhlich, et al., “Human Migration in the Era of Climate Change,” *Review of Environmental Economics and Policy* 13 (2019): 189–206.

50. M. J. Greenwood, “Internal Migration in Developed Countries,” in *Handbook of Population and Family Economics*, vol. 1 (Gulf Professional Publishing, 1997), 647–720.

51. D. J. Kaczan and J. Orgill-Meyer, “The Impact of Climate Change on Migration: A Synthesis of Recent Empirical Insights,” *Climatic Change* 158, no. 3 (2020): 281–300.

52. J. R. Rosés and N. Wolf, *The Economic Development of Europe’s Regions: A Quantitative History Since 1900* (Routledge, 2018).

53. C. Lesk, E. Coffel, J. Winter, et al., “Stronger Temperature–Moisture Couplings Exacerbate the Impact of Climate Warming on Global Crop Yields,” *Nature Food* 2, no. 9 (2021): 683–691.

54. M. Dell, B. F. Jones, and B. A. Olken, “Temperature Shocks and Economic Growth: Evidence From the Last Half Century,” *American Economic Journal: Macroeconomics* 4, no. 3 (2012): 66–95.

55. M. Heino, P. Kinnunen, W. Anderson, et al., “Increased Probability of Hot and Dry Weather Extremes During the Growing Season Threatens Global Crop Yields,” *Scientific Reports* 13, no. 1 (2023): 3583.

56. G. Hutton, “Financial Services: Contribution to the UK Economy,” 2022, https://researchbriefings.files.parliament.uk/documents/SN06193/SN06193.pdf.

57. R. Best and P. J. Burke, “Electricity Availability: A Precondition for Faster Economic Growth?,” *Energy Economics* 74 (2018): 321–329.

58. G. S. Eskeland and T. K. Mideksa, "Electricity Demand in a Changing Climate," *Mitigation and Adaptation Strategies for Global Change* 15 (2010): 877–897.

59. G. Gozgor, C. K. M. Lau, and Z. Lu, "Energy Consumption and Economic Growth: New Evidence From the OECD Countries," *Energy* 153 (2018): 27–34.

60. G. S. Mutumba, T. Odongo, N. F. Okurut, and V. Bagire, "A Survey of Literature on Energy Consumption and Economic Growth," *Energy Reports* 7 (2021): 9150–9239.

61. I. Ozturk, "A Literature Survey on Energy–Growth Nexus," *Energy Policy* 38, no. 1 (2010): 340–349.

62. P. Zhang, O. Deschenes, K. Meng, and J. Zhang, "Temperature Effects on Productivity and Factor Reallocation: Evidence From a Half Million Chinese Manufacturing Plants," *Journal of Environmental Economics and Management* 88 (2018): 1–17.

63. S. M. Hsiang and D. Narita, "Adaptation to Cyclone Risk: Evidence From the Global Cross-Section," *Climate Change Economics* 3, no. 2 (2012): 1250011.

64. S. Mishra, I. Tewari, and S. Toosi, "Economic Complexity and the Globalization of Services," *Structural Change and Economic Dynamics* 53 (2020): 267–280.

65. J. Glückler, "Economic Geography and the Evolution of Networks," *Journal of Economic Geography* 7, no. 5 (2007): 619–634.

66. T. Deryugina and S. M. Hsiang, "Does the Environment Still Matter? Daily Temperature and Income in the United States, Technical report, National Bureau of Economic Research," 2014.

67. M. Donadelli, M. Jüppner, and S. Vergalli, "Temperature Variability and the Macroeconomy: A World Tour," *Environmental and Resource Economics* 83, no. 1 (2022): 221–259.

68. M. Ciccarelli and F. Marotta, "Demand or Supply? An Empirical Exploration of the Effects of Climate Change on the Macroeconomy," *Energy Economics* 129 (2024): 107163.

69. L. E. Emediegwu and C. L. Ubabukoh, "Re-Examining the Impact of Annual Weather Fluctuations on Global Livestock Production," *Ecological Economics* 204 (2023): 107662.

70. M. Kotz, L. Wenz, A. Stechemesser, M. Kalkuhl, and A. Levermann, "Day-To-Day Temperature Variability Reduces Economic Growth," *Nature Climate Change* 11, no. 4 (2021): 319–325.

71. UK Government, "PM Statement at COP27: 7 November 2022," 2022.

Supporting Information

Additional supporting information can be found online in the Supporting Information section.