Monitoring and modelling disturbances to the Niger Delta mangrove forests

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Abstract

The Niger River Delta provides numerous ecosystem services (ES) to local populations and holds a wealth of biodiversity. Nevertheless, they are under threat of degradation and loss mainly due to the population increase and oil and gas extraction activities. Monitoring mangrove vegetation change and understanding the dynamics related with these changes is crucial for the short and longer-term sustainability of the Niger Delta Region (NDR) and its mangrove forests.

Over the last two decades, open access remote sensing data, together with technological and algorithmic advancements, have provided the ability to monitor land cover over large areas through space and time. However, the analysis of land cover dynamics over the NDR using freely available optical remote sensing data, such as Landsat, remains challenging due to the gaps in the archive associated with the West African region and the issue of cloud contamination over the wet tropics.

This thesis applies state-art-of-the-art remote sensing techniques and integrated modelling approaches to provide reliable information relating to monitoring and modelling of land cover change in the NDR, focusing on its mangrove forests.

Spectral-temporal metrics from all available Landsat images were used to accurately map land cover in three time points, using a Random Forests machine learning classification model. The performance of the classification was tested when L-band radar data are added to the Landsat-based metrics. Results showed that Landsat based metrics are sufficient in mapping land cover over the study region with high overall classification accuracies over the three time points (1988, 2000, and 2013) and degraded mangroves were accurately mapped for the first time. Two additional assessments: a change intensity analysis for the entire NDR and, fragmentation analysis focusing on mangrove land cover classes were carried out for the first time ever.

The drivers of mangrove degradation were assessed using a Multi-layer Perceptron, Artificial Neutral Networks (MLP-ANN) algorithm. The results reveal that built-up infrastructure variables were the most important drivers of mangrove degradation between 1988 and 2000, whilst oil and gas infrastructure variables were the most important drivers between 2000 and 2013. Results also show that population density was the least important driver of mangrove degradation over the two study periods.

Future land cover changes and mangrove degradation were predicted under two business-as-usual scenarios in the short (2026) and longer-term (2038) using a Multi-Layer Perceptron neutral network and Markov chain (MLP-ANN+MC) model. The model's accuracy was assessed using the highly-accurate land cover classification of 2013. Results show that that mangrove forest and woodlands (lowland and freshwater forests) are demonstrating a net loss, whilst the built-up areas and agriculture are indicating a net increase in both the short and longer-term scenarios. However, degraded mangroves are demonstrating a net increase in the short-term scenario. Interestingly, in the longer-term scenario, more than double the net increase of mangroves degraded in the short-term scenario, are predicted to recover to their healthier state.

The thesis results could provide useful information for planning conservation measures for sustainable mangrove forest management of the entire NDR.

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Special thanks to my dear mother Hafsat Ibrahim, siblings, and friends for the prayers, moral support, and encouragement.

Dedication

I dedicate this work to my late father Ishaku Nababa Chonoko who passed away doing his PhD, there is no other way I could have honoured you better than completing a PhD. Also, to my late brother Jibril Ishaku Nababa who died just recently, I dedicated this to you.

Contents

List of Figures

List of Tables

List of Acronyms

ACE2	Altimeter Corrected Elevations 2
ANN	Artificial Neural Networks
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
ATSRs	Along-Track Scanning Radiometers
AUC	Area Under Curve
AVHRRs	Very High-Resolution Radiometers
BAU	Business-as-usual scenarios
CA	Cellular Automata
CLUEs	Conversion of Land Use and its Effects
DEM	Digital Elevation Model
ENN_SD	Euclidean nearest neighbour distance Standard Deviation
EO	Earth observation
ES	Ecosystem services
ESA	European Space Agency
GDP	Gross Domestic Product
GDEM	Global Digital Elevation Model
GHSL	Global Human Settlement layer
GLCM	Gray-Level Co-Occurrence Matrix
GLS	Global Land Survey
GMTED	Global Multi-resolution Terrain Elevation Data
GMW	Global Mangrove Watch
gROADSv1	Global Roads Open Access Data Set version 1
IPCC	Intergovernmental Panel on Climate Change
JIV	Joint Investigation Visit
LAI	Leaf Area Index
LCC	Land cover change
LPI	Largest Patch Index
LCM	Land Change Modeller
LULC	Land use Land cover
MC	Markov Chains
MCA	Markov chain analysis
MLP	Multi-layer Perceptron

NDR	Niger Delta Region
NDVI	Normalised Difference Vegetation Index
NISHA	Nigerian Hydrological Services Agency
NOSDRA	National Oil Spill detection Agency
NP	Number of patches
NRD	The Niger River Delta
OBIA	Object-Based Image Analysis
OSM	OpenStreetMap
ROC	Receiver Operating Characteristic
SEEA	System for Environmental Economic Accounting
SLR	sea level rise
SML	Symbolic Machine learning
SPDC	Shell Petroleum Development Company
SRTM	Shuttle Radar Topography Mission
UNSDI-T	UN Spatial Data Infrastructure Transport
UTM	Universal Transverse Mercator
VGI	Volunteers Geographic Information
WGS	World Geodetic System

Chapter 1

Introduction

1.1 The Niger Delta region (NDR): important but in danger

The Niger River Delta is the largest river delta in Africa (Goudie, 2005) and home to a rapidly increasing human population. It sits directly on the Gulf of Guinea on the Atlantic Ocean (Figure 1.1). It is endowed with Africa's most extensive mangrove forest and the fifth largest in the world after Indonesia, Brazil, Australia and Mexico, located on the East Atlantic West African coast (Spalding, 2010; Bunting et al., 2018).

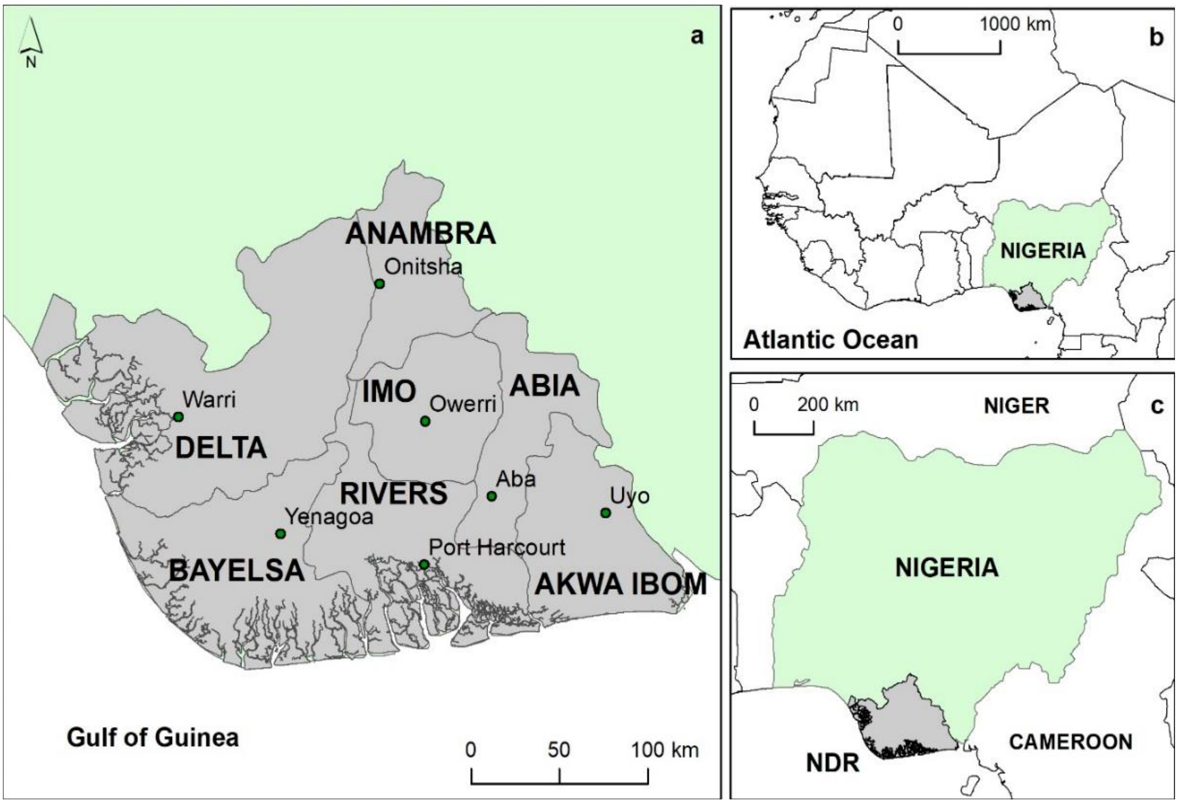

Figure 1.1: (a) The Niger Delta Region (comprising of the states of Abia, Akwa Ibom, Anambra, Bayelsa, Delta, Imo, and Rivers), and its location within (b) West Africa and (c) Nigeria

Mangroves of the Niger Delta Region (NDR) are highly recognised for their great economic and ecological value despite their low species and diversity (Feka and Ajonina, 2011), providing ecosystem service (ES) such as fisheries, carbon storage and sequestration, fuelwood, construction material, flood protection, medicinal products, recreation, and tourism (Zabbey et al., 2010; Okonkwo et al., 2015; Numbere, 2014). They also hold an important spiritual value to local communities (James et al., 2013). These ES are categorised into provisioning, regulating, supporting to cultural services (MEA, 2005). About 62% of inhabitants in the NDR depend on mangroves for fuelwood (Numbere, 2019) and more than 70% of fish catch in the region are mangrove related which are important source of income and protein nutrition (Udoh, 2016).

Mangroves are, therefore, indisputably important resource crucial for livelihood sustenance of local inhabitants. However, they are under threat of degradation from anthropogenic sources mainly due to oil and gas exploration activities (Figure 1.3a) and human population pressures (Kadafa, 2012; Onyena and Sam, 2020; Nwobi et al., 2020). The mangrove forest of the NDR also suffers from degradation from climatic change impacts as temperature and rainfall regimes are altered (Uyigue and Agho, 2007). Climate change related disturbances such as sea level rise, extreme floods, storm surges, erosion, subsidence, and salinity intrusion are also projected to increase (Szabo et al., 2016). Furthermore, tropical coastal populations are estimated to increase significantly in the coming decades (Sale et al., 2014). Both of these changes are expected to further aggravate the degradation process of mangrove forest of the NDR. Mangroves are in fact projected to disappear by the end of the century given present disturbance rates (FAO, 2007; Duke et al., 2007a).

Degradation of mangrove ecosystem is most noticeable when healthy or an ecological condition that represents this ecosystem’s baseline state (Figure 1.2) has changed in their composition (species assemblage and abundance), structure (biomass and canopy cover), and functioning, such that it is unable to provide a number of ES and support biodiversity as the healthy mangroves (Thomas et al., 2017; Begam et al., 2020).

Given the benefits provided by mangrove forest of the Niger Delta River, and the perceived degradation from anthropogenic and environmental pressures, it is essential to fully understand the dynamics of this vital ecosystem. Currently, there is lack of reliable information on the extent and condition of mangrove forest in the NDR which is essential for short and long-term management.

Figure 1.2. Healthy mangroves in the coastal area of the NDR (EnvironNews Nigeria, 2018).

Figure 1.3. Mangroves degradation in the NDR: (a) degradation due to activities of oil and gas (oil spills; CEHRD, 2019); (b) Highway road construction induced degradation (Amadi, 2020); (c) degradation through fuel wood (Chima and Larinde, 2016); (d) degradation to reclaim land for residential settlements (Chima and Larinde, 2016).

1.2 Earth Observation for addressing the NDR crisis

Two main reasons have been identified limiting mangrove monitoring studies in the NDR. One is the difficulty in accessing mangrove environments due to their complex root systems and regular inundation of tide along the coast, the average tidal range being 1.5m in the NDR (James et al., 2007). The other, is security volatility in the region resulting from disputes amongst local communities, private oil companies, and the government, as well as activities of militants and oil bunkering.

Earth observation (EO) technologies are therefore the only viable means of assessing land condition and change over such large and inaccessible area. EO-based monitoring studies have commonly looked at land cover and land cover change and have employed multi-temporal Landsat data, owing to its history of long and consistent data archive for ~ 50 years. Nevertheless, assessing land cover change over certain parts of the world (e.g., western and eastern Africa) are challenging due to significant data gaps in Landsat archive and problems of cloud contamination, especially over wet tropics (Martinuzzi et al., 2007; Colby and Keating, 2001; Okoro et al., 2016; Kuenzer et al., 2014a; Kirui et al., 2013). Previous, “traditional” approaches have used image mosaics or single images from single-sensor data to map two (before and after) dates and assess change from these (James et al., 2007; Ayanlade and Drake, 2015; Mena, 2008; Gao and Liu, 2010; Obiefuna et al., 2013; Kuenzer et al., 2014a). However, this approach is unable to provide accurate maps of land cover change (Martinuzzi et al., 2007; Colby and Keating, 2001; Okoro et al., 2016).

Mangrove restoration projects in the NDR have mostly failed due to lack of appropriate and reliable information to inform rehabilitation programs (Isebor, 2001; Abere and Ekeke, 2011; Zabbey and Tanee, 2016). Unfortunately, there is only a limited number of studies mapping change in mangroves in the NDR (Ayanlade and Drake, 2016; James et al., 2007; Nwobi et al., 2020). Even fewer studies have attempted to monitor the extent of degradation (Salami et al., 2010; Kuenzer et al., 2014a). The successful study by Salami et al. (2010) covered a small section of the western NDR, while the study by Kuenzer et al., (2014a) reported very low accuracies in their attempt to map the extent of degraded mangroves for the entire NDR.

Over the last decade, open-access data availability, together with technological and algorithmic advancements have given birth to new approaches to multi-temporal assessment of land cover e.g., image compositing (Frantz, 2019), and spectral-temporal metrics (Griffiths et al., 2013; Mueller et al., 2015). The combination of optical and radar data has also been hailed as an important advancement in regional-scale land cover mapping as certain land cover types, such as mangroves and savannah woody vegetation, are mapped successfully using radar backscatter data, taking advantage of their ability to 'see' through cloud (Nwobi et al., 2020; Hansen et al., 2011; Verhulp and Denner, 2010; Basuki et al., 2013; Nascimento et al., 2013; Kamal et al., 2015; Wicaksono, 2017; Bunting et al., 2018).

1.3 Mangrove degradation and its effects on fisheries

Mangroves reduces its biomass and tree cover when degraded, and results to decline in ecosystem services provision and biodiversity loss (Thomas et al., 2017). One of the effects of degradation on mangroves is the decline in fish production (Primavera, 2005; Manson et al., 2005a) (Figure 3a-d & 1.4). Many studies have reported that the reduction in mangrove area and quality has led to declining fish catch and depletion of species composition of some commercial fishes and crustaceans in the NDR (Zabbey et al., 2010; Numbere, 2014; Okonkwo et al., 2015; Adeyemo et al., 2009; Onyena and Sam, 2020; Osuji et al., 2010; Moffat and Linden, 1995; Ukoli, 2005). However, this has not been assessed due to inadequate fisheries data for the region. There is therefore a need to assess and understand the shifts in the functioning of mangrove ecosystems to enable appropriate sustainable management of the fisheries sector.

Figure 1.4. Fishing landing site in mangroves impacted by oil spills in the NDR (Onyena and Sam, 2020).

1.4 Aims and Objectives

The study aims to assess mangrove degradation and current land cover dynamics in the NDR and model mangrove evolution for the same region. It will do so by achieving the following objectives:

- Map land cover and quantify the extent of degradation of mangroves in NDR between 1988 and 2013;
- Identify the drivers of mangrove degradation using a quantitative modelling approach over the same period;
- Predict land cover change and analyse mangrove degradation under business-as-usual-scenarios in the short (2026) and long term (2038).

1.5 Research Questions

The following research questions contribute towards achieving the aims and objectives:

- Can land cover and extent of mangrove degradation in the NDR be reliably mapped?
- How has land cover and the extent of degradation of mangroves changed in in the NDR between 1988 and 2013?
- What are the drivers of mangrove degradation and how do they interact over the same period?
- Can land cover change and mangrove degradation be reliably modelled in the NDR?, and how would areal extent of degraded mangroves change in the short (2026) and long term (2038) in the future?

1.6 Thesis Structure

The thesis is structured following an alternative format, comprising of seven (6) chapters, with three (3) of the chapters (3-5), focusing on addressing specific objectives.

Chapter One introduces the research, describing why the research is being undertaken. It also states important issues related with the rationale, around different themes, and in various spatial scales including, global, regional, national, and local. Furthermore, the aims and objectives of the research is outlined here.

Chapter 2 reviews themes surrounding the thesis, including the importance of tropical deltas, importance of mangroves with particular focus to fisheries ES, mangrove monitoring challenges and gaps and so on.

Chapter 3 is a methodology study of land cover dynamics and mangrove degradation in the Niger Delta region (Nababa et al., 2020). The main land cover types were accurately mapped over the NDR using spectral-temporal metrics from all available Landsat data in three time points and the performance of classification is tested when L-band radar data is included to Landsat-based metrics. Additionally, two additional analyses focusing on mangroves namely: change intensity analysis and fragmentation analysis were carried out.

Chapter 4 builds on the accurate land cover mapping of the “mangrove class” in Chapter 3 into a study aimed at examining the causes of mangrove degradation in the NDR using spatial driver datasets. Assessing the drivers of mangrove degradation is important for development of appropriate policies and measures for the sustainable management of mangrove ecosystems. Using the mangrove information derived from Chapter 3 and spatial drivers of mangrove degradation, a model was developed using a Multi-layer Perceptron Artificial Neutral Network (MLP-ANN) algorithms in-order to assess the interaction between land cover change and the drivers over two time periods in the NDR.

Chapter 5 extends from results produced in Chapter 3 into a modelling study. It presents a land cover modelling approach, representing spatial regional drivers applied in the NDR. The land cover model incorporates six sub-models developed based on information derived from land cover maps in Chapter 3 and their peculiar spatial driving forces. Multi-layer Perceptron Artificial Neutral Network and Markov Chain (MLP-ANN +MC) methods were applied to predict future land cover change and mangrove degradation under two business-as-usual scenarios for the short (2026) and long term (2038). The model’s accuracy was assessed using predicted land cover map of 2013.

Chapter 6 presents the conclusions for the thesis. Here the thesis is concluded by summarising the main findings and discussing policy implication in relation to mangrove and fisheries management. The thesis contribution to knowledge in regards the approaches used to address data gaps and accuracy issues in Sub-Saharan African regions with similar data problems are highlighted. Also, limitations and recommendation and future research directions are presented.

Chapter 2

Literature review

2.1 Importance of tropical deltas

Deltas are natural dynamic landforms uniquely formed at the interface land-ocean as a result of fluvial and marine processes. Deltas forms diverse and rich ecosystems such as mangroves, salt marshes and seagrass (Loucks, 2019), and some contain hydrocarbon deposits. They are economic and environmental hot spots (Foufoula-Georgiou, 2013). They take up less than 1% of the Earth's surface but are home to more than ca. 7% of the global population—a density more than 10 times the average (Ericson et al., 2006). Deltas are able to support such high human populations thanks to the high productivity, biodiversity, and the ability to use the waterways for transport. They are key contributors to the production of agricultural goods, fisheries and are, therefore, highly important in the fight against global food insecurity (Szabo et al., 2015; Lauria et al., 2018). They can serve as raw materials such sand and gravel for construction purposes. They can be utilised in construction of water systems such as dams to meet domestic and industrial demands (Loucks, 2019). Deltas can also enhance human development related to tourism and recreation and plant-based medicine. Studies have reported that the annual worth of ecosystem services (ES) provided by major deltas globally to be in trillions of US dollars, thanks to its physical structure and high biodiversity (Loucks, 2019) (Figure 2.1).

Tropical coastal deltas are some of the most populated areas of the world, yet their populations are estimated to increase by 45% in the coming decades, and particularly, in developing countries (McGranahan et al., 2007; Neumann et al., 2015; Sale et al., 2014).They are characterised by some of the largest socio-economic activities around the world, including urbanization, agriculture and industrial development (Chu, 2010; Loucks, 2019).They contain the major river deltas in the world and have substantial coverage of critically important but vulnerable ecosystems such as mangrove forests. Tropical deltas particularly, are significant hot spots for biodiversity (e.g. contribute to sustaining substantial mangrove forests, support wetland animals and plant communities, serve as shelter for juvenile fishery) and hold a rich historical and cultural resources (e.g. in terms of aesthetic and spiritual value) (Chu, 2010).

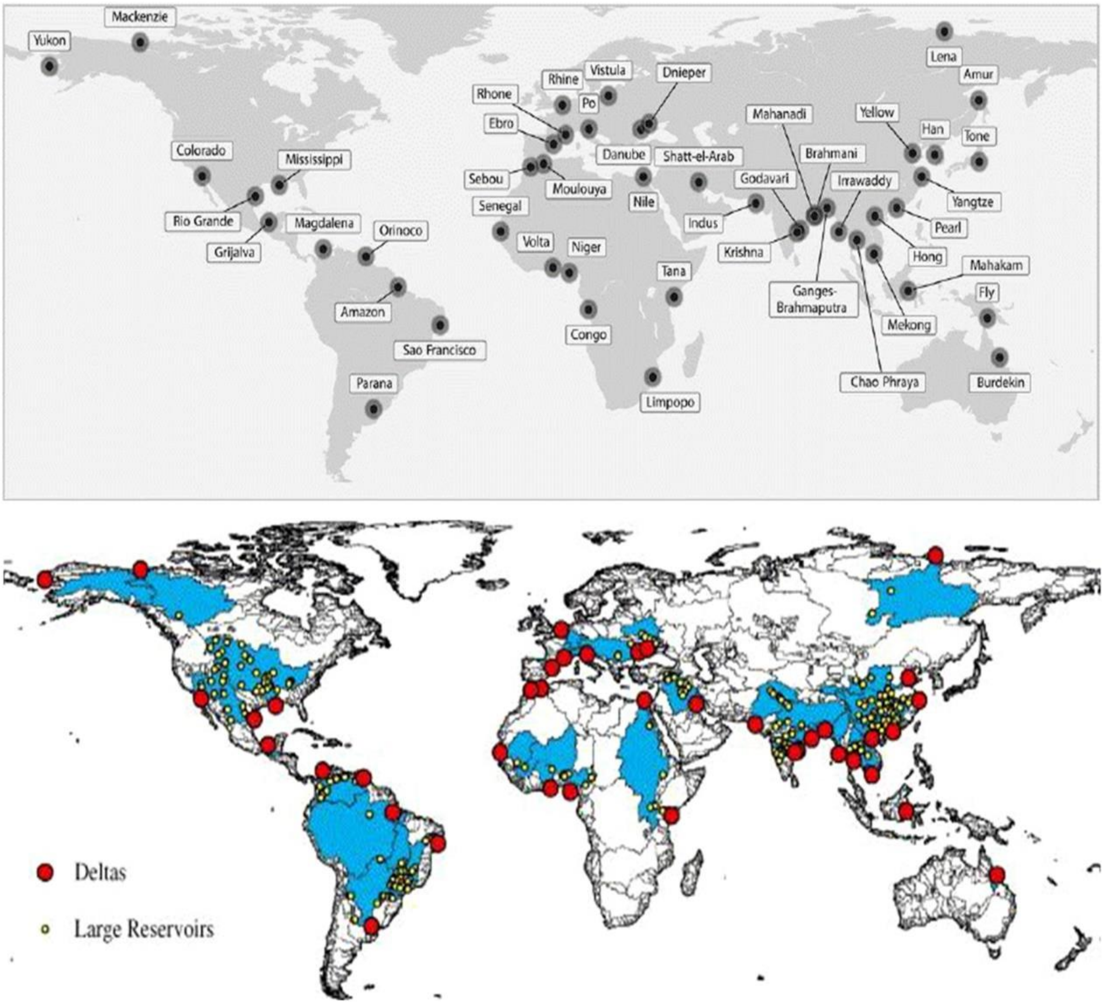

Figure 2.1. World's major deltas (Tessler et al., 2015). Areas depicting blue colours are watersheds whose runoff flows into their deltas.

Tropical coastal regions as stated often inhabited by some of the poorest population in the world, depend on agriculture and fishing as their major source of livelihood. Fisheries resources are substantially supported by the productive mangroves provided in the tropical deltas. They are important as source animal protein and serve as means of income for local populations and help in the growth of the economy on the larger scale. Nevertheless, they are under risk of numerous threats from anthropogenic and natural (sea level rise) sources, which are both expected to increase in the coming decades (Szabo et al., 2016; Sale et al., 2014). Tropical river deltas are therefore, definitely expected to change over time. The importance of this ecosystem cannot be overstated; therefore, reliable information on its dynamics is needed for sustainable management. The changes that occur on the deltaic environments whether through man or natural causes are complex and multi-faceted (socio-economic, environmental, political factors). This makes monitoring and modelling studies related to its sustainability a challenging task; hence, deltas are poorly understood. Increased studies to better understand dynamics of deltaic ecosystems is essential for their sustainability and continuous ES provision.

2.1.1 The Niger River Delta and its Importance to fisheries

The Niger River Delta (NRD) is the largest river delta in Africa (Goudie, 2005) and home to a rapidly increasing human population. It features the largest mangrove forest in Africa, estimated to be ~5% of the global mangrove coverage and the fifth largest mangrove forest in the world (Spalding, 2010). Substantial oil and gas deposits are found under the mangrove ecosystem of the NRD. It is recognised as having great economic and ecological value despite their low species and diversity (Feka and Ajonina, 2011), providing numerous ES ranging from provisioning, regulating, supporting to cultural services (MEA, 2005). According to the Zabbey (2010), mangroves are a critically important resource to the local inhabitants of the NDR, just like taxes to national governments. Table 2.1 and Figure 2.2 identifies ES provided by mangroves of the NRD.

Arguably, the most crucially important resource provided by the NRD, is fisheries ES. This is due to its productive mangrove ecosystems, aided by many river channels that deposit sediment, and contributing to nutrient cycling. Over 90% of local populations in the coastal areas globally rely on fisheries related activities for their livelihoods (Davies, 2005; Gbigbi and Enete, 2014). This is interestingly representative of the statistics in the Niger Delta region (NDR), where ~90% of the population rely on agriculture and fishing for means of livelihood, of which fishing is the main the focus (Gbigbi and Enete, 2014). More than 80% of fish production in Nigeria comes from artisanal fishery sector which largely supported by mangrove forest (FAO, 2017; Udoh, 2016). Fish is an important source of protein in many Nigerian homes, accounting for 28% of animal protein intake of the population (Edet and Williams, 2007). It contains a high nutritional value consisting of amino acids, vitamins, and minerals; notably, fish or fish oil containing omega-3 have been medically proven to reduce mortality related with cardiovascular diseases (Akinrotimi et al., 2007; Shahidi and Miraliakbari, 2004). This is particularly, beneficial to inhabitants in the NDR given the cheap price of fish products there due to its location at the coast and the prevalence of many diseases resulting from oil pollution. Aside, being a source of income to the local population of the NDR, employing thousands of people at both the artisanal and industrial sector, fisheries have positive impact on the economy of the country. For example, it contributed to the nation's GDP:1.37%, 1.37%, 1.36%, 1.37%, 1.37%, and 0.5% in 2003, 2004, 2005, 2006, 2007, and 2015 respectively (FAO, 2017; CBN, 2009). Fisheries also hold a strong cultural value such as fishing festivals and are important for recreational purposes in the NDR.

Table 2.1: Ecosystem goods and services provided by mangroves in NDR.

Services / Benefits	Products or Goods and Services / Comments
Provisioning	
Food	Fishing activities and aquatic foods such as crabs, shrimps, oysters; invertebrate species (Davies, 2005; Zabbey et al., 2010) and hunting hippopotamus, squirrel, tortoises, bush meat e.g., monkeys (Onyena and Sam, 2020; Numbere, 2014).
Fibre and Fuel	Timber products: canoe building, poles for fishing and traps, transmission and building, saw logs, fuel wood, chew sticks (World Bank, 1995b; NDDC, 2006).
Biochemical	Aquatic insects (Ugochukwu and Ertel, 2008; Ebeku, 2006)
Genetic resources	Medicine: Roots, leaves and seeds (Ndukwu and Ben-Nwadibia, 2005; Corcoran et al., 2007).
Regulating	
Climatic regulation	Reduction of greenhouse gas effects of CO_2 and CH4, temperature, precipitation, and other climatic conditions and chemical composition in the atmosphere (Numbere and Camilo, 2018; Onyena and Sam, 2020).
Natural Hazard regulation	Flood control and Storm protection (James et al., 2007; Odemerho, 2015).
Pollution control and detoxication	Retention, recovery and removal of excess nutrients and pollutants (Numbere, 2020).
Biological regulation	Resistance to non-native species, control of relationship amongst tropic levels of food chain, maintaining a functional balance and interaction of species (Osuji et al., 2010).
Erosion protection	Soil retention (Corcoran et al., 2007).
Supporting	
Soil formation	Habitat for organic matter (Numbere, 2020).
Nutrient cycling	Nutrient sinkage, formation and recycling (Osuji et al., 2010).
Biodiversity	Habitat for locals and transient species (Mmom and Arokoyu, 2010)
Cultural	
Spiritual and inspirational	Sense of belonging and security (James et al., 2007; Onyena and Sam, 2020)
Recreational	Tourism and recreational e.g., fishing sites (Corcoran et al., 2007)
Aesthetic	Protected sites e.g., sacred sites (James et al., 2007)
Educational	Prospects for formal and informal education e.g., due to vast Biodiversity (World Bank, 1995b; Nnamdi et al., 2013).

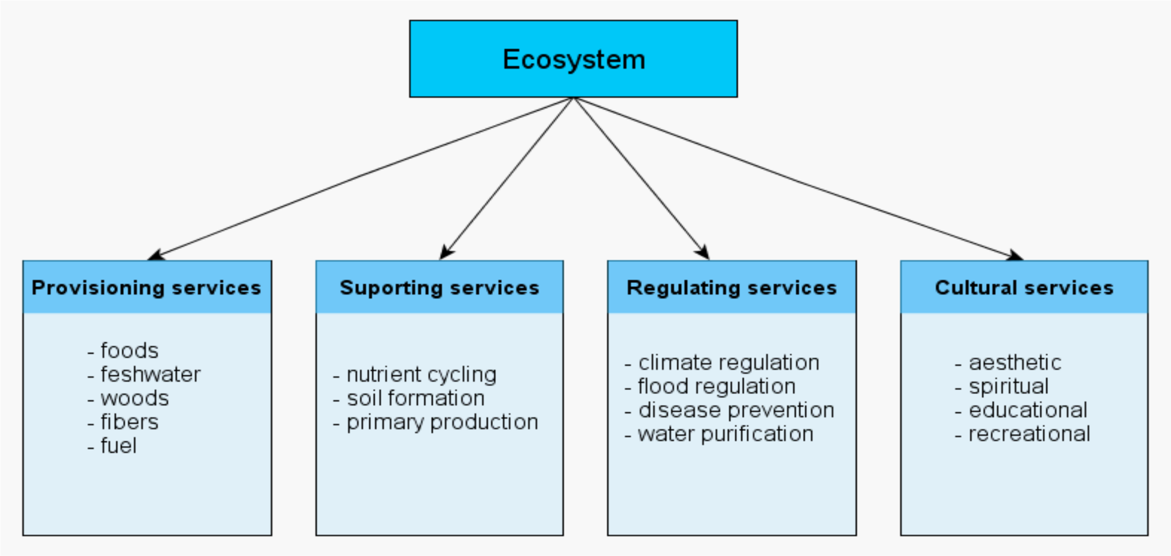

Figure 2.2. Mangrove Ecosystem services (Modified from MEA, 2005)

2.2. General overview on mangroves

Mangroves are commonly referred to assemblage of diverse, woody, salt tolerant and evergreen plants and shrubs that thrive successfully along the inter-tidal zone between the land and sea in the tropical and subtropical region of the world (Alongi, 2002; Tomlinson, 1986). They grow specifically in river deltas, lagoons and estuarine networks (Thom, 1984). They are able to thrive in harsh environmental settings with high salinity, high temperature, extreme tides, high sedimentation and muddy anaerobic soils (Giri et al., 2011), due to their unique structural features. Mangroves are often considered to be single species as they often referred to as “mangrove community”, “mangrove ecosystem”, “mangrove forest” or even “mangal” (Duke, 1992). However, it is a diverse ecosystem of ~70 distinct species with 9 orders, 20 families, and 27 genera (Spalding et al., 1997). Tomlinson (1986) classified mangroves into true and minor or associates’ mangroves. The true mangroves are those with the capacity to thrive harsh environments due to their unique adaptive features such as prop roots, viviparous propagule, pneumatophores and lenticels. Minor or associate mangroves are relatively ones with low stand that can be found in a mangrove and non-mangrove community.

Over the past decades, mangroves were considered unproductive and often treated as marshy wastelands with little or no value (Carter et al., 2015), leaving them susceptible to conversion to alternate land uses (Ronnback, 1999). Recently, awareness through restoration campaigns have been an eye opener to the way mangroves are viewed and utilised in some parts of the world. They are recognised with great economic and ecologically important value providing multiple services vital to the well-being of inhabitants at local level (Hussain and Badola, 2010; Gnanappazham and Selvam, 2011), national level (Aburto-Oropeza et al., 2008) and even at global scale (Costanza et al., 1997; Mukherjee et al., 2014; Costanza et al., 2014). Nevertheless, humans consider mangroves as an obstruction to their economic activities and subjected them to threats of degradation and loss.

2.2.1. Global distribution of mangrove forest

There are contradictory reports on global estimates of mangrove extent in the literature mainly due differences of epoch mapped and methodological approach that was used. However, most recent global coverage of mangrove forest was estimated at 137,600km^2 (Bunting et al., 2018). Interestingly, ten countries cover 65% of the world's total mangrove. Amongst these ten only five countries, namely: Indonesia, Australia, Brazil, Nigeria and Mexico account for 48% of it. A hundred and fourteen countries are home to the remaining 35% of the world's total mangrove area, and of which a maximum of 100km^2 coverage is spread over 60 countries (FAO, 2007). The largest coverage of the world's mangrove is situated in the Asian countries and territories, with estimated coverage of ~60000km^2 (FAO, 2006a). Particularly, Southeast Asian is the area with the most extensive mangroves in the world, a third of the world's coverage (Spalding, 2010). This region's mangroves are also one that remains strongly protected (Hishamunda et al.,2009). Figure 2.3 shows global mangrove coverage.

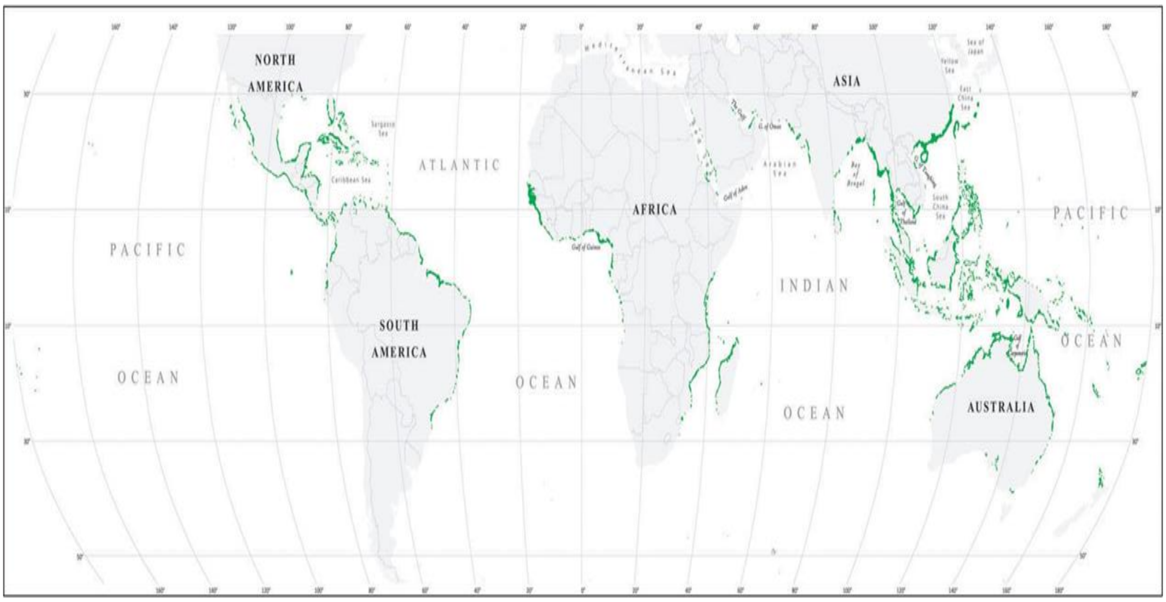

Figure 2.3. Distribution of the World’s mangrove forest using Landsat imagery (Giri et al., 2011). The green areas represent mangrove distribution.

2.2.2 Distribution of the status of mangrove in Mangrove in Africa

Africa’s mangroves are home to ~19% of global mangrove coverage and are situated at the Western and Eastern Eco regions of the continent, covering three coastal zones namely: the West Atlantic, Central Atlantic, and the Eastern Indian Ocean. At the West Atlantic coast, mangroves extend from the North Western area in Mauritania to Senegal at Saloum Delta, Lower Casamance spanning over Guinea Bissau, South Guinea, to the Gulf of Guinea (Ajonina et al., 2008). It further stretches from Liberia to Angola, flanking on the coastline West and Central region, with the largest coverage in Nigeria, stretching across the Niger Delta region. Mangroves at Western and Central region cover 12% of Africa’s 19% global coverage (Feka and Ajonina, 2011). At the Eastern Indian Ocean, include the East Africa mangroves within Rufji delta at Mozambique, Tanzania, Kenya in Tana and Sabari rivers, and a greater part of Madasgcar (Ajonina, 2008). Also, at the Mediterranean coast on the Eastern region, are of few random mangroves thriving at Alexendra Egypt, and similarly at the Red Sea in Somalia and Djibouti (Ajonina, 2008). Other countries with mangroves in the Eastern African eco-regions are South Africa and Seychelles. Generally, there are mangroves in almost all the countries in the Western and

Eastern Africa; with the exception of Nambia, largely due unfavourable climatic conditions and topography that the mangrove ecosystem require to thrive (FAO, 2007). There are variations of reported mangrove coverage of the world, and similarly for Africa's mangrove. Recent reliable estimate of mangrove cover for Africa place it over 27 000km^2 for the year 2000, over 20% of the global coverage (Giri et al., 2011).

2.2.3. Distribution and floristic composition of Mangroves in Nigeria

Nigeria's mangrove is the largest in Africa and fifth in the world (Spalding et al., 2010). Recent estimate of Nigeria's mangrove for the year 2000 place it at 6537 km^2; of which is 46.8% of Africa's mangrove, and 4.7% of total world's mangrove coverage (Giri et al., 2011). The ecosystem extends across the entire coastline of the country supported by fresh swamp and rain forests. Mangrove found on the coastal zone of Nigeria spreads across three coastal regions namely: the Western, the Eastern and the NDR. The Western coastal areas are largely bordered by the extensive Lagos tidal coastal lagoon which is fringed by mangroves stretching to the Lekki lagoon down to the East coastal zone where fewer mangroves are found (Spalding et al., 2010). The NDR is largely the host of Nigeria's mangrove. The extent of Niger Delta's mangrove and floristic composition have been documented in the literature (FAO, 2005; Spalding et al., 2010). Although, reports on the extent of mangroves have been contradictory. Mangrove in the NDR stretches over 400 km and can reach inland for 30 to 40km (Spalding et al., 2010; Abere and Ekeke, 2011). They are found at west of zone in Benin River and to the East in Calabar, Rio del Rey estuary (FAO, 2005), adjacent to the developing mangroves of Rio del Rey in Cameroun (Spalding et al., 2010).

Niger Delta's mangrove forest consist of typically six species belonging to three families (Abere and Ekeke, 2011; Spalding et al., 2010). *Rhizophora racemosa* is the dominating species, covering about 90% of the mangrove system (Abere and Ekeke, 2011). Its canopy level can reach 40m, although are usually between 10-12m (Spalding et al., 2010). *R. mangles* are commonly prevalent in inner mangrove communities, with *R. harrisonii* at the middle immediate zones. Similarly, the canopy height of *R mangle* is less than 5m, with *R. harrisonii* capable of attaining heights of 5-10m (Abere and Ekeke, 2011). The other three species namely: *Avicennia geminnas, Languncularia racemosa, Conocarpus erectus* are sparsely found; hence the former are the commonest species found in the region. James et al., (2007) reported that in the lower saline areas of estuaries and channels of the coastline, Nypa *fruticans* that was introduced at Calabar in 1960 is already widespread and thriving continuously. However, their presence is a threat is mangrove growth.

2. 3. Decline of Nigeria's mangrove forest

The benefits offered by mangroves to support the terrestrial, marine environments, and the human society at large have been well documented (Aburto-Oropeza et al., 2008; Millennium Ecosystem Assessment (MEA), 2005; Barbier, 2016; Brown et al., 2018; Polidoro et al., 2010). However, mangroves are reported to be disappearing at a rate that surpasses or equals to the rainforest and coral ecosystems which are a popular endangered ecosystem (Duke et al., 2007b). Reliable estimates of Nigeria's mangrove for 2000 place it at 653, 669 ha (Giri et al., 2011), meaning 36.4% of Nigeria's mangroves have been lost over the previous two decades (Table.2.2). Furthermore, mangroves that are degraded have lower productive functions (Dahdouh-Guebas et al., 2005; Van et al., 2014; Romanach et al., 2018). Mangrove degradation and loss have been traced to the undervaluation of the ecosystem (Ronnback, 1999; Brander et al., 2012; Malik et al., 2015); usually in pursuit of developments, and often neglecting or disregarding the multiple benefits they provide (Del Claro et al., 2009; Badola and Hussain, 2005; Ronnback et al., 2007). Unless the true value of mangroves is accounted for, the ecosystem will be left vulnerable to alternative land-uses such as agriculture, aquaculture, coastal developments that promise tangible economic benefits (Malik et al., 2015; Ronnback et al., 2007).

In Nigeria, one of the major drivers of mangrove loss and degradation have been attributed to the development of the oil and gas industry; as the industries are located around the mangrove forests (Abere and Ekeke, 2011). These activities include dredging, infrastructure developments uch as pipe and seismic lines, oil spills by oil companies such as Shell, Agip, Mobil etc., and urbanisation (Moffat and Linden, 1995; NDES, 1997; World Bank, 1995a; Chindah et al., 2011; Abere and Ekeke, 2011). Another common driver of mangrove decline in Nigeria is wood extraction used for fuel wood and building construction (Adegbehin and Nwaigbo, 1990; Ayanlade and Drake, 2016). More than 200 000 poles and wooden items are reportedly extracted yearly (Adeyemo et al., 2009). In addition to reports on concerns about climate change effects (coastal erosion) in NDR (World Bank, 1995a; Uyigue and Agho, 2007), and sea level rise (Okali and Eleri, 2004) as potential threats to mangroves in the region. Awosika (1995) reported loss of vegetation constituting mainly of mangroves in the NDR resulting from coastal erosion.

Table 2 .2 Most recent reliable estimate of Nigeria's mangrove status over time. (FAO, 2005; Giri et al., 2011), Modified. These estimates are based on two progressive studies considered to be reliable.

1980	1990	2000	2005
km^2 9990	km^2 9980	km^2 6537	km^2 9970

2. 4 Sustainable Management of Mangroves in NDR.

The importance and values of mangroves to the sustenance of livelihood of local communities and even at regional scale in the NDR has been extensively established in the literature (Mmom and Arokoyu, 2010; James et al., 2013; Kinako, 1977; Udoh, 2016; Okpiliya et al., 2013). The way mangrove forest in the NDR has dramatically declined (36.4%), based on calculation from reliable estimate of 1980 to 2011 is alarming. Given the dependence of local communities on the mangrove ecosystem in the NDR, as well as its recognizable values at regional level, there is a need to carry out optimal use of these valuable, yet fragile ecosystem resources, in order to better manage the ecosystem to meeting its needs for the present and future generation. Numerous methods and tools exist for developing and implementing the sustainable management of the good and services that our forest ecosystem provide (World Bank, 1995a; Primavera and Esteban, 2008). However, the effectiveness of any sustainable management approach is dependent on integrated approach that usually entails participation of stakeholders at all levels including local and national, corporate institutions, as well as institutions directly or indirectly associated to managing coastal forest resources (Primavera and Esteban, 2008).

2.4.1 Policy, Legislation and Management of Mangroves in Nigeria.

Attention is gradually tilting to the sustainable management of wetland resources, which also includes mangroves. This is due to increased awareness and recognizable economic and ecological benefit they offer. The federation system of Nigeria consists of the federal, State, and the local governments, and they all have powers to make their own laws. However, whilst, the federal laws can apply at the State and Local Government level, it is not the case for the State and Local laws, as they are restricted to their territorial jurisdiction. Furthermore, in the event of unresolvable conflict of interest amongst these levels, the law at the higher level takes precedence. Therefore, mangrove management in Nigeria comes under the complex structure and interaction of the Federation system, as well as functions alongside other institutions of the country.

To now, Nigeria, like many other African countries, is yet to enact management policies that is exclusively targeted at protecting its mangrove forest. Furthermore, it is reported that there is no form of protection for the mangrove forest of the country (Mmom and Arokoyu, 2010) at least, formally. In Nigeria, laws and regulations that tend to govern the management of mangroves are enshrined within general environmental and forest laws and policies of the country, with no specific mention to the mangrove forest. An updated policy documents and acts that are directly or indirectly involved in management of mangroves in Nigeria are presented in Table 2. 3.

Table 2.3 Strategic documents/policies and Legislations for mangrove management in Nigeria

Country	**Strategic documents and policies for mangrove forests management**	**A select number of legislative documents under which mangrove forests are assimilated**
Nigeria	Federal Ministry of Environment (2015) National Biodiversity and action plan 2016-2020; Niger Delta Biodiversity project (2010); National Adaptation strategy and plan of action on climate change for Nigeria (NASPA-CCN) 2011; USAID- Industry Action Plan for Nigerian Shrimp and Prawns 2002; National Oil Spill Contingency plan (NOSCP); Acquisition of 9 hectare piece of land for establishment of an Integrated Mangrove Conservation and Research Centre to educate and rural communities in mangrove conservation; GEF – World Bank Local Empowerment and Environmental Management Project Nigeria; GEF-UNEP – Reversal of Land and Water Degradation in the Niger River Basin;The Regional development plan for the Niger Delta; Road map for the growth and development of mining in Nigeria, 2016.	National policy for environment of 1989; National forestry policy, 2006; Agricultural Policy for Nigeria 2011; Sea Fisheries Decrees of Nigeria. 1992; Inland fisheries Decree 1992; AI04 2000 No.6 *Niger-Delta Development* Commission *Act 2000; Environmental Protection Agency (Amendment) Decree N0 59 of 1992;* National Environmental Standard and Regulation Enforcement Agency Act 2004; National Oil Spill Detection and Response Agency Act 2006; The Nigerian Minerals and Mining Act. 2007; Environmental Impact Assessment Act (Cap E12 LFN 2004).

2.5 Mangrove monitoring through remote sensing

Conventional observation and field surveys methods in monitoring ecosystems such as the mangrove system is time consuming and very expensive. Hence, cost-effective methods of remote sensing (RS) technology were developed. RS techniques have continued to evolve over time with advancement in Information

Technology (IT) and Computing, and improvement in expert knowledge spurring utilization of Earth observation data and techniques. Satellite remote sensing offers the opportunity for a large area mapping providing comprehensive information covered with its different spectral bands. The capabilities of remote sensing in mapping and monitoring mangroves have been reviewed by Kuenzer et al., (2011) and recently by Giri (2016) and Purnamasayangsukasih et al., (2016). Different remote sensing sensors, techniques, and applications were covered.

Mangrove characterization with remotely sensed image is influenced by seasonal and everyday intertidal interactions as its pixel composition comprises of vegetation, soil and water due to its location between land and sea. This feature of mangrove is greatly considered as it interferes with radiometric characterization (Blasco et al., 1998). Additionally, the diversity of mangrove species can significantly affect spectral characterization of image components, aggravating discrimination problems due to increased presence of unique species. Structural manifestation of mangroves is influenced by their component attributes including species composition, distribution pattern, density and stand height, presenting them relatively similar or varied.

Mangroves are often discriminated through the textural and spectral characteristics of their canopy and leaves (Ramsey and Jensen, 1996). Spectral variations of canopy reflectance are attributed to optical properties including leaf area Index (LAI), background reflectance and leaf inclination (Diaz and Blackburn, 2003). Factors such as age, vitality phenological and physiological features determine the spectral signature of single species of mangroves (Blasco et al., 1998). Seasonal climatic variations that impact on leaf foliation change and leaf senescence, can affect spectral response (Wang et al., 2008) of mangrove species. Studies by Wang et al., (2008) in Panama suggested high spectral discrimination among mangrove species in the early wet season. Furthermore, spectral responses of plant communities are affected by intertidal effects and soil types (Blasco et al., 1998). Mangroves with attributes such as lower density stands and sparse vegetation cover are greatly affected by intertidal effects, that can cause greater effects on the ground surface. This results in a mixture of ground surface with other Earth's surface materials, leading to confusion in spectral characterization. Gao (1998) indicated that mudflats in the background can result in confusion of spectral signal with built up areas whilst using medium resolution imagery.

Mangrove observation, mapping, and monitoring has long been undertaken using various remote sensing data and techniques. Many studies over the last two decades have utilized various types of remotely sensed data (e.g. Everitt et al., 1996; Lucas et al., 2000; Manson et al., 2005a; Benfield et al., 2005) aerial photography (e.g. Pastor-Guzman et al., 2015; Shapiro et al., 2015; Kanniah et al., 2015), medium resolution data (e.g. Vaiphasa et al., 2005; Wang and Sousa, 2009) hyperspectral data (e.g. Lucas et al., 2007; Cougo et al., 2015; Brown et al., 2016) radar data, and furthermore, recent studies Kamal (2015) and Wicaksono (2017) used multi resolution data sets to monitor and map mangroves. These studies used different remote sensing techniques to obtain valuable spatio-temporal information from varying applications including mangrove extent, mangrove distribution, species composition and differentiation, forest health, and forest density of mangrove forest application can the derived using techniques of monitoring in remote sensing methods.

2.6. Landsat data for time series analysis of forested landscapes

Landsat data have long been used to study the dynamics of the Earth's surface over decades owing to its history of long data archive and unique spatial coverage (30m) (Kennedy et al., 2014) with temporal recurring cycle of 16 days (Wulder et al., 2008).

The advancement in IT and computing has enabled substantial data storage and robust computing capabilities (Hansen and Loveland, 2012), hence aiding LTS analysis. In 2008, change in data policy of the United States Geological Survey (USGS) lead to the opening of Landsat data archive, allowing free accessibility on the internet to users at free cost (Woodcock et al., 2008). This dramatically changed the way Landsat data was utilized; allowing for increased and extensive research and application using time series data (TS) (Wulder et al., 2012), and over a large area. Dense TS data are now available annually for mapping and monitoring forest change (e.g. Hansen et al., 2013; Hermosilla et al., 2016; Potapov et al., 2015) over varying spatial scales. TS approach has long been identified capable to provide detailed understanding of complexity of the forest ecosystem dynamics (Cohen and Goward, 2004; Senf et al., 2017). Banskota et al., (2014) and Zhu et al., (2017) reviewed studies for mapping and monitoring of forested landscapes such as mangroves. These studies both focused on important aspects of LTS analysis including pre-processing techniques algorithms, applications, approaches as well as validation issues. Recent studies (e.g. Hansen et al., 2013; Potapov et al., 2015; Hermosilla et al., 2015; Hermosilla et al., 2016; Hughes et al., 2017; Zhu et al., 2012) have emerged using dense LTS to map forest disturbance dynamics. Similarly, few studies recently of varying application e.g. (Ghosh et al., 2016; Bullock et al., 2017; Ghosh et al., 2017) species composition and distribution, (Alatorre et al., 2016) vegetation phenology have appeared in the literature using the LTS approach in mangrove studies.

Chapter 3

Land Cover Dynamics and Mangrove Degradation in the Niger Delta Region

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Abstract

The Niger Delta Region is the largest river delta in Africa and features the fifth largest mangrove forest on Earth. It provides numerous ecosystem services to the local populations and holds a wealth of biodiversity. However, due to the oil and gas reserves and the increase of human population it is under threat from overexploitation and degradation. There is a pressing need for an accurate assessment of the land cover dynamics in the region. The limited previous efforts have produced controversial results, as the area of western Africa is notorious for the gaps in the Landsat archive and the lack of cloud-free data. Even fewer studies have attempted to map the extent of the degraded mangrove forest system, reporting low accuracies. Here, we map the eight main land cover classes over the NDR using spectral-temporal metrics from all available Landsat data centred around three epochs. We also test the performance of the classification when L-band radar data are added to the Landsat-based metrics. To further our understanding of the land cover change dynamics, we carry out two additional assessments: a change intensity analysis for the entire NDR and, focusing specifically on the mangrove forest, we analyse the fragmentation of both the healthy and the degraded mangrove land cover classes. We achieve high overall classification accuracies in all epochs (~79% for 1988, and 82% for 2000 and 2013) and are able to map the degraded mangroves accurately, for the first time, with user's accuracies between 77% and 87% and producer's accuracies consistently above 82%. Our results show that mangrove forests, lowland rainforests, and freshwater forests reported net and highly intense losses (mangrove net loss: ~500 km^2; woodland net loss: ~1400 km^2), while built-up areas have almost doubled in size (from 1990 km^2 in 1988 to 3730 km^2 in 2013). The mangrove forests are also consistently more fragmented, with the opposite effect being observed for the degraded mangroves in more recent years. Our study provides a valuable assessment of land cover dynamics in the NDR and the first ever accurate estimates of the extent of the degraded mangrove forest and its fragmentation.

Keywords: Niger Delta Region; mangroves; land cover dynamics; intensity analysis; fragmentation; spectral-temporal metrics; land degradation; Landsat; ALOS PALSAR-2; JERS-1; GLCM

3.1. Introduction

Deltas are economic and environmental hot spots (Foufoula-Georgiou, 2013). They take up less than 1% of the Earth's surface but are home to more than ca. 7% of the global population—a density more than 10 times the average (Ericson et al., 2006). Deltas are able to support such high human populations thanks to the high productivity, biodiversity, and the ability to use the waterways for transport. They are key contributors to the production of agricultural goods and are, therefore, highly important in the fight against global food insecurity (Szabo et al., 2015). However, these important systems are highly delicate and vulnerable. In specific, tropical delta regions are under risk of numerous threats, including sea level rise, extreme floods, storm surges, erosion, subsidence, and salinity intrusion, amongst others, which are expected to increase both in frequency and magnitude with the climate crisis (Szabo et al., 2016). These problems have been proven to increase out-migration rates and human security risks in developing regions, often inhabited by some of the poorest populations in the world. Given the importance and the vulnerability of tropical deltas, monitoring and understanding the land cover dynamics in these regions is vital for achieving efficient policy planning and progress toward achieving the Sustainable Development Goals (Chow, 2018).

The Niger River Delta (NRD) is the largest river delta in Africa (Goudie, 2005) and home to a rapidly increasing human population. It features the largest mangrove forest in Africa, estimated to be ~5% of the global mangrove coverage and the fifth largest mangrove forest in the world (Spalding, 2010). It is recognised as a highly important resource for the local communities, as it is utilised for fisheries, fuelwood, construction material, flood protection, medicinal purposes, recreation, and tourism, and holds an important spiritual value (Zabbey et al., 2010; James et al., 2007; Okonkwo et al., 2015; Numbere, 2014; NDDC, 2006; World Bank, 1995b). Substantial oil and gas deposits are found under the mangrove ecosystem of the NRD. Over the last decades, this highly significant ecosystem is under threat of loss or degradation, mainly due to oil and gas exploration activities, the overexploitation of the mangroves for fuelwood, urbanisation, and the invasion of the Nipa palm species (*Nypa fruticans*) (Numbere, 2014; Kadafa, 2012; Balogun, 2015; Onyena and Sam, 2020; Duke, 2016; Twumasi and Merem, 2006; Nwobi et al., 2020). Climate change (World Bank, 1995b; Uyigue and Agho, 2007), sea level rise (Okali and Eleri, 2004), and coastal erosion (Awosika, 1995) are also threats to the mangrove system. Despite the importance of the NDR resources, and the perceived degradation from anthropogenic and environmental pressures, reliable information on land cover dynamics and, particularly, on the extent and condition of the mangrove forest, is still lacking.

Assessing land cover dynamics over large areas is only possible via Earth Observation technologies, which is commonly done with multi-temporal Landsat data. The Landsat archive is truly invaluable as it constitutes the only global medium-scale data available for ~50 years. More ‘traditional’ approaches have used image mosaics or single images from single-sensor data to map two (before and after) dates and assess change from these (James et al., 2007; Ayanlade and Drake, 2015; Mena, 2008; Gao and Liu, 2010; Obiefuna et al., 2013; Kuenzer et al., 2014a). However, over certain parts of the world, e.g., western and eastern Africa, the data archive has significant gaps (Kuenzer et al., 2014a; Kirui et al., 2013). Moreover, the use of optical data for accurately mapping and monitoring land cover dynamics over the tropics can be problematic due to the extensive cloud contamination, which renders the creation of image mosaics over large areas an unachievable task (Martinuzzi et al., 2007; Colby and Keating, 2001; Okoro et al., 2016).

Recent advances in data availability, computing power, cloud computing, and algorithm development (e.g., machine and deep learning) have given rise to new approaches to multi-temporal assessments of land cover, e.g., image compositing (Frantz, 2019), and spectral-temporal metrics (Griffiths et al., 2013; Mueller et al., 2015). The combination of optical and radar data has also been hailed as an important advancement in regional-scale land cover mapping as certain land cover types, such as mangroves and savannah woody vegetation, are mapped successfully using radar backscatter data, taking advantage of their ability to ‘see’ through cloud (Nwobi et al., 2020; Hansen et al., 2011; Verhulp and Denner, 2010; Basuki et al., 2013; Nascimento et al., 2013; Kamal et al., 2015; Wicaksono, 2017; Bunting et al., 2018) . Over the last decade, object-based image analysis (OBIA) approaches have also been tested to successfully separate mangrove species from other coastal vegetation (Heumann, 2011), to map the Amazonian mangrove belt (Nascimento et al., 2013), and to assess long-term variations of forest loss, fragmentation, and degradation using a combination of OBIA and spatial autocorrelation indicators (Shirvani et al., 2020).

There has been a limited number of studies that mapped land cover dynamics in the NDR (James et al., 2007; Ayanlade and Drake, 2015; Kuenzer et al., 2014a; Onojeghuo and Blackburn, 2011) as the area is one of the most affected worldwide from the gaps in the Landsat archive and a consistent cloud contamination. With the exception of Nwobi et al., (2020), these have employed ‘traditional’ remote sensing approaches and results have been contradictory. Even fewer studies have attempted to estimate the spatial extent of the degraded mangrove cover. Kuenzer et al., (2014a) used mosaics of

Landsat images to map land cover change in the NDR over three dates but reported low per class classification accuracies for both the “tall mangrove” and the “degraded mangrove” classes, making area calculations unreliable. Salami et al., (2010) compared the accuracies achieved by using Landsat ETM+, ASTER and NigeriaSat-1 data to map the six main land cover classes. For the mapping of degraded mangrove, they reported high accuracies for all three platforms. However, their study covered a small fraction of the NRD.

Based on the initial assessment of land cover transitions and dynamics, land cover change studies often move on to explain the changes in terms of explanatory variables (i.e., land use change drivers) or to forecast spatial patterns of future land cover under different scenarios (i.e., land use change models) (Kamwi et al., 2018; Geist and Lambin, 2002; Quezada et al., 2014; Campos et al., 2012; Fernandez et al., 2015). The success of these next stages greatly depends on the ability to carry out an accurate initial assessment of the dynamics. Moreover, apart from the need to map land cover accurately, there is also a requirement to understand the dynamics more fully. For example, a simple comparison among the land cover maps does not determine whether the observed changes derive from processes that are systematically more intensive than random processes. Over the last years, new approaches have been suggested for characterising land cover change patterns quantitatively so that any potential subsequent analyses can focus more efficiently on the important patterns and processes of change, such as the intensity analysis proposed by Aldwaik and Pontius (2012). Other studies, with a specific interest on the fragmentation of habitats for example, have focused on the calculation of landscape metrics from the initial assessment of land cover. These studies have shown that the fragmentation of forests has detrimental effects for the health of the ecosystem and the services that it is able to provide (Fernandez et al., 2015; Gounaridis et al., 2014; López et al., 2020). A number of indices have been created to quantify landscape structure and spatial heterogeneity based on the composition and configuration of the landscape (Coppin et al., 2004; Liu and Zhou, 2005; Seto and Fragkias, 2007; Chen, 2002).

To date, no study related with the assessment of land cover change in the NDR has incorporated recent analytical approaches (e.g., intensity and fragmentation analyses) and the technological and algorithmic achievements (e.g., multi-sensor data, machine learning algorithms) to improve classification accuracies and our understanding of the land cover dynamics. Therefore, there is a need for a comprehensive study of land cover change in the region. In this paper, we aim to accurately assess the land cover dynamics in the NDR over the last decades and improve our understanding of the extent of the degradation of the delta's mangrove forest. We will do so by:

- Mapping the main land cover types of the NDR in three epochs using Landsat data, spectral-temporal metrics, and a machine learning algorithm;
- Testing the performance of the classifier when radar L-band data are added to the Landsat;
- Assessing land cover change intensity over the two periods; and
- Quantifying the mangrove forest degradation and its fragmentation using landscape metrics.

3.2. Study Area

The Niger Delta is a flat alluvial plain located in Nigeria on the Gulf of Guinea (Figure 3.1). It is the largest river delta in Africa formed primarily by sediment deposition. It has a coastline of 470 km and consists of a number of ecological zones, including mangrove swamps, freshwater swamps, forests, and lowland rain forests. The Delta has two distinct seasons (wet and dry) with an average temperature of 27 °C throughout the year and annual rainfall of 3000 to 4500 mm (World Bank, 1995b). The Niger Delta Region covers an area of 56,000 km^2 that consists of 7 administrative states (Abia, Akwa Ibom, Anambra, Bayelsa, Delta, Imo, and Rivers) and is home to more than 33 million inhabitants (265 people per km2;NBS, 2018). More than 70% of these people depend on the natural environment for their livelihoods. The NDR is considered a hot spot for biodiversity in the world with 3 sites designated as Ramsar Wetlands of International Importance (IUCN, 1992). It is a hub for oil and gas exploration, home to 80% of the refineries in Nigeria and extensive infrastructure (e.g., c. 900 oil wells, c. 100 flow stations and gas plants, c. 1500 km trunk lines, and c. 45,000 km flow lines) (Ugochukwu and Ertel, 2008). Nigeria's GDP, which rose from ~292 billion USD in 2009 to over 448 billion USD in 2019 (World Bank, 2020), is mainly generated by the oil and gas sector. Yet, the NDR remains under-developed, and its inhabitants impoverished. The Nigerian Land Use Act excludes the ownership of oil minerals by the state. This is perceived by many as socially inequitable and has resulted in continuous instability in the region (Ako, 2009). Additionally, more than 220 oil spills and 17 billion cubic metres of gas flares per year, together with the impacts of the human population explosion, have led to the degradation of the Niger Delta ecosystem (James et al., 2007; Okonkwo et al., 2015; Nwobi et al., 2020; Kuenzer et al., 2014a; Imevbore et al., 1997).

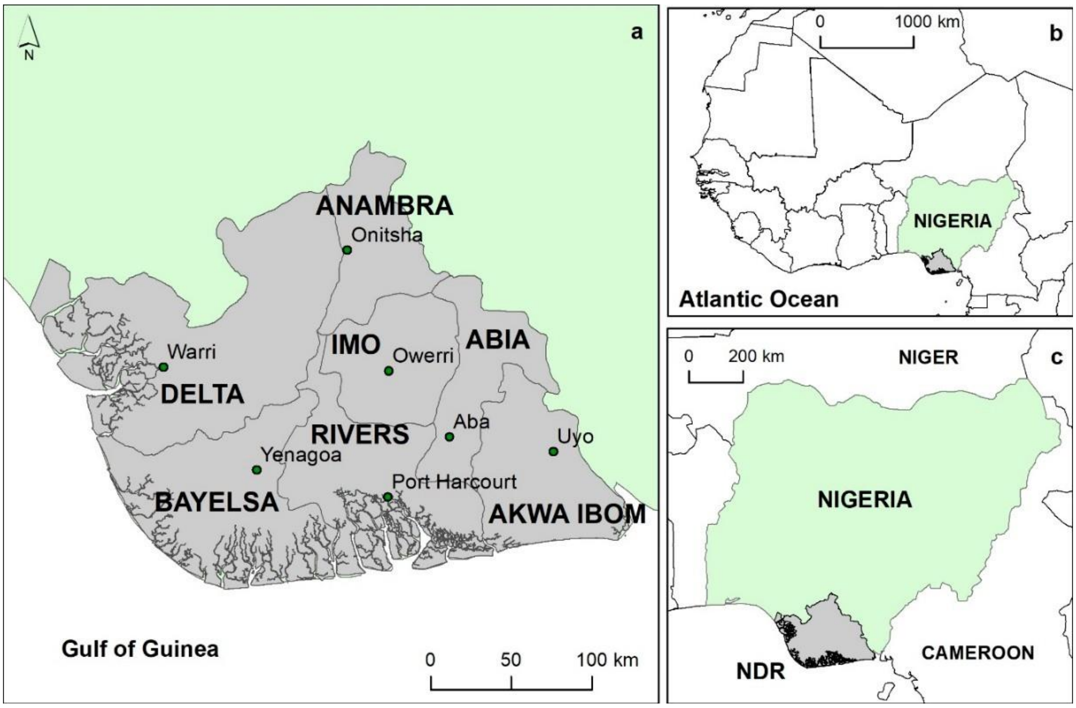


Figure 3.1: (a) Our delineation of the Niger Delta Region (comprising of the states of Abia, Akwa Ibom, Anambra, Bayelsa, Delta, Imo, and Rivers), and its location within (b) West Africa and (c) Nigeria.

3.3. Materials and methods

We mapped the main land cover types in three epochs centred around 1988, 2000, and 2013, and assessed land cover change and change intensity in the two respective periods. The chosen classes were: Water, urban (i.e., built-up), woodland (i.e., lowland rainforest and freshwater forest), bareland, agricultural land, grassland, mangroves, and degraded mangroves. The choice of the classes was based on our knowledge of the area, the nomenclature used by ESA’s 20 m land cover data for Africa and the 30 m-pixel Landsat-based

GlobeCover30, and our desire to separate healthy mangroves from degraded ones. By definition, degraded is the land that has temporarily or permanently undergone a lowering of its capacity to deliver ecosystem services (Safriel and Adeel, 2008). In the case of mangroves, the degraded forest has less biomass and tree cover, and is unable to provide a number of services at the same level as the healthy system, e.g., support for local livelihoods, carbon sequestration, erosion protection, provision of habitat for numerous fauna species, amongst others (Thomas et al., 2017). We also assessed the fragmentation of the mangrove forest during these two periods. Additionally, we tested the performance of the classifier when radar data are added to the optical. Figure 2 is a flowchart of our methodological framework.

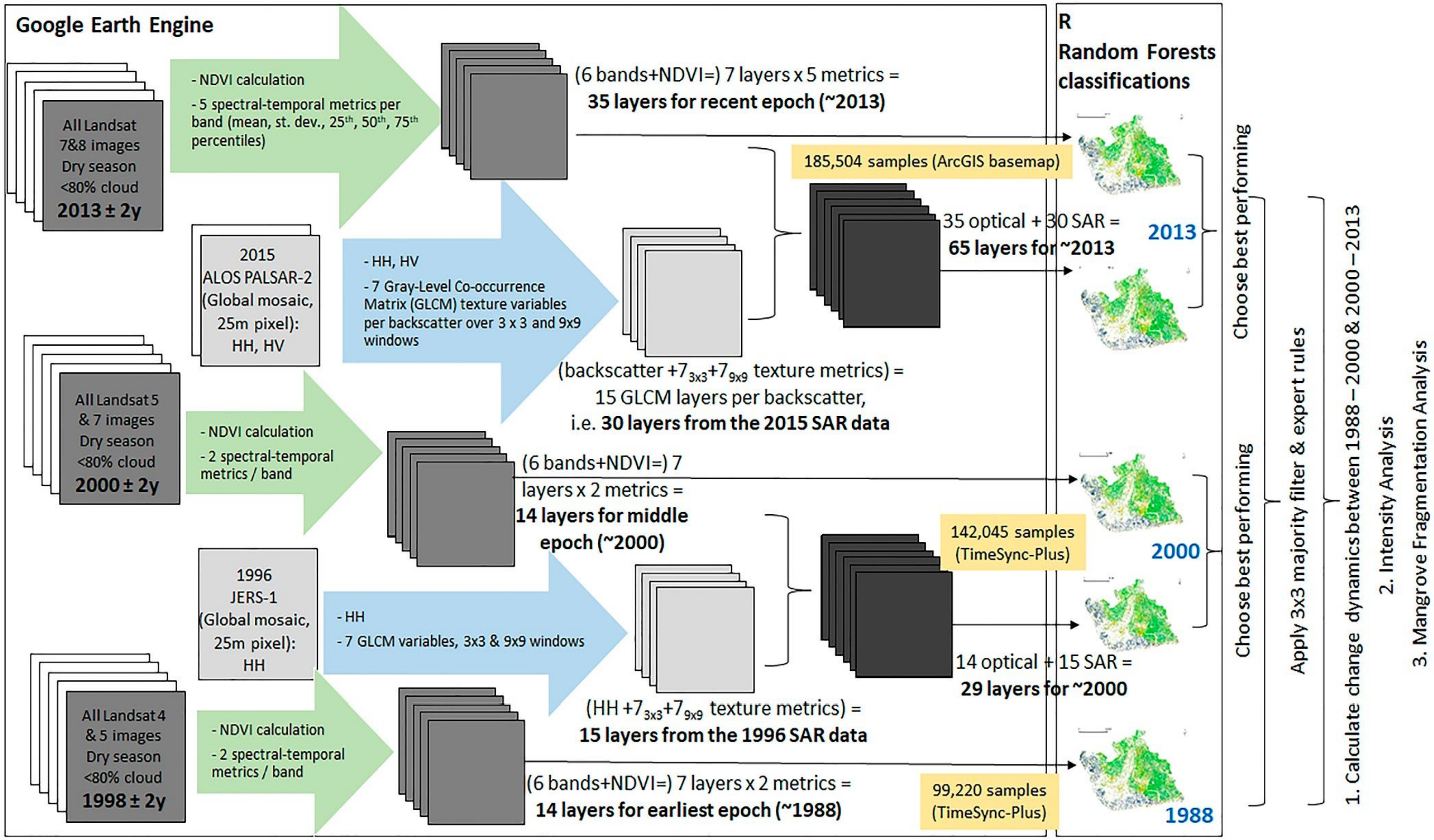


Figure 3. 2: Methodological flowchart

3.3.1. Data

3.3.1.1. Reference Data

Very high-resolution reference data were used for the recent epoch. This dataset is available as a MAXAR Vivid basemap within the ArcGIS software (ESRI, 2020; Maxar and Technologies, 2020). These cover the study area with data from November 2009 to January 2017. About 90% of the study area is covered with 46-cm-pixel data from GeoEye-1 (10 December 2010, 16 December 2011, 3 January 2013, 17 December 2013, 10 April 2014, 8 January 2015), 60-cm-pixel data from QuickBird-2 (11 February 2010, 3 October 2010, 12 June 2013), and 50-cm-pixel data from WorldView-2 (1 December 2011, 16 February 2013, 13 January 2014, 12 March 2015, 17 December 2015). Thanks to the familiarity with the study area, the broad land cover classes that were targeted in this paper were relatively easily identifiable on the very high-resolution imagery. This was also the case for the degraded mangroves, which presented the additional advantage of being spatially confined within the coastal zone, in general, and the mangrove system, in particular.

3.3.1.2. Landsat Data

The choice of Landsat data was driven by the need to coincide with as many other NDR studies as possible, so that comparisons could be drawn between them. Two such studies were identified: the one by Ayanlade and Drake (2016) and the study by Kuenzer et al., (2014a). The latter was particularly targeted, as it is the only one that has attempted to map the “degraded mangrove” class. The choice of the three epochs was also driven by the availability of the reference data and the SAR imagery.

We used all the dry season (December to February) Level 2 surface reflectance Landsat 4, 5, 7, and 8 images centred around 1988 (±2 years), 2000 (±2 years), and 2013 (±2 years) with less than 80% cloud cover from the USGS EROS Data Center for the eight WRS-2 tiles covering the study area (path 187, row57; p188, r55; p188, r56; p188, r57; p189, r55; p189, r56; p189, r57; p190, r56). Only the non-thermal bands were used, and clouds and cloud shadows were removed using F-mask (Masek et al., 2006; Zhu and Woodcock, 2012). Finally, the Normalised Difference Vegetation Index (NDVI) (Tucker, 1979) was calculated. From the resulting 7-band image stacks (i.e., six non-thermal bands, plus the NDVI), spectral-temporal variability metrics were calculated (Griffiths et al., 2013; Mueller et al., 2015; Symeonakis et al., 2018; Higginbottom et al., 2018). For the recent epoch, five statistics for each of the seven bands were calculated: the standard deviation, the mean, and percentiles (25th, 50th, and 75th). This brought the total layers for this epoch to 35. However, as data availability for the first two epochs was problematic (Figure 3.3) we limited the number of statistics per band to 2 (mean and st. dev.) and the total number of layers to 14.

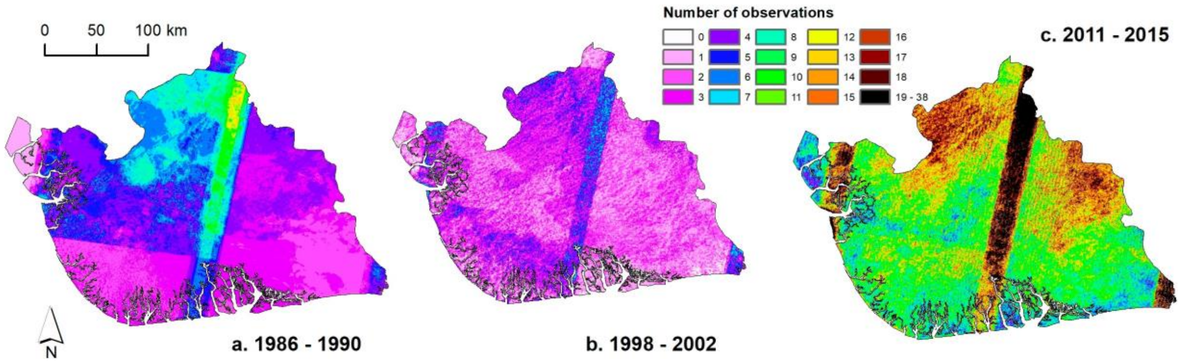


Figure 3. 3: Number of available observations from the Landsat USGS Level 1 archive for (a) the first epoch; (b) the middle epoch, and (c) the more recent epoch.

3.3.1.3. Radar Data

Radar data were chosen for testing whether their addition to the optical metrics could improve the land cover classification. For the recent epoch, we employed the 2015 global 25 m resolution L-band Synthetic Aperture Radar data from the Advanced Land Observing Satellite-2 (ALOS-2) PALSAR-2 sensor via Google Earth Engine's API. The data are free and open access with two polarisations (HH and HV) and are currently available for 2015 to 2018. To increase the utility of the SAR data, we used Google Earth Engine to calculate a series of Gray-Level

Co-Occurrence Matrix (GLCM) texture variables (Symeonakis et al., 2018). GLCMs are a series of localised texture metrics that quantify the statistical properties of a layer over a moving window (Haralick, 1979). We calculated seven GLCM layers (mean, variance, homogeneity, contrast, dissimilarity, entropy, and second moment) (Thapa et al., 2015). These statistics were calculated over both 3 × 3 and 9 × 9 windows, resulting in 15 layers per SAR backscatter (one backscatter + seven 3 × 3 GLCM layers + seven 9 × 9 GLCM layers), totalling 30 layers for the year 2015.

For the middle epoch, we acquired JAXA's 25 m resolution JERS-1 tropical region mosaics for the year 1996, the only year that such data are available over the Niger Delta Region. One polarisation is available (HH), from which we calculated 15 GLCM layers to use in the classification.

3.3.2. Land Cover Mapping

3.3.2.1 Sampling and Validation

In total, 185,504 samples were taken for the epoch centred around 2013 from very high-resolution dataset which is available as a MAXAR Vivid basemap within the ArcGIS software (ESRI, 2020; Maxar and Technologies, 2020). For the first and second epochs (i.e., 1988 and 2000), TimeSync-Plus v4.6 was used (Cohen et al., 2010) to check for unchanged pixels at the 2013 sample locations from classified map with very high overall accuracy of the same period. This resulted in 142,045 and 99,220 samples, respectively, for which we could confidently say that no change in the Landsat time series occurred. During classification, half of these samples were used for training and half for validation.

3.3.2.2 Image Classification & Post-Classification Processing

We developed the land cover classification using Random Forests classification models. Random Forests have been used successfully to classify Landsat imagery, thanks to their effective handling of correlated predictors and reduced tendency toward overfitting (Pal, 2005). We used the 'RStoolbox' and 'randomForest' packages within the R statistical environment (Team, 2017). One optical only model was tested for the first epoch, while for the middle and most recent ones, we tested the performance of optical only and optical + SAR metrics (Figure 3. 2). Based on the accuracies achieved, the outputs from the best performing models were chosen for the middle and more recent epochs. A 3 × 3 majority filter was applied to the outputs from all 3 epochs to get rid of the 'salt and pepper' effect of the classification. Finally, based on our knowledge of the study area, expert rules were applied to correct for some classification errors (Symeonakis et al., 2018).

3.3.2.3. Intensity Analysis

Aldwaik and Pontius (2012) devised a methodology that characterises patterns of land change quantitatively. It provides a mathematical framework that compares a uniform intensity to observed intensities of temporal changes among land cover classes (or 'categories') (Pontius et al., 2013). There are three levels of analysis, with each level exposing different types of information given the previous level of analysis. The first level, i.e., the interval level, examines how the size and speed of change vary across time intervals. The intensity of the rate of annual change is estimated using the following equations (Aldwaik and Pontius, 2012) (for notation, see Table S3.1 in the Supplementary Material, appendix 1):

$$S_t = \frac{area\ of\ change\ during\ interval\ [Yt\ ,\ Yt+1]/area\ of\ study\ region}{duration\ of\ interval\ [Yt\ ,\ Yt+1]} \times 100\%, \tag{1}$$

$$U = \frac{area\ of\ change\ during\ all\ intervals/area\ of\ study\ region}{duration\ of\ all\ intervals} \times 100\%. \tag{2}$$

The second level is called "category level" and it examines how the size and intensity of gross losses and gross gains in each land cover class vary across classes for each time interval. This level identifies which land cover classes are relatively dormant or active in each time interval (Aldwaik and Pontius, 2012). Equations (3) and (4) provide the intensity of a class' annual gain and loss, respectively:

$$G_{tj} = \frac{area\ of\ gross\ gain\ of\ class\ j\ during\ [Yt\ ,\ Yt+1]/duration\ of\ [Yt\ ,\ Yt+1]}{area\ of\ class\ j\ at\ time\ Yt+1} \times 100\%, \quad (3)$$

$$L_{ti} = \frac{area\ of\ gross\ loss\ of\ class\ I\ during\ [Yt\ ,\ Yt+1]/duration\ of\ [Yt\ ,\ Yt+1]}{area\ of\ class\ i\ at\ time\ Yt} \times 100\%. \quad (4)$$

The third level, the “transition level”, examines how the size and intensity of land cover class’ transitions vary across the other classes that are available for that transition (Aldwaik and Pontius, 2012). At each level, the method tests for stationarity of patterns across time intervals and identifies which land cover transitions are particularly intensive in a given period. Aldwaik and Pontius (2012) provide a detailed explanation of the limitations concerning where the transition from a particular land cover class *m* to a class *n* can occur. For example, if a given land cover class *n* exists at a particular location at the initial time, then class *n* cannot gain at that place. If class *n* gains, then it must gain from locations that, initially, are not class *n*. If class *n* gains uniformly across the study area, then this class will gain from other classes, in proportion to the initial sizes of these land cover classes. Alternatively, class *n* might intensively avoid gaining from some particular class(es) and might intensively target gaining from some other class(es). Given the observed gross gain of class *n*, Equations (5) and (6) identify which other classes are intensively avoided versus targeted for gaining by class *n* in a given time interval:

$$R_{tin} = \frac{area\ of\ transition\ from\ i\ to\ n\ during\ [Yt\ ,\ Yt+1]/duration\ of\ [Yt\ ,\ Yt+1]}{area\ of\ class\ i\ at\ time\ Yt} \times 100\%, \quad (5)$$

$$W_{tn} = \frac{area\ of\ gross\ gain\ of\ class\ n\ during\ [Yt\ ,\ Yt+1]/duration\ of\ [Yt\ ,\ Yt+1]}{area\ that\ is\ not\ class\ n\ at\ time\ Yt} \times 100\%. \quad (6)$$

We used the *intensity.analysis* package in R to carry out the processing (https://cran.r-project.org/web/packages/intensity.analysis/vignettes/README.html).

3.3.2.5. Landscape Pattern Analysis

Post-classification comparison is most informative about changes in the composition of a landscape but gives us little—only visual—information about the spatial characteristics of these changes and the distribution of landscape elements. Landscape pattern analysis using landscape metrics provide us with additional information about the structure of changes, such as landscape fragmentation and patch aggregation or dispersion, as well as their changes in time. With the latter, we can observe changes in landscape spatial configuration through time.

We followed the approach used by Gounaridis et al., (2014) and selected a number of class-level metrics (McGarigal, 1995) in order to study the changes in the spatial configuration and patterns of the 'mangrove' and 'degraded mangrove' land cover classes. We used 'Percentage of Landscape' (PLAND) as a measure of class abundance, and the 'number of patches' (NP), 'landscape patch index' (LPI), and 'patch area median' (AREA_MD) to study fragmentation of the classes of interest. With regard to patch shape analysis, we used the 'area weighted mean patch shape index' (SHAPE_AM), and for the aggregation of these classes, we used the 'area weighted mean Euclidean nearest neighbour distance index' (ENN_AM) along with its standard deviation (ENN_SD). Finally, we also used the aggregation index of 'percentage of like adjacencies' (PLADJ). Table 1 provides a listing of the selection of landscape metrics used in this study, together with a short description of their correlation with mangrove forest fragmentation. For more information, refer to McGarigal and Marks (1995) who provide a full description of the metrics, including their mathematical formulas

Table 3.1. Selection of landscape metrics used in this study with a short description of their relationship with mangrove forest fragmentation

Name	Abbreviation	Description
Percentage of Landscape (%)	PLAND	Class percentage in landscape proportion abundance)
Patch area median (ha)	AREA_MD	The median of patch areas in a class (a summary metric for the size of patches in the class, which is not influenced by very large patches)
Number of patches	NP	The number of patches in each class (Simple measure of fragmentation)
Area weighted Mean Patch Shape Index	SHAPE_AM	Patch shape complexity at class level (Indicative of changes at the edges)
Largest Patch Index (%)	LPI	Percentage of total landscape area occupied by the largest-sized patch (Measure of dominance)
Percentage of like adjacencies (%)	PLADJ	The proportions of like adjacencies to the total adjacencies for the class' cell (aggregation)
Area weighted mean Euclidean nearest neighbour distance (m)	ENN_AM	Euclidean distance measured form patch edge to the closest patch edge from the same class dispersions). Here we use the area weighted mean for the class to balance the influence of large patches
Euclidean nearest neighbour distance standard deviation	ENN_SD	Measure of variation of ENN in the class (in comparison the mean shows the form of distribution of patches in the class)

3.4. Results

3.4.1. Land Cover Mapping and Validation

Figure 3. 4a–c are the outcomes of the classification of the metrics for the three epochs and are accompanied by pie charts that summaries the proposition covered by each class. For the middle and latest epochs (Figure 3.4b, c), the combination of the optical with the SAR data produced slightly better results (Table 2) and were, therefore, the ones chosen for the subsequent analyses. The largest land cover class is by far woodland, which covers ~40% of the area (~23,000 km^2). Agricultural land is the second largest in all three time points (~12,000 km^2), while mangroves (degraded and non-degraded) and grassland occupy significant portions of the delta, too (~8000 km^2).

The classification results produced high overall accuracies of 79% (95% CI: ±3%), 83% (95% CI: ±3%), and 82% (95% CI: ±2.6%) for the three epochs, respectively (Table 3. 2. Per-class accuracies (% correct, producer's and user's Accuracies; Table 3. 2) were also high, with the exception of the bareland and grassland classes. The lower accuracies for these two types are attributed to the spectral confusion with the agricultural class: when fields are fallow, it gets confused with bareland, while when they are covered with vegetation, it is mostly confused with grassland (Tables S3.1–S5, Appendix 1). The latter is also confused with woodland, as open woodland pixels contain a significant amount of spectral response from grasses.

Most importantly for the objective of this study, the mangrove class was mapped with high accuracy, with percentage correct and user's and producer's accuracies above 90% in all three-time steps and models (Table 3. 2). The degraded mangrove class was also mapped accurately, with producer's accuracies being consistently very high for all epochs and data combinations. However, there was some confusion between this class and the non-degraded mangroves (confusion matrices Tables S3.2–S6 in the Supplementary Material, Appendix 1), resulting in lower user's accuracies, ranging from 77% to 79% for the first two time points (Table 3. 2).

The inclusion of the SAR data in the classification of the more recent epochs generally improved the results but only slightly (Table 3. 2). The most noteworthy improvements were achieved by the inclusion of the PALSAR-2-based metrics in the latest time point, with the user's accuracies of the water and urban classes improving by 4% (Table 3.2).

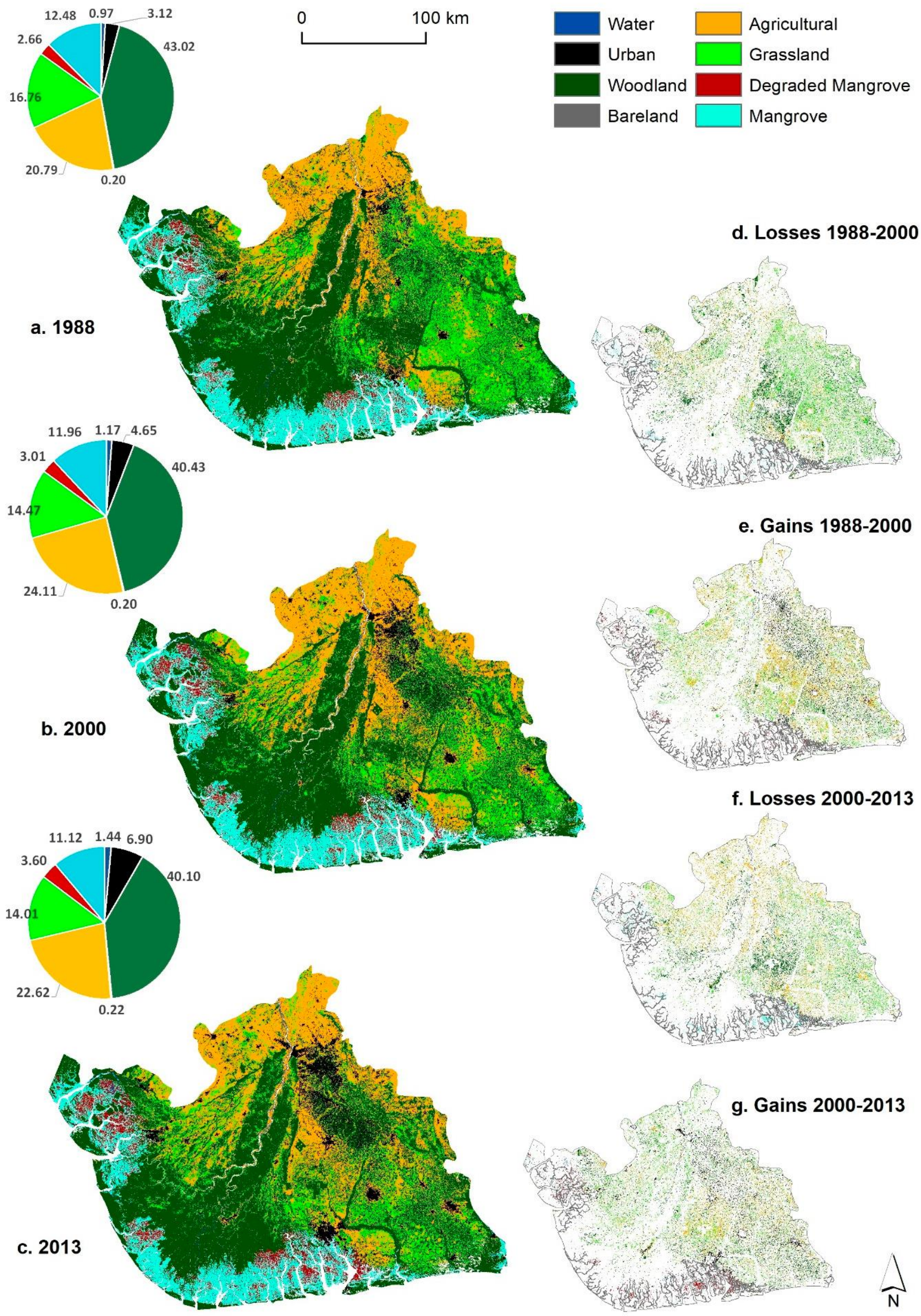


Figure 3. 4. Land cover over the Niger Delta Region in (a) 1988, (b) 2000, and (c) 2013. Pie charts show the respective estimates of the area covered by each land

cover type (%); scale bar corresponds to (a–c). Figures (d,e) are the losses and gains of each land cover type between 1988 and 2000; (f,g) the same for 2000–2013. The white background in (d–g) signifies persistence.

Table 3.2. Overall and per-class accuracy statistics for the three epochs (Wa: Water; U: Urban; Wo: Woodland; B: Bareland; A: Agricultural; G: Grassland; DM: Degraded Mangrove; M: Mangrove; CI: Confidence Interval; C = Correct; PA: Producer’s Accuracy; UA = User’s Accuracy).

	1998 Landsat			200 Landsat			2000 Landsat + JERS-1			2013 Landsat			2013 Landsat+PALSAR-2		
Overall Accuracy	79.48			82.36			82.61			81.27			82.9		
95% CI	+0.003			±0.0029			±0.003			±0.0027			±0.0026		
	C	**PA**	**UA**	**C**	**PA**	**UA**	**C**	**PA**	**UA**	**C**	**PA**	**UA**	**C**	**PA**	**UA**
Wa	73	79	73	75	85	75	75	83	75	74	85	74	78	87	78
U	70	92	70	81	92	81	81	96	81	84	92	84	88	92	88
Wo	84	79	84	87	83	87	87	83	87	84	85	84	84	85	84
B	61	77	61	49	84	49	48	80	48	50	85	50	50	86	50
A	81	80	81	88	81	88	88	81	90	88	79	88	87	79	87
G	71	65	71	53	65	53	54	64	54	56	65	56	57	64	57
DM	77	82	77	78	86	78	79	85	79	86	82	86	87	82	87
M	91	90	91	90	90	90	91	90	91	90	92	90	90	93	90

3.4.2. Land Cover Change Dynamics

The three land cover maps were used to calculate the contingency matrix in Table 3.3. The matrix summarises, for the two periods, the area that has remained unchanged and the area and the type of change observed for each individual class. It also provides a summary of the area covered by each class in the beginning and in the end of each period as well as of the gains and losses they experienced. The spatial distribution of the latter is also illustrated in Figure 3. 4d–g.

Table 3.3. Contingency matrix for the two periods of study representing stable (in bold) and changed areas in km^2. (a) 1988–2000; (b) 2000–2013. Wa: Water; U: Urban; Wo: Woodland; B: Bareland; A: Agricultural: G: Grassland; DM: Degraded Mangrove; M: Mangrove. A: Agricultural: G: Grassland; DM: Degraded Mangrove; M: Mangrove.

a.					2000km^2						
		Wa	**U**	**Wo**	**B**	**A**	**G**	**DM**	**M**	**1988 total**	**Gross loss**
	Wa	**395.7**	9.34	3.59	12.93	7.72	0.63	51.66	20.58	502.16	106.46
	U	4.3	**1444.71**	95.36	4.59	341.98	85.32	6.09	7.56	1989.91	545.2
	Wo	11.61	310.44	**193,54.71**	3.6	1655.9	2020.54	49.81	363.9	23,770.52	4415.81
	B	10.1	10.09	0.3	**72.67**	19.14	0.19	0.12	0.28	112.9	40.23
1988	**A**	20.52	543.09	647.15	39.38	**8868.25**	1439.74	7.48	5.89	11,571.48	2703.24
	G	0.55	572.51	2419.61	0.87	2883.36	**3534.56**	1.62	8.34	9421.41	5886.86
	DM	149.47	8.17	13.41	0.35	3.45	1.64	**1169.07**	454.69	1800.27	631.2
	M	40.9	26.06	536.28	0.64	8.09	6	535.47	**5743.7**	6897.15	1153.45
	2000 Total	633.15	2924.41	230,70.43	135.03	13,787.88	7088.63	1821.33	6604.94		
	Gross Gain	237.46	1479.7	3715.71	62.36	4919.64	3554.07	652.25	861.24		
b.					**2013km^2**					**2000 total**	**Gross loss**
	Wa	**522.59**	2.09	4.91	10.26	4.16	0.48	76.77	13.16	634.42	111.83
	U	19.64	**2150.29**	173.38	18.35	357.87	184.36	10.72	10.19	2924.8	774.51
	Wo	10.12	371.43	**18,959.22**	21.03	1251.56	2038.85	67.2	351.52	230,70.92	4111.7
	B	58	5.09	1.99	**57.13**	12.33	0.38	0.09	0.09	135.1	77.97
	A	25.86	933.43	939.59	46.28	**9083.42**	**2754.41**	3.55	1.58	13,788.12	4704.71
2000	**G**	1.34	253.81	1784.19	5.44	1922.06	3113.85	**5.57**	2.38	7088.64	3974.79
	DM	157.76	3.64	26.83	5.21	4.52	2.07	1158.61	**462.79**	1821.42	662.81
	M	65.3	7.86	377.77	14.21	7.68	7.84	595.84	5529.72	6606.22	1076.5
	2013 Total	860.61	3727.63	22267.88	177.91	12,643.60	8102.24	1918.34	6371.43		
	Gross Gain	338.02	1577.34	3308.66	120.78	3560.18	4988.39	759.74	841.71		

3.4.3. Intensity Analysis

The interval level of the intensity analysis identifies the time interval in which the overall annual rate of change is faster. The total change in both intervals was found to be relatively similar: ~17% of the total area in the first period and ~15% in the second. However, the intensity of the annual area of change in the first interval is faster than in the second (1.42% and 1.16%, respectively; Figure 3. 5). The output of Equation (2) is 1.28%, depicted as a dashed line in Figure 3. 5. Compared to this value, the rate in the first period is considered 'fast', while in the second 'slow'.

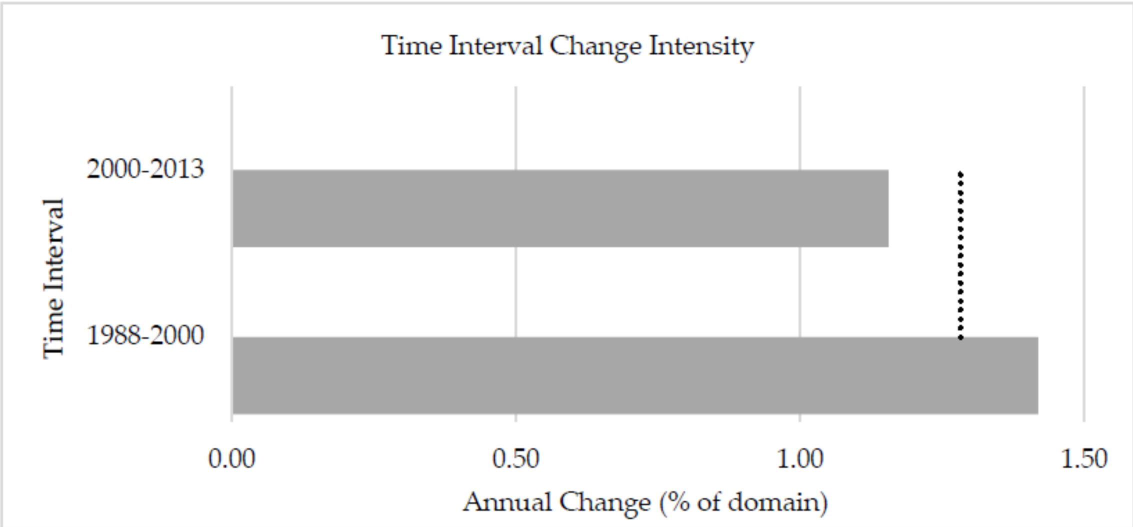


Figure 3. 5. Intensity of the annual area of change within the two-time intervals of the study. The dashed line is the uniform line (i.e., the output of Equation (2)

Figure 3. 6 is the graphical representation of the 'category level' of the intensity analysis. Figure 6a,c depict the size of the annual gain of loss of each land cover class in the first and the second period, respectively. Figure 5b,d show the intensity for a class' annual gain or loss, as calculated by Equations (3) and (4). The two dashed lines show the output of Equation (1) for each period, i.e., the uniform line for each period at this category intensity level (Aldwaik and Pontius, 2012). When an intensity bar remains to the left of the uniform (dashed) line, then the change is relatively dormant for that land cover class and period. On the contrary, if the bar extends to the right of the dashed line, then the

change is relatively active for that class and period. If, for a given land cover class, the intensity of the gains or losses remain active or dormant during all study periods, then the specific type is considered stationary.

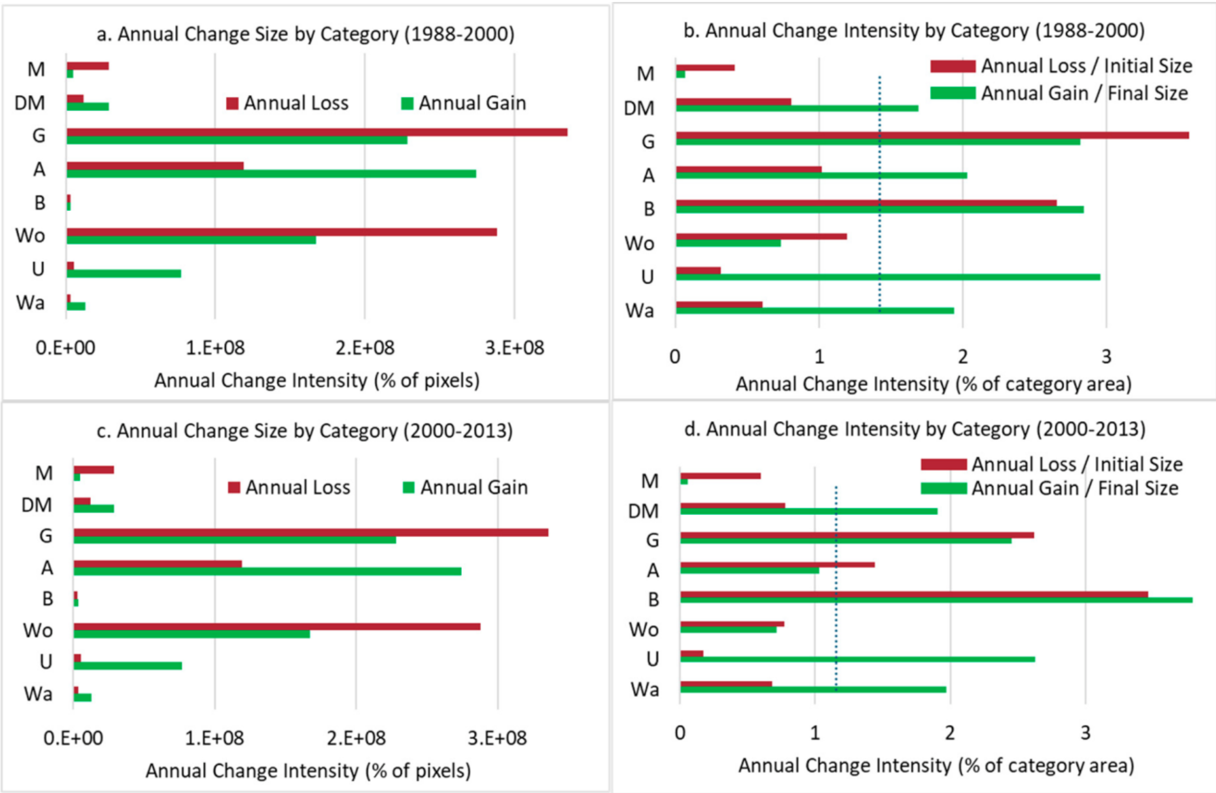


Figure 3.6. Category intensity analysis for the two periods. (a,c): gross annual area of gains and losses. (b,d): intensity of annual gains and losses within each land cover category. "# of elements" is the number of pixels. The dashed lines in (b,d) signify the uniform intensity value. Wa: Water; U: Urban; Wo: Woodland; B: Bareland; A: Agricultural: G: Grassland; DM: Degraded Mangrove; M: Mangrove.

At the transition level, the intensity analysis identifies which transitions are more intensive in a given time interval. Given the scope of the present paper and the need to keep the presentation of the results as succinct as possible, Table 3.4 summarises the results only for the transition from mangrove to any other class for the two periods. The outcome for all the other transitions is provided in Tables S3.7 and S8 of the Supplementary Material, Appendix 1.

Table 3 4. Transition level intensity analysis FROM-Mangrove TO-all other classes (1988–2000 and 2000–2013). In bold and underlined: targeted classes (compared to uniform). Deg.: Degraded.

Transitions FROM	Mangrove			
Time Interval	1988–2000		2000–2013	
TO Category	Observed Annual Transition (km^2)	Transition Intensity % of 2000 Category	Observed Annual Transition (km^2)	Transition Intensity % of 2013 Category
Water	206	0.03	332	0.05
Urban	717	0.03	540	0.02
Woodland	506	0.00	1431	0.01
Bareland	40	0.04	221	**<u>0.20</u>**
Agricultural	485	0.00	298	0.00
Grassland	244	0.00	461	0.01
Deg. Mangrove	23,799	**<u>1.57</u>**	32,742	**<u>1.80</u>**

3.4.5. Landscape Pattern Analysis

Figure 3.7 depicts the evolution of the selected landscape metrics through time for the healthy and the degraded mangroves classes

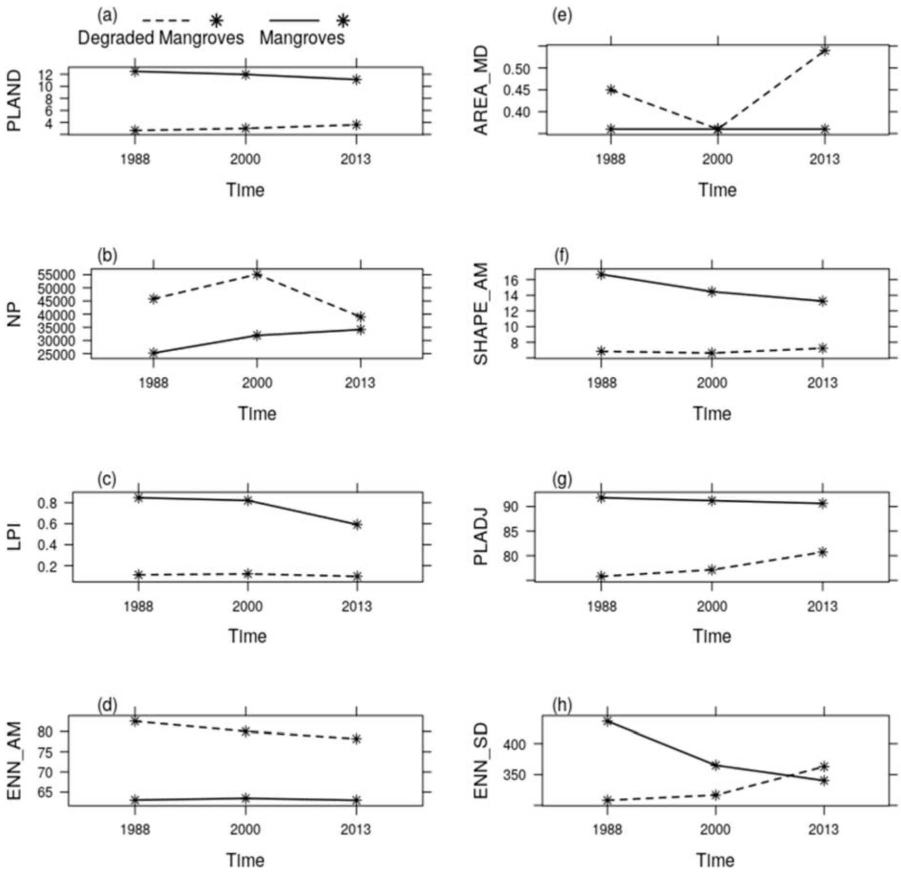


Figure 3.7. Landscape metrics for the mangrove and degraded mangrove classes. (a) Percentage of Landscape (%; PLAND); (b) Number of patches (NP); (c) Largest Patch Index (%; LPI); (d) Area weighted mean Euclidean nearest neighbour distance (m; ENN_AM); (e) Patch area median (ha; AREA_MD); (f) Area weighted Mean Patch Shape Index (SHAPE_AM); (g) Percentage of like adjacencies (%; PLADJ); (h) Euclidean nearest neighbour distance Standard Deviation (ENN_SD).

3.5. Discussion

Accurate and reliable information of land cover dynamics is essential for the sustainable management of tropical deltas and mangrove ecosystems and their capacity for ecosystem service provision. The 'traditional' remote sensing mapping approach involving the use of image mosaics of optical data from two dates, together with likelihood function maximisation image classification algorithms, is not reliable in the humid tropics due to cloud cover (Martinuzzi et al., 2007; Okoro et al., 2016), data availability (Kuenzer et al., 2014a; Kirui et al., 2013) , and algorithm performance. This has led to conflicting land cover change estimates for the largest river delta in Africa and the failure to assess the extent of degradation of one of the most endangered ecosystems in the world (IUCN, 1992). Our results show that, by incorporating novel image compositing techniques, spectral-temporal metrics, and machine learning classification algorithms, a reliable assessment of the change dynamics over the Niger Delta Region can be made. Our accurate land cover estimates also allowed for a more comprehensive land change analysis that incorporates an assessment of change intensity and the fragmentation of a key component of the NDR: its mangrove forests.

3.5.1. Land Cover and Change Dynamics

There is an inherent difficulty in mapping land cover in tropical deltas, in general, and mangrove forests, in particular, as they are affected by seasonal and intertidal effects, with pixels often comprising of a mixture of vegetation, soil, and water due to their location between land and sea and the average tidal range in the Niger Delta being 1.5m (James et al., 2007). Nevertheless, we mapped the eight main land cover types for the entire NDR, achieving high overall accuracies in all epochs (~79% for 1988, and 82% for 2000 and 2013; Table 3. 2) and high producer's accuracies for all classes and years. With the exception of the grassland and bareland classes, user's accuracies were also high (from 70% to 91%). Our results compare favourably with other studies in the NDR (Nwobi et al., 2020; Ayanlade and Drake, 2016; Onojeghuo and Blackburn, 2011; Salami et al., 2010). Regarding the mapping of degraded mangroves, one of the main objectives of this paper, our study is the first to map this accurately with user's accuracies between 77% and 87% and producer's consistently above 82%. The only other study that attempted to map degraded mangroves reported very low accuracies

The results reveal some interesting dynamics:

- There is consistent net loss in mangrove and woodland types and a consistent net gain of the urban class in both periods of study
- The area covered by non-degraded mangroves was reduced by ~250 km^2 in each period (=Gross Loss – Gross Gain)
- About 10% of mangroves are degraded in each interval, and an additional 34 km^2 of mangrove were converted to urban land use in both periods
- A portion of degraded mangrove is able to bounce back into its healthier state
- The net loss for the woodland class was more than 700 km^2 in each period. A part of this class is converted to grasses (~8% and ~9%) and to agricultural land (~7% and ~5%)
- A quarter of the area mapped as grassland in the initial dates is converted to woodland by the end date
- The built-up areas increased by 47% (~900 km^2) in the first period, an area

larger than the size of New York City. In the second period, the increase was smaller (~800 km^2) but still it amounted to 27% of the area covered in 2000

More specifically, according to our findings, healthy mangroves reported a net loss in both study periods: 292 km^2 in the first and 235 km^2 in the second, while degraded mangroves consistently reported a net gain (21 km^2 in the first and 97 km^2 in the second). Interestingly, our study and the studies by Kuenzer et al., (2014a) and James et al., (2007) found a similar decrease in the overall combined (degraded and non-degraded) mangrove area. According to our results, this area was 270 km^2, while, in an almost identical period of study, Kuenzer et al., (2014a) found that the loss was 239 km^2. In the James et al. (2007) study between 1987 to 2002, the loss was 213 km^2. However, our more accurate findings identify the total areas covered by the mangrove classes to be very different to the areas in the Kuenzer et al., (2014a) study: we found that mangroves and degraded mangroves occupied an area between 8697 and 8428 km^2 in the two periods, while Kuenzer et al. (2014a) claim that these numbers were 10,311 and 10,072 km^2, respectively. These figures differ by almost a fifth and can play a significant role in the setting of conservation targets, management policies, and sustainability goals. Moreover, our mangrove results compare favourably with three studies that mapped mangroves as one class accurately: the study of Nwobi et al., (2020), who found that mangroves occupied an area of 9115 km^2 in 2007 and 8017 km^2 in 2017; the study of Ayanlade and Drake (2015) (9965 km^2 in 1987, 9255 km^2 in 2001,and 8430 km^2 in 2011); and the study by James et al., (2007) (7037 km^2 in 1987 and 6824 km^2 in 2002).

While it is relatively simple to compare the results on the extent of mangroves between the different studies that mapped land cover change in the NDR, as this class is confined in the coastal belt and is always included within the study area, it is not as straightforward to compare the findings on other land cover types, as the study areas do not match. In the case of woodland, for example, the biggest land cover type in the NDR, our study found that it occupied 23,770 km^2 in 1987 and suffered net losses in both periods: ~700 km^2 in the first and ~800 km^2 in the second. The study by Ayanlade and Drake (2016) also found net losses in both periods for the combined “lowland rainforest” and “freshwater forest” classes but found that these occupied 31,200 km^2 in 1987, 25,400 km^2 in 2001, and 21,470 km^2 in 2011. However, their study area far exceeds the boundaries of our delineation of the NDR. The study by Kuenzer et al., (2014a) also agrees that “forest” and “swamp forest” experienced net losses in both periods. They report far smaller areas than both our study and the study by Ayanlade and Drake (2016): 18,325 km^2 in 1987 and 15,408 km^2 in 2013. Finally, the Nwobi et al., (2020) study also agrees that “tropical forests” were reduced but reported that these occupied 29,000 km^2 in 2007 and 25,500 km^2 in 2017. As all of these studies, including ours, reported high per-class accuracies in the mapping of forests, it is difficult to ascertain which on is closer to the true figure.

The difficulty in comparing the findings of different studies remains for the agricultural class, which we found to significantly increase in the first period (from 11,571 to 13,787 km^2) and decrease in the second (12,645 km^2 in 2013). An additional issue to the problem of relating to different study areas around the NDR is the choice of land cover nomenclature. Based on our knowledge of the region and on the classification systems of the ESA 20m African land cover data for 2016 and the GlobeLand 30 m data for 2010, we included a grassland class in our mapping efforts, which were found to decrease in the first period (from 9421 to 7089 km^2) and increase in the second (8102 km^2 in 2013). Our figures for the agricultural class are significantly lower to those in Ayanlade and Drake (2016), Kuenzer et al., (2014b), and Nwobi et al. (2020). However, none of these studies included a separate class for grassland but, according to their spatial outputs, appear to have mapped this together with the agricultural class. We recognise that separating these classes poses difficulties, as the spectral separability between them is low: our user’s accuracies for grassland are testament to that (Table 2) However, we strongly believe that it is a shortcoming to map these two classes as one, as this precludes the identification of very important land cover dynamics between either of these classes and, for example, the woodland or urban classes. If summed together, our estimates of agricultural and grassland compare favourably with those of Nwobi et al., (2020), who estimated the area covered by “agricultural land” as 21,733 km^2 in 2007 and 24,179 km^2 in 2017.

An important change that occurred in both periods is the expansion of the built-up areas: from 1990 km^2 in 1988, to 2924 km^2 in 2000, to 3728 km^2 in 2013, i.e., an 87% increase. As in the previous land cover types, the difference in the extent of the study area makes comparison to the other studies difficult. For example, the Ayanlade and Drake (2016) study reports much higher figures, but their study includes the city of Benin, the fourth largest Nigerian city, which lies outside of our delineation of the NDR. Similarities exist between our findings and the Nwobi et al., (2020) study: their 'built-up-area' class occupied 3950 km^2 in 2007 and 5938 km^2 in 2017. Their higher estimates can be attributed to the fact that they include the city of Calabar and a number of built-up areas in the northeast of their study area that lie outside our delineation of the NDR.

According to the results of our intensity analysis (Figure 3.6b), in the first period of study, only mangroves and woodland demonstrated dominant gains, while all the other categories had active gains. Interestingly, only the grassland and bareland types had active annual change intensities, with the former having the largest size of losses in this period (Figure 3.6a). However, these two are the classes that scored lower user's accuracies and the respective intensity results need to be treated with caution. Notable results from this period are the ~five times greater annual intensity of mangrove loss than gain and the ~ten times greater annual intensity of urban gain than loss. The intensity of agricultural expansion is also noteworthy, reporting ~two times greater gain than loss.

In the first period, the land cover class that mangroves 'target' most intensively when they change is degraded mangroves, with a transition intensity of 1.57% of the total area of degraded mangroves in the end of the first period. This is much higher than the estimated uniform change intensity of 0.06%. An area of 535 km^2 of mangroves was degraded by the year 2000. In the second period, this change is even more intense (1.80%, higher than the uniform intensity of 0.08%) and leads to a conversion of a total of 596 km^2 of mangrove to degraded mangrove by 2013. Bareland is also found to be a targeted class for mangroves with an estimated transition intensity of 0.20% (221 km^2). Water also targets bareland, as well as mangroves and degraded mangroves, with transition intensities higher than the estimated uniform change intensity. As this is the first paper to undertake an intensity analysis in the NDR, we are unable to compare our findings to existing studies.

3.5.2. Fragmentation and Degradation of the Niger Delta Mangrove Forest

The Niger Delta's mangrove forest is a hub for substantial oil and gas deposits. As a consequence, it is highly vulnerable to activities of oil and gas extraction, e.g., land clearing, dredging, construction of flow stations, pipe and seismic lines, well blowouts, leakages or corrosion, equipment failure, error during operation or maintenance, accidents during transportation, sabotage, etc., as well as urbanisation, selective logging, and the proliferation of the invasive Nipa palm species (*Nypa fruticans*) that lead to the forest's destruction, fragmentation, and degradation (James et al., 2007; Okonkwo et al., 2015; Nwobi et al., 2020; Kuenzer et al., 2014a; Imevbore et al., 1997).

Our land cover change and intensity analyses showed that degraded mangroves increased in both periods of study and mangroves losses were five times more intense than gains. To further assess the condition of the Niger Delta mangrove forest, we carried out the first ever fragmentation analysis of the area. Our fragmentation results show that the 'number of patches' (NP) for the healthy mangroves increased persistently while the 'total percentage of landscape' (PLAND) decreased (Figure 3. 7a-b). The 'largest patch index' (LPI), a measure of dominance (Figure 3. 7c), shows that in the second period, larger patches are on a decrease. The 'area weighted mean shape index' (SHAPE_AM; Figure 3. 7f) is also decreasing for the healthy mangroves, in both periods: this indicates that changes are happening in the perimeter of patches, uniformly. The 'area weighted mean Euclidean nearest neighbour distance' index (ENN_AM; Figure 3. 7b) is slightly decreasing, indicating less dispersion of the healthy mangrove patches. The standard deviation of this index (ENN_SD; Figure 3. 7h) is decreasing but with high values compared to the mean, which indicates a more uneven distribution of patches. The high and steady values of PLADJ (Figure 3. 7g) confirm the ENN results: the healthy mangrove patches remain relatively aggregated throughout the study period. This was expected, as mangroves are very localised within the delta and naturally only occur by the coast.

Figure 3. 7 also shows the change in landscape metrics through time for the degraded mangroves. The size of this class (PLAND; Figure 3. 7 a) is constantly increasing but shows some fluctuation in the number of patches (NP; Figure 7b). A divergent pattern is observed in the evolution of the number of patches and the median of patch area metrics (AREA_MD; Figure 3. 7e):

NP increases in the first period and AREA_MD decreases, while in the second period, this is reversed. The latter means that this class becomes less fragmented, with more patches and lower patch size in the first period. Between 2000 and 2013, there are fewer patches and larger patch sizes, indicating that some of the first period's patches have merged to form larger ones.

A visual examination of the land cover maps and derived change maps from these revealed three areas that demonstrate higher concentrations of degraded mangrove. One such area is in the eastern part of the NDR, around the city of Port-Harcourt and the towns of Bonny, Okrika, and Degema (Figure 3. 8a). Mangrove degradation here can be attributed to the effects of rapid urbanisation and oil extractive activities (Kadafa, 2012; Duke, 2016), as demonstrated by the overlap with the locations of the oil wells, the pipelines, and the oil spills in Figure 3. 8a. At the central part of the study area, mangrove degradation is mainly due to oil spills resulting from crude oil extractive activities, notably near River Bayelsa and the towns of Nembe, Southern Ijaw, Ekeremor, Brass, and Oloibiri, where oil extraction first began as early as the 1950s (Figure 3.8b). The highest concentration of degraded mangroves is, however, in the western part of the NDR, in the Delta state (Figure 3. 8c). This area shows widespread degradation, with a notable increase in the second and third date around the towns of Wari South and Wari Southwest. Several oil spill and gas incidents have been reported in the literature around this area and period (Kadafa, 2012; Balogun, 2015; Duke, 2016; Twumasi and Merem, 2006).

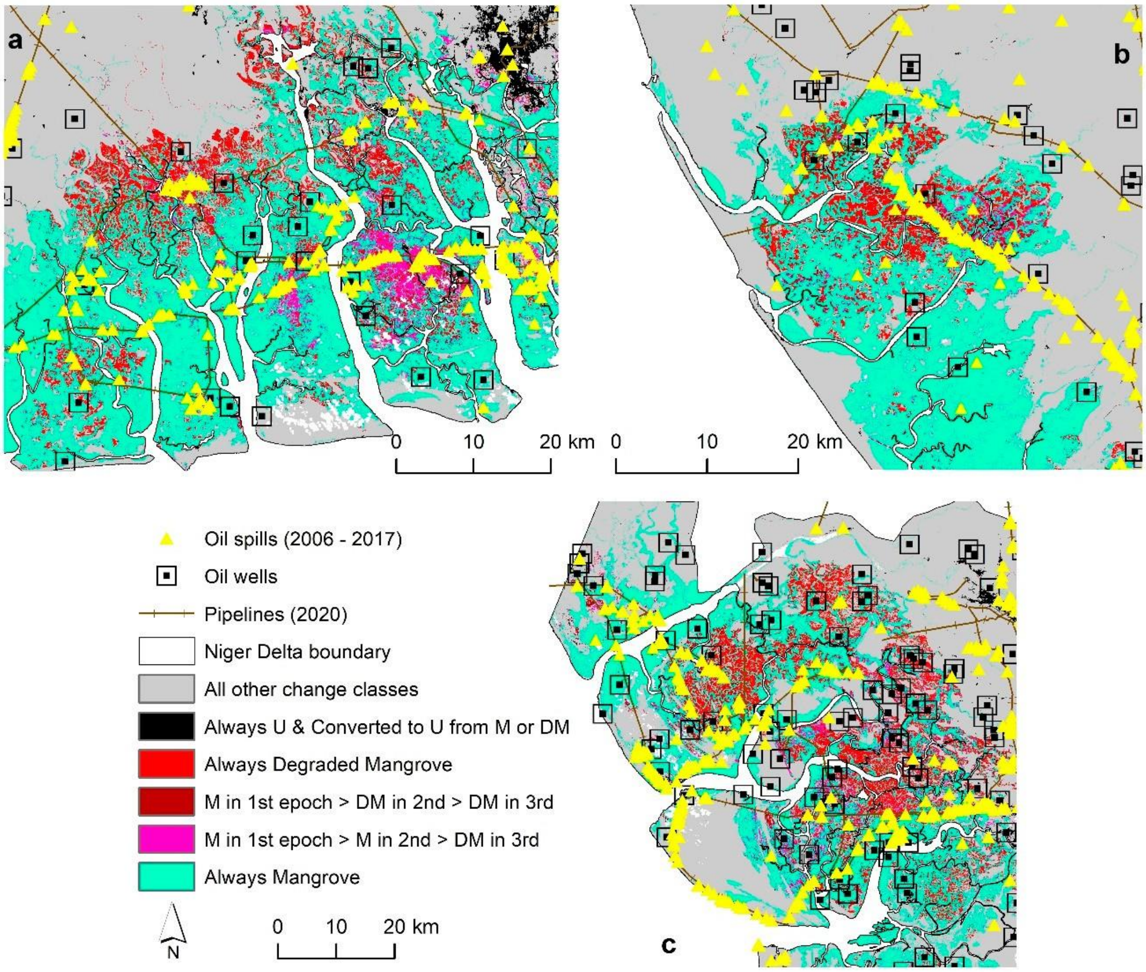


Figure 3.8. Oil wells, pipelines, oil spills, and mangrove degradation hotspots in three parts of the study area: (a) the eastern area, around the city of Port-Harcourt; (b) the central area, near the river Bayelsa, and (c) the western area around the cities of Wari South and Wari South West. U: Urban; M: Mangrove; DM: Degraded Mangrove. (Oil spill data: https://www.nosdra.gov.ng and https://oilspillmonitor.ng. Oil wells and pipeline data: https://www.shell.com.n

3.6 Conclusions

The Niger Delta Region (NDR) is an important ecosystem, providing numerous services to the millions of its human inhabitants. Despite its undisputable importance, it is under threat of degradation, mainly due to human pressure, and especially as a direct consequence of the activities related with the significant oil and gas reserves in the region. Understanding the extent of the problem requires an accurate assessment of the land cover dynamics in the region, which can only be achieved through the use of state-of-the-art remote sensing technologies and analytical techniques. Cloud contamination and gaps in the commonly employed Landsat archive makes this a fathomable task.

Here, we were able to accurately assess the land cover dynamics over a period of 25 years using the Google Earth Engine cloud computing platform to estimate spatial-temporal Landsat-based metrics in three epochs. Our results showed that mangroves, the lowland rainforests, and the freshwater forests have demonstrated a net loss, while the built-up areas have almost doubled in the period of study. By performing a land cover change intensity analysis, we were also able to demonstrate how highly intense these changes were. We also tested the ability of L-band SAR data in improving the Random Forests classifications of the main land cover types in the delta and found that these only improve the mapping of the urban and water classes, provided that more than one polarisation is available. Our results provide a valuable quantification of the land cover dynamics in the NDR and the first ever accurate assessment of the spatial extent of the degraded mangroves in the region. Such assessments are imperative for successfully addressing a number of the Sustainable Development Goals and achieving Land Degradation Neutrality by 2030, as envisaged by the United Nations LDN Target Setting programme.

Chapter 4

Assessing the Spatial Drivers of Mangrove Degradation in the Niger Delta Region

4.1 Introduction

Mangroves are one of the most ecologically important ecosystems in the coastal tropics and have great socio-economic value to local inhabitants. They provide powerful shoreline protection against climate related hazards, such as storm surges, extreme flood and erosion, tsunamis or cyclones, and sea level rise (Guannel. 2016; Narayan et al., 2016; Ellison, 2015), in addition to stabilising coastal sediments, nutrient cycling, filtering and absorption pollutants, enhancing water quality, and acting as powerful carbon sinks (Chaudhuri et al., 2019; Twilley and Day, 1999; Blasco et al., 1996; Nor and Obbard, 2014; Wong et al., 1997; Donato et al., 2011). They act as nursery grounds for juveniles of many commercially important fish species and crustaceans (Saenger et al., 2013a; Sheridan and Hays, 2003; Manson et al., 2005b; Ronnback, 1999; Kenyon et al., 2004).

In Nigerian coastal areas (i.e., predominantly the NDR), mangroves are important habitats responsible for more than 70% of fisheries catches (Udoh, 2016), with more than 90% of local inhabitants depending on them for their livelihood (Davies, 2005). In 2000, shrimp species which are entirely wild caught in the NDR, worth US$ 46,495, 000 (N5.58 billion), contributed to over 43% of Nigeria's total fish export (Zabbey et al., 2010). They play a key role in human sustainability and livelihood. Hence, they utilized by coastal communities to meet subsistence need for food, including fisheries, bush meat, extraction of timber for fuel wood and construction (Zabbey et al., 2010; Numbere, 2014).

Despite the value of mangroves and their considerable conversation successes (Friess et al., 2020), mangroves continue to regress at a global rate of 0.13% annually (Goldberg et al., 2020). An estimated global mangrove area of 1389km^2 were reported to be in various forms of degradation condition between 1996 and 2016 (Worthington and Spalding, 2018). In tropical regions, forest degradation often precedes their loss (Vancutsem et al., 2021). As such, mangroves risk total disappearance by the end of the century due to present disturbance rates (FAO, 2007; Duke et al., 2007a). Global mangrove degradation occurs mainly due to human activities and climate changes, including exploitation of timber and fuelwood, seawall construction, reclamation for agri-and aquaculture overfishing, coastal pollution, sea level rise, flooding, and cyclone loss of mangroves (Meng et al., 2016; Mmom and Arokoyu, 2010; Wenqing Wang et al., 2020; Olaniyi et al., 2012; UNEP, 2011).

In the NDR, mangrove area has relatively remained stable over the last few decades (James et al., 2007; Kuenzer et al., 2014a; Nwobi et al., 2020; Nababa et al., 2020). However, mangrove degradation is widespread and is increasing consistently over time (Salami et al., 2010; Kuenzer et al., 2014a; Nababa et al., 2020). The causes of degradation in mangroves in the NDR have been attributed to selective logging for fuel wood and housing construction, pollution from oil spills, coastal pollution, dredging activities, population increase, settlement expansion, and nypa palm invasion, lack of political frameworks for appropriate policies and management, and lack enforcement of existing forest laws (Macintosh and Ashton, 2003; Duke, 2016; Kadafa, 2012; CEDA, 1997; Ohimain, 2004; Balogun, 2015; Ayanlade and Howard, 2017). Additionally, the low-lying nature and the average tidal range in the Niger Delta being 1.5m makes mangroves of the region vulnerable to climate change (World Bank, 1995b; Uyigue and 2007, 1990), particularly, the impact of sea level rise (Okali and Eleri, 2004), coastal erosion and flooding (Awosika, 1995; Chima and Larinde, 2016) impacts.

Mangrove degradation leads to mangrove loss. For example, in the Democratic Republic of the Congo, ~30% of total primary forest that was lost was initially degraded (Shapiro et al., 2021). Mangrove degradation has great consequent on carbon emission than deforestation (Pearson et al., 2017; Duke, 2016), loss of biodiversity (Begam et al., 2020), and ultimately leads to the reduction of numerous ecosystem services. This can have far reaching negative socio-ecological and environmental effects on the local communities who primarily depend on mangroves for their means livelihood.

Twenty percent of global population inhabits the tropical coastal regions (100km from shoreline), representing 7% of all land worldwide, and a density twice the global average (Sale et al., 2014). The NDR, is somewhat representative of these statistics, with ~17% of population living in the coastal urban centres, representing 12% of Nigeria’s total surface area (Ojile et al., 2017). An estimated 60% of the population in the region heavily relies on mangroves for their livelihoods (Mmom, 2007; James et al., 2011). This number is expected to increase, given that global tropical coastal population is estimated to grow by 45% by 2050 (Sale et al., 2014). Coastal population growth has been suggested to be the main factor driving mangrove degradation and loss worldwide (Romañach et al., 2018; Atkinson et al., 2016). Spatial features including, road networks (Rideout et al., 2013; Hayashi et al., 2019) proximity to coastal population centers (Wang et al., 2021; Hirales-Cota et al., 2010), infrastructure (Cardenas et al., 2017), distance from rivers (Wang et al., 2021), and distance from coastlines (Wong et al., 2020) are also factors driving mangrove degradation. Given the undisputable importance of mangroves and the multiple threats they are facing, an understanding of the spatial drivers of mangrove degradation, their magnitude, and how they interact is necessary for improved policy development related to their protection (Griscom et al., 2020).

Modelling techniques in attempts to identify spatial change drivers within the tropical forests context have either emphasized deforestation (Newman et al., 2014; Ludeke et al., 1990; Cropper et al., 1999) or forest loss (Reddy et al., 2017; Fagua et al., 2019), and general land use change (Olaniyi et al., 2012; Kamwi et al., 2018; Nakakaawa et al., 2011). However, recently, very few studies have emerged in the literature addressing forest degradation drivers (Shapiro et al., 2021) and forest degradation and deforestation in combination (Schleicher et al., 2017; Van Khuc et al., 2018), mostly likely due to the importance of reducing emissions as stipulated by the various the Intergovernmental Panel on Climate Change (IPCC) reports such as the 5th assessment reports (Mastrandrea et al., 2010).

Land-use simulation models allow for the assessment of the relationship between drivers of change and land use changes (e.g., mangrove degradation). The remote sensing-based approach, where land cover classification maps and change, maps are examined to identify land uses that replace mangrove has been the long-standing approach to understanding mangrove change drivers (James et al., 2007; Kuenzer et al., 2014a; Numbere, 2014; Ferreira and Lacerda, 2016; Thomas et al., 2017; Villate Daza et al., 2020; Ma et al., 2019; Zhang and Su, 2020). However, mangroves are dynamic and so are the driving forces and needs to be quantitatively and progressively assessed. For example, as the drivers of mangrove deforestation change and in rate, degradation drivers can rapidly dominate (Friess et al., 2019).

There are inherent difficulties in accessing the mangrove ecosystem (Carugati et al., 2018). Moreover, in some regions of the world, e.g., the sub-Saharan Africa tropical regions data availability and accuracies is a big issue (Lambin, 1997). In the NDR, security instability combines to make assessment of land cover drivers difficult (Ayanlade and Howard, 2017).

The advancement in spatial data availability, high computing power together with algorithm improvements (e.g., neural networks) allow the creation of complex statistical and simulation models achievable (Rideout et al., 2013). One of such models is the logistic regression models (Verburg et al., 2004) and the other is artificial neural networks (ANN) (Pijanowski et al., 2002; Lin et al., 2011). The ANN has been praised as a robust alternative for logistic regression-based models, providing better fit between driving variables and land use patterns (Lin et al., 2011; Mas et al., 2004; Liu and Seto, 2008).

The multi-layer perceptron (MLP) being the most common ANN used to successfully quantify interaction between driver variables and land use changes (Voight et al., 2019; Armenteras et al., 2019; Shooshtari and Gholamalifard, 2015; Reddy et al., 2017), takes advantage of its capability of modelling multiple transitions simultaneously (Eastman, 2016) and ability to resolve spatial autocorrelation issues and account for non-linearities which undermines the predictive accuracy of models (Pijanowski et al., 2002; Vahidnia et al., 2010).

Despite the demonstrated potentials of quantitative predictive modelling approaches, there are very limited studies in the literature quantitively assessing drivers of mangrove change (Hayashi et al., 2019; Rideout et al., 2013; Hirales-Cota et al., 2010; Ilman et al., 2016). Even fewer studies have attempted to quantitatively assess the drivers of mangrove degradation. Meng et al., (2016), used k-means cluster analysis to identify human driven drivers of mangrove degradation over three historic periods based on mangrove-derived organic matter and mangrove pollen as proxies to reconstruct mangrove development in Maowei Sea, China. Omo-Irabor et al., (2011) used Multi-Criteria Analysis, incorporating a number of environmental and socio-economic criteria (i.e. driver variables) determined by expert opinion to develop a mangrove vulnerability model which identified the influence of driver variables used in modelling potential degradation in the Western, Niger Delta region. However, this was not validated.

To date, there is no study in the literature quantitatively assessing, in particular, the drivers of mangrove degradation in the NDR. There is a need to advance the speculative assessment of mangrove degradation drivers by previous studies in NDR, in order to support appropriate development of polices and measures for sustainable mangrove management in the region. This aims to do so by incorporating remote sensing and geographical information techniques, and land-use simulation models to:

- Identify the spatial drivers of mangrove degradation in the NDR.
- To understand how the drivers influence mangrove degradation over two period of the study.

4.2. Study Area

The Niger Delta is a flat alluvial plain located on the Gulf of Guinea along the Atlantic Ocean in the inner southern part of Nigeria (Figure 1). It is the largest river delta (over 29, 900km^2) in Africa formed primarily by sediment deposition (Goudie, 2005). The Delta has a coastline of 470km bordered by a dense mangrove forest and covered by ~50% of water bodies comprising of the diverse networks of river systems and brackish lagoons (Atakpo and Ayolabi, 2009; Umoh, 2008; Ikelegbe, 2005). It has tropical monsoon climate with an average temperature of 27^{o}C throughout the year, and annual rainfall of 3000 to 4500 mm (World Bank, 1995b). It is considered a hot spot for biodiversity in the world with 3 sites designated as Ramsar Wetlands of International Importance (IUCN, 1992). With a coverage of slightly above 56, 000km^2, the Delta comprises of 7 administrative states (Abia, Akwa Ibom, Anambra, Bayelsa, Delta Imo, and Rivers) and has a population of over 33 million (265 people per km^2) (NBS, 2018). Most of the populace live in the rural areas near the coast and depend on their natural environment such the mangrove forests for their livelihoods (Onyena and Sam, 2020). Mangroves in the region are mainly confined at the edges of the coastal Delta.

The Niger Delta has the largest mangrove forest in Africa (5000 – 8600km^2) and the fifth largest mangrove forest in the world (Spalding, 2010). It is recognised as one of the most developed and productive mangroves in the world and yet one degraded by activities of oil and gas, amongst other land uses (Duke, 2016; Mark Spalding, 2010). Mangroves in the region are recognised important resource with great socio-economic, cultural, and spiritual value to local inhabitants, providing food (e.g., Fisheries), income, and guaranteeing survival of the local communities (James et al., 2007; Numbere, 2014).

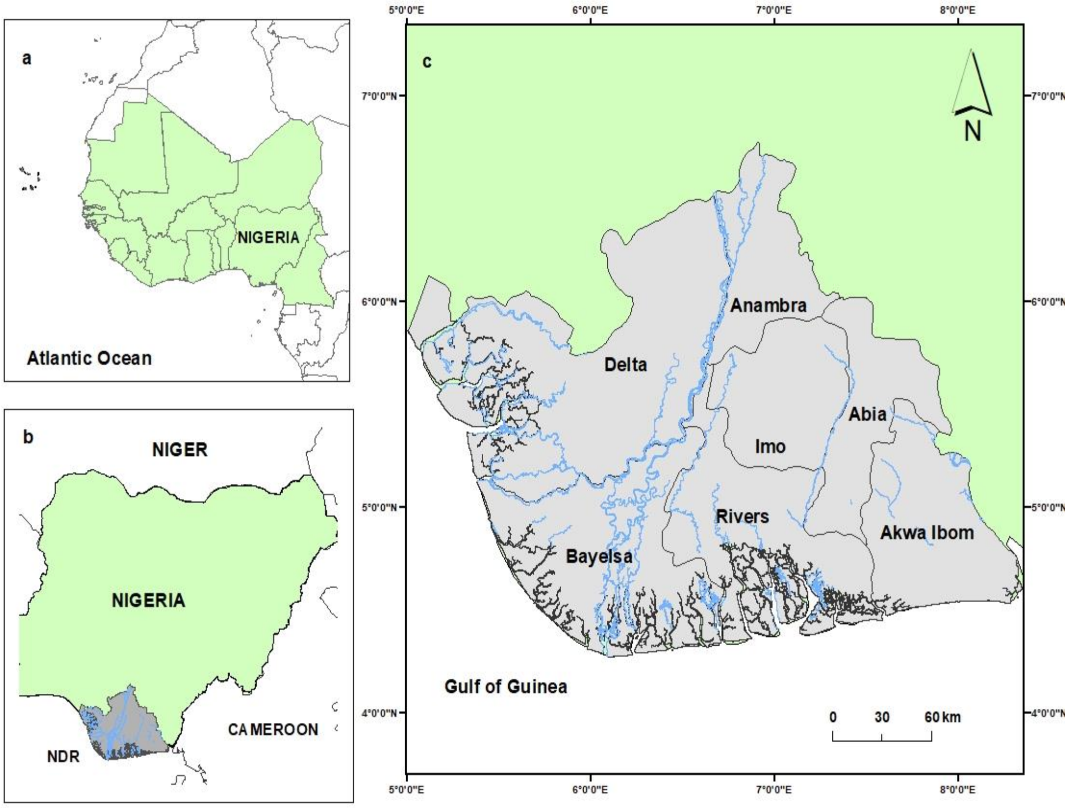
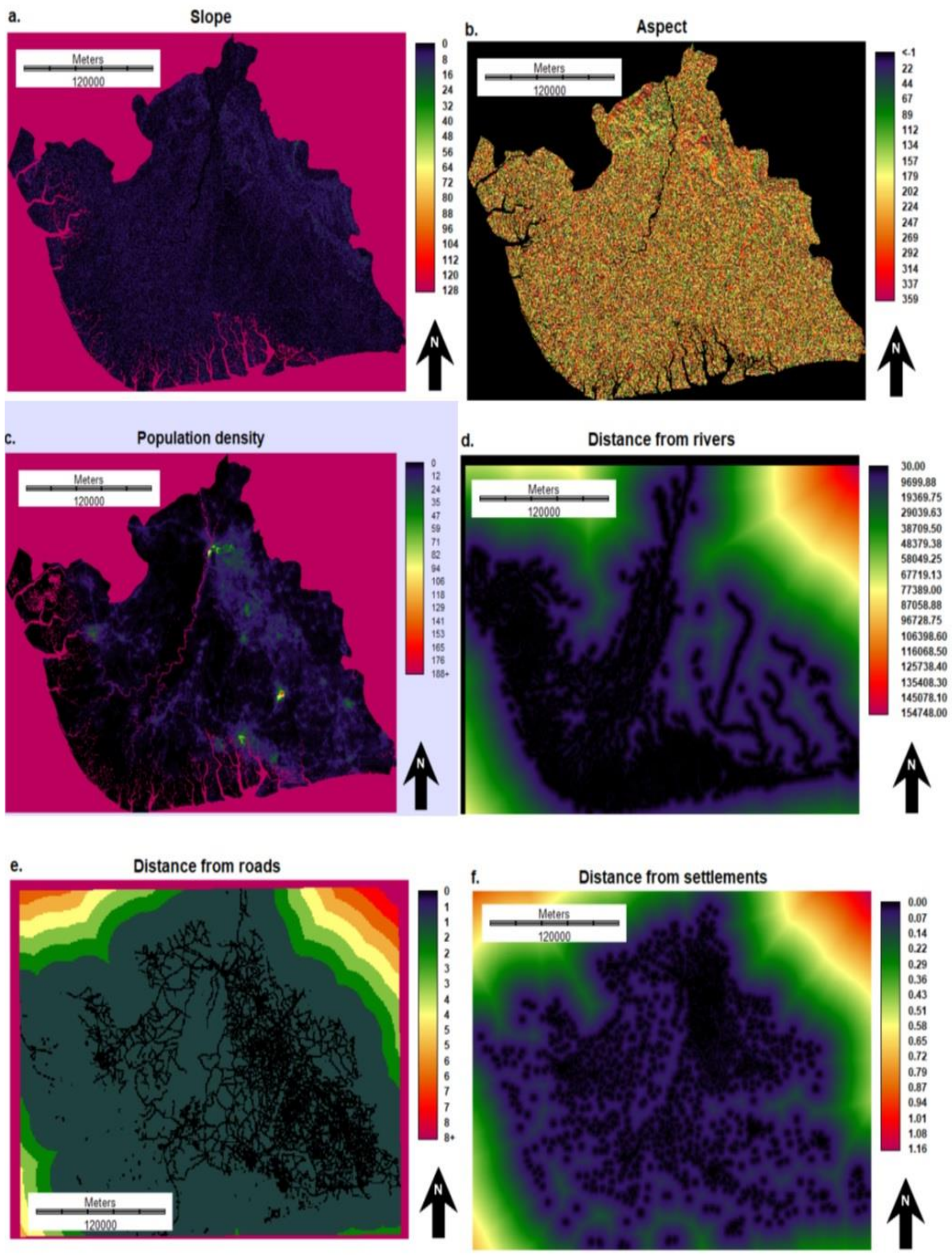


Figure 4. 1: (a) Our delineation of the Niger Delta Region (comprising of the states of Abia, Akwa Ibom, Anambra, Bayelsa, Delta, Imo, and Rivers), and its location within West Africa (b) and (c) Nigeria.

4.3. Materials and Methods

4.3.1. Data description

Understanding changes in relation to explanatory variables (i.e., drivers of change) in land cover changes studies usually require a broad range of data due to its complexity, dynamic and nonlinearity. The driving forces of mangrove degradation were assessed for two periods: first period (1988 – 2000) and second period (2000-2013). Eight spatial datasets spatial driver variables: dynamic (population density, distance from settlement, distance from roads) and static: (distance from pipelines, distance from oilfields, distance from oilwells, distance from oil spills, distance from rivers) were used (Figure 4.2). The choice of variables was selected based on knowledge of driving forces of mangrove degradation in the area, the availability of spatial driver data, and their explanatory power of Cramer's V coefficient (~0.15 and ~0.4). As the study emphasizes on anthropogenic disturbances, only human induced driving variables of mangrove degradation were considered whilst climatic variables were ignored. By definition, degraded mangroves are a development in the condition of mangroves where they have less biomass and tree cover, and loss their capacity in provision of various ecosystem services such as fisheries, flood and erosion protection, carbon sequestration, amongst others (Nababa et al., 2020).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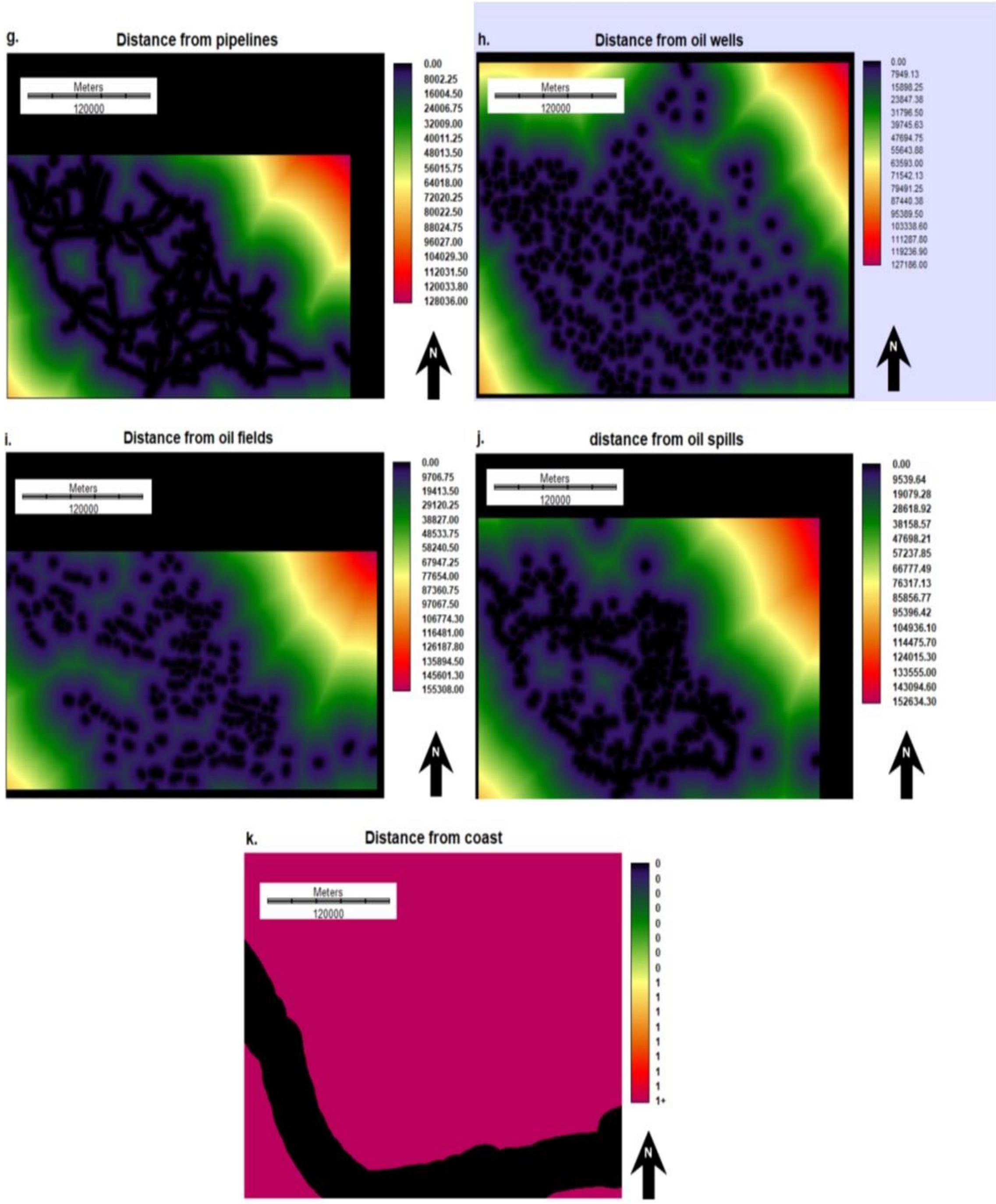


Figure 4.2: Spatial driver variables used in the study. (a) slope; (b) aspect; (c) population density; (d) distance from rivers; (e) distance from roads; (f) distance from settlements; (g) distance from pipelines; (h) distance from oil wells; (i) distance from oil fields; distance from oil spills; (k) distance from coast.

4.3.1.1 Land cover data

Land cover maps and land cover change are key to understanding the driving factors of such change. Land cover maps centred around three epochs (1988, 2000 and 2013) over the study period were used in this study. The land cover data are outputs of land cover classification carried out in the chapter 3 using a machine learning classifier called the Random Forests classification models within the R statistical environment. The land cover categories classified included the main land cover types in the study area: Urban, Woodlands, Agriculture, Grasslands, Bareland, Mangroves, and Degraded Mangroves. The decision for this was in-order to provide a general understanding of the main land cover dynamic types in the study region. To keep the study as succinct as possible, the mangrove class data (i.e, healthy mangroves and degraded mangroves), being the land cover category of particular interest to the study was used. For more information about data sources and methodologies used in deriving the mangrove cover classification, refer to chapter 3 of the study.

4.3.1.2. Population density data

Population dynamics plays a key role in understanding interactions between humans and the environment; hence it is an important driving force to land cover change. It provides valuable information to changing pattern of human distribution on the landscape which can be useful to understanding certain land cover change. Kok (2004), opined those changes in Land use cover change (LUCC) patterns is greatly influenced by population density.

Population data used in this study included data sourced from WorldPop (https://www.worldpop.org/geodata/listing?id=77;Tatem, 2017) and Global Human Settlement layer (GHSL) database (https://ghsl.jrc.ec.europa.eu/download.php?ds=pop;Florczyk et al., 2019). Data for 1990 and 2000 -2013 respectively were sourced from the two different sources due to constraint in the availability of population data for the study period in a consistent data source. Additionally, for the first period (1988-2000), the GHS population grid (GHS-POP) for 1990 being the closest date available was used to substitute for the earliest date of the study (1988) due to unavailability of data for the period. The

GHS-POP data used contains distribution and estimates population density expressed as the number of people per cell with a 1km resolution. Estimates were derived through dasymetric mapping approaches, where mainly best vector population estimates are combined with the finest spatial extents of human settlements estimated from Landsat data (Freire et al., 2016). The datasets contain estimates for 1975,1990, 2000, and 2014.

The WorldPop contains population density estimates with a 100 by 100m resolution. Its population estimates were produced by using census data and several geospatial covariates through the Random Forests machine learning methods (Stevens et al., 2015). The datasets contain yearly population density estimates for period 2000- 2020. The WoldPop develop a number of estimates of gridded population count dataset that allows decision makers and data users with the option to assemble population estimates into varying spatial units within existing or customized areas (Tatem, 2017).

4.3.1.3. Spatial Infrastructure datasets

Infrastructure developments such as construction activities e.g., roads (primary and secondary), airports, schools, settlements amongst others have been identified as an important drivers of land cover change and mangrove change in many studies of the tropical forest regions (Newman et al., 2014; Kamwi et al., 2018; Olaniyi et al., 2012; Monteiro et al., 2011; Hayashi et al., 2019; Rideout et al., 2013). In this study, infrastructure data are divided into two categories: the built-up and oil and gas infrastructure dataset. The built-up data comprises of roads and settlements, whilst the oil and gas infrastructure comprise of oil spills data, data for pipelines, oil wells, and oil fields.

4.3.1.4. Built up infrastructure

Data for roads used were sourced from Global Roads Open Access Data Set version 1 (gROADSv1) (https://sedac.ciesin.columbia.edu/data/set/groads-global-roads-open-access-v1;CIESIN and ITOS, 2013) and OpenStreetMap (OSM) (https://download.geofabrik.de/africa/nigeria.html;GmbH and Contributors, 2018).

The gROADSv1 data are characterised by data granularity (notably only primary roads) which pose a problem for usage (Ilie et al., 2019). Therefore, these data were harmonised with relevant OSM data (with more quality and reliability) which included all roads categories and information, including primary and secondary roads, footways, amongst others. These were then used for first period (1988-2000) of the study. For the second period (2000- 2013), relevant OpenStreetMap roads extracts were used.

The gROADS data contain aggregation of global road coverage of roads networks between1980s to 2010 with a resolution of 30m, although spatial and temporal variation exists amongst countries (most countries have no confirmed date) (Ilie et al., 2019). It is prepared using the UN Spatial Data Infrastructure Transport (UNSDI-T) version 2 as a common data model, where quality public road dataset by country is aggregated (Ilie et al., 2019).

The OSM contain freely accessible, open-source, frequently updated road networks data. OSM is a volunteered geographic information (VGI) project initiated in 2004. Community volunteers collect and submit geo-spatial information to the global OSMgeospatial database (Ciepluch et al., 2009). It enables public data users have access to freely geo-spatial data of the world, volunteers contribute and collaborate via its VGI platform (Minghini and Frassinelli, 2019; Witt et al., 2021). Many land use mapping studies have identified the OSM as a valuable and structured data source with high positional accuracy compared to other similar datasets (e.g. Ggroadsv1) (Arsanjani et al., 2013; Estima and Painho, 2013; Johnson and Iizuka, 2016). This drove the choice for OSM roads data in this study.

4.3.1.5. Settlement (GHS-BUILT) data

The choice of GHS-BUILT data was driven by the need to coincide the Landsat pixel with that of the study area so that built up class are comparable. Settlement (GHS-BUILT) data for 1990 and 2000 were obtained from the Global Human Settlement (GHS) database (https://ghsl.jrc.ec.europa.eu/download.php?ds=bu;Florczyk et al., 2019). The GHS-BUILT data for 1990 being the closest date for the first epoch (1988) was used for the first period (1988-2000) of the study due data unavailability for 1988 that should ideally be representative of baseline data. Moreover, given the local knowledge of the study area, settlements may not likely expand significantly within a 2-year interval. For the second period (2000-2013), data for 2000 were used.

The GHS-BUILT dataset used is an estimate of classification of built-up presence derived from the Global Land Survey (GLS) Landsat image collections with a 1km resolution. The built-up classification estimates were carried out through Symbolic Machine learning (SML) methods (Florczyk et al., 2019). The products are a set of multi-temporal and multi-resolution grids centred in 1975, 1990, 2000 and 2014 epoch (Florczyk et al., 2019).

4.3.1.6. Oil and gas infrastructure datasets

The Nigeria oil and gas sector consist of two main sectors: upstream and downstream. The upstream is the exploration and production centre; with more extensive oil and gas infrastructures (oil wells and fields, flow stations, gas plants, trunk and flow lines). However, the downstream is the centre for logistics of refined crude oil products, hence more vulnerable to oil pollution. Pipeline network cut across the upstream and downstream areas due to its purpose for crude oil transportation.

Pipelines, oil wells and oil fields data were digitised in ArcMap 10.7 (ESRI, 2020; Maxar and Technologies, 2020), from map of oil and gas infrastructure of the Niger Delta obtained from Shell Petroleum Development Company (SPDC), Nigeria, and produced by IHS matrit (SPDC Nigeria, 2007). A very high resolution basemap imagery in the ArcMap 10.7 (Maxar and Technologies, 2020), was also utilised to digitise the pipeline networks in order to correct positional accuracy errors detected from the oil and gas infrastructure map of the Niger Delta. Consequently, pipeline data used were a harmonisation of two sources. The oil and gas infrastructure map contains information of pipelines, oil wells, oil fields, oil blocks, and list of right owners to facilities with a scale of 1:750 000. These data are available for a single temporal year (2007).

Oil spill data were obtained from the National Oil Spill detection and Response Agency, (NOSDRA) Nigeria, extracted from the oil spill monitor platform (https://oilspillmonitor.ng/;Nigerian OIl Spill Monitor, 2007). The study utilised oil spill

data between 2007-2013 for the second period of the study. Available oil spill data only date back to 2007, consequently, not used for the first period of the study.
Oil spill data is collected upon Joint Investigation Visits (JIV) using the Handheld GPS collection units. The JIV consists of a team of stakeholders, including NOSDRA staff, host community, and representative of the pipeline operators. Oil spill data recorded are prepared and submitted to the oil spill database, with updates made when spill situation changes. Data collected contains valuable information of spill, including the date, time and location (GPS coordinates) of spills, spill duration, oil type, spill volume, and the cause of spill. The Nigerian Oil spill data are currently available for 2007 to date.

4.3.1.7. Water bodies data

Waterways such as rivers, canals and creeks and the coastline are important drivers of land cover change in a tropical river delta. Coastline data and rivers (minor and major) were obtained from the Nigerian Hydrological Services Agency (NISHA through the data request form (https://nihsa.gov.ng/data-request/;NISHA, 2021). However, for the purpose of this study only the rivers (minor and major) data were considered useful and utilized both for the first and second period of the study. The NISHA is a government agency under the Federal Ministry of Water resources in Nigeria. It houses the hydrological and hydrogeological of the country. The NISHA is tasked with the country’s sustainable management of its water resources.

Table 4. 1. Spatial variables used in the Land Change Model (LCM).

Layer	Spatial resolu.	T.resolu.	Description	Source
Slope	30m	single	STRM	(Farr et al., 2007)
Aspect	30m	single	STRM	(Farr et al., 2007)
Population density	1km	yearly	GHSL	(Florczyk et al., 2019)
Population density	1km	yearly	Worldpop	(Tatem, 2017)
Distance from settlements	250m	yearly	GHSL	(Florczyk et al., 2019)
Distance from roads	30m	yearly	gROADS	(CIESIN and ITOS, 2013)
Distance from roads	30m	yearly	OSM	(GmbH and contributors 2018)
Distance from rivers	30m	single		(NISHA, 2021)
Distance from pipelines	1 :750 000	single	IHS	(SPDC Nigeria, 2007)
Distance from oilfields	1 :750 000	single	IHS	(SPDC Nigeria, 2007)
Distance from oilwells	1 :750 000	single	IHS	(SPDC Nigeria, 2007)
Distance from oil spills	30m	single		(OSM, 2007)
Distance from coast	30m	single		(NISHA, 2021)

4.3.2. Methods

Pre-processing and preparation of spatial datasets is central to land cover modelling in-order to meet requisite data standard required of the model and to avoid potential contribution to uncertainties associated with probabilistic modelling approaches.

In this chapter, only pre-processing and data preparation for spatial drivers are described. Information about pre-processing steps carried out for the remote sensing data is available in Chapter 3.

4.3.2.1. Transformation, georeferencing and projection

To ensure all data are in the same co-ordinate systems, GHSL datasets: population density for 1990 and settlement data for 1990 and 2000 in Mollweide coordinate systems were converted to a geographic coordinate system (GCS_WGS_1984) using the projection tool in QGIS 3.4 (QGIS Development Team, 2017). These data were then geo-registered using classified raster image (1988) as reference data, with 12 control points with a root mean square error of 0.27 (Hansen et al., 2013); using the geo-referencing tool in QGIS 3.4 (QGIS Development Team, 2017). All spatial drivers eleven were projected into Universal Transverse Mercator (UTM) Zone 31 North and World Geodetic System (WGS) 1984 datum in the course of the modelling process using the Project Tool in the LCM within the TerrSet 2020 software.

4.3.2.2. Spatial data rasterization and variable derivations

With the exception of the population density, settlements, and the SRTM datasets (in grid format), all other spatial datasets including roads, rivers, coastal and the entire oil and gas Infrastructure datasets (pipelines, oilwells, oil fields, and oil spill) were in vector format. For the pipeline, oil well, and oil spill data, the pipeline spill maximum impact radius buffer of 2.5km (Shittu, 2014; Obida et al., 2018), was created around them. The impact radius is dependent upon the pressure, type of pipeline and volume of spills; whilst the buffer here represents the potential area of impact (Obida et al., 2018). The spatial datasets, including for oil fields were converted into a grid format to be consistent with other datasets within the Conversion Data Management Toolbox in the ArcGIS 10.7. Distance variables: distance from roads, distance from settlements, distance from rivers, distance from coastline, distance from pipelines, distance from oil wells, distance from oil fields, and distance from oil spill were then derived using the Euclidean distance module in the ArcGIS 10.7 (ESRI, 2020) (Table 4.1).

For the population density data, a population density distribution layer was created in ArcGIS 10.7 (ESRI, 2020) (Table 4. 1& 2). All variables were then converted to integer type raster for analysis in the TerrSet software using the Spatial Analyst Int Toolbox in ArcMap 10.7 (ESRI, 2020).

Table 4.2. Definitions of explanatory used of variables

Explanatory variables	**Descriptions**
Slope	Average level of slope
Aspect	Average level of aspect
Population density	Population distribution per square km^2 over study period
Distance from settlements	Nearest distance (km^2) of settlements to the mangrove pixels
Distance from roads	Nearest distance (km^2) of roads into the mangrove pixels
Distance from rivers	Nearest distance (km^2) of rivers into the mangrove pixels
Distance from pipelines	Distance of pipelines within 2.5 (km^2) radius to the mangrove pixels
Distance from oilfields	Nearest distance of oil fields in (km^2) to the mangrove pixels
Distance from oilwells	Distance of pipelines within 2.5 (km$^{2)}$ radius to the mangrove pixels
Distance from oilspills	Distance of oil spills within 2.5 (km^2) radius to the mangrove pixels
Distance from coast	Nearest distance (km^2) of oil fields into the mangrove pixels

4.3.2.3. The Multi-layer perceptron artificial neural network (MLP-ANN) model

Aside predicting future land use cover change (LUCC) patterns, land cover change models are built with the capacity to analyse spatio-temporal relationship between land cover change and its drivers. Previously, logic regression models were used to evaluate LUCC relationship and its driving factors, until the recent modification of empirical land cover models (Lin et al., 2008). The logistic regression models usually encounter spatial auto-correlation issues when dealing with spatial reference data (Hu and Lo, 2007). Evaluating relationship between land cover and multiple driving factors using logistic regression models are altered due to: lack of capacity to recognise many drivers, limited information associated with the drivers, and the inherent limitation of the functional capacity of the model (Ojima et al., 1994; Lambin and Geist, 2008).

Artificial neutral networks (ANN) were built with much sophistication, wider and robust functional power in-order to resolve the in-capabilities of logistic regression models. It is built to replicate neurons functional powers in way that computers are able to mimic the brain's functional capabilities in order to detect relationship in data through resolving issues of spatial patterns and learning by trial and error (Pijanowski et al., 2002). Additionally, ANN can consider non-linear complex relationships between driving factors and land cover (Pijanowski et al., 2002).

The Multi-layer perceptron (MLP) is the commonly used ANN and have been successfully applied to land cover modelling studies (Mas et al., 2014; Reddy et al., 2017; Voight et al., 2019; Armenteras et al., 2019; Pijanowski et al., 2002; Mishra and Rai, 2016; Shooshtari and Gholamalifard, 2015; Hakim et al., 2019), to particularly, observe relationship between land cover change and its driving factors prior to land cover modelling. Additionally, recent studies have revealed that MLP is the most robust algorithm amongst others for transitional modelling, notably for capacity to process non-linear relationships and capacity to eliminate multi-collinearity (Fuller et al., 2011; Lin et al., 2011; Sangermano et al., 2012). The MLP-ANN approach was therefore employed for the study.

Firstly, the relationship between spatial drivers and degraded mangrove cover class were initially examined using the Cramer's V coefficient to evaluate their potential explanatory power for inclusion to the model (MLP-ANN) methods using the Test explanatory Power tool in LCM (Eastman, 2009). Spatial drivers with a Cramer's V coefficient near 0.15 and above 0.4 were considered with strong predictive power and selected for inclusion to the model (Eastman, 2009; Shooshtari and Gholamalifard, 2015). Consequently, eight spatial drivers: population density; distance from settlements; distance from roads; distance from river; distance from pipelines; distance from oilfields; distance from oilfields; distance from oilwells; and distance from oil spills were considered for inclusion to the model. Distance from coast and topographical derivatives, namely slope and aspect were also tested as potential mangrove degradation drivers but were discarded as they were assessed to be weak predictors of change.

Cramer's V is a statistical matrix that change chi-square to values ranging between 0-1, resulting to a given value demonstrating total agreement between two nominal variables (Reddy et al., 2017). A high Cramer's V suggests the potential of the explanatory variable in predicting change (Reddy et al., 2017; Tajbakhsh et al., 2018). Cramer's V coefficient of ~0.15 or higher are useful, values ~0.4 or higher as good, and values that are lower are discarded (Reddy et al., 2017; Chim et al., 2019; Armenteras et al., 2019; Shooshtari and Gholamalifard, 2015; Voight et al., 2019; Eastman, 2009).

Secondly, a stepwise approach using the MLP-ANN was used to measure the strength of association between spatial variables and mangrove change (SM1) over two periods of the study: 1988 – 2000 and 2000 -2013. Six spatial drivers were used for the first period and eight spatial drivers for the second. Variables used were ether static or dynamic (Table 4.3). In the second period, distance from oil wells and distance to oil spills were included to the model as it increased the prediction accuracy (model performance). However, in the first period, inclusion of the distance from oil wells variables reduced the model performance and was therefore discarded. Oil spill data were not available between the first period of the study, hence was used only for the second period to which it was suitable. Table 4.3 shows the spatial variables used over the two periods of the study, their overall Cramer V's coefficient and per-class Cramer V's coefficient.

Table 4.3. Explanatory variables used in the multi-perceptron layer model for the two study periods and their Cramer V's coefficient. SM1: Mangrove degradation sub-model class; X denotes variables not used.

		1988 -2000		2000-2013	
Explanatory variables	**Variable type**	**SM 1**	**Overall Cramer V**	**SM 1**	**Overall Cramer V**
Population density	dynamic	0.0619	**0.1709**	0.0715	**0.2203**
Distance from settlements	dynamic	0.1317	**0.1678**	0.0674	**0.1496**
Distance from roads	dynamic	0.1238	**0.1094**	0.0255	**0.0322**
Distance from rivers	static	1306	**0.1867**	0.1384	**0.1709**
Distance from pipelines	static	0.1935	**0.1357**	0.1022	**0.1248**
Distance from oilfields	static	0.1006	**0.1346**	0.079	**0.1186**
Distance from oilwells	static	x	**x**	0.1123	**0.1031**
Distance from oil spills	static	X	**X**	0.1001	**0.1444**

4.4. Results

The MLP-ANN is a non-parametric algorithm designed to compute fit connection weights between the input and hidden layers and between the hidden and output layers for classifying unknown pixels (Eastman, 2009). The output of the MLP-ANN methods is a HTML file that provide several information of the training process, including the strength of association of explanatory variables used and other computations for assessing transitional potential modelling.

Table 4.4 are outcomes of the MLP-ANN model over the two study periods:1988 - 2000 and 2000 – 2013. For the second period (Table 4.4b), inclusion of the distance from oilwells and distance from oil spills variables produced a slightly better result (~4%) in relation to the performance of the model to hindcasting mangrove degradation. Moreover, available oil spill data was only suitable for the later period. Notably, the model performance in both periods was found to be similar 60.26% accuracy and class skill measure (M to DM; 0.4173) and 62. 04% accuracy and class skill measure (M to DM; 0.4296) (Table 4.4).

In relation to the explanatory variables, results show that driving forces of mangrove degradation are dynamic over the two-study period. In the first period, distance from roads (major, minor and footways) was identified as the most important driver of mangrove degradation; followed by distance from settlements and distance from pipelines, and so on (table 4a). However, in the second period, distance from oil wells was the principal driver of mangrove degradation, followed by distance from oil fields and distance from oil spills, distance from roads, and so on (Table 4b). In both periods, results reveal that oil and gas infrastructure driver variables and distance from roads takes the lead as driving forces of mangrove degradation in the study region.

Table 4. 4. The relative strength of association of explanatory variables used in the mangrove degradation sub-model (SM 1). (a) 1988–2000: class skill measure (0.4173); (b) 2000–2013: class skill measure (0.4296).

a	**1988-2000**		
Explanatory variables	**Accuracy%**	**Skill measure**	**Influence order**
All variables	60.26	0.2053	N/A
Distance from roads	53.69	0.0738	1(most influential)
Distance from rivers	60.22	0.2045	5
Distance from oilfields	60.20	0.2041	4
Distance from pipelines	60.01	0.2003	3
Distance from settlements	57.32	0.1462	2
Population density	60.28	0.2057	6 (least influential)

b	**2000-2013**		
Explanatory variables	**Accuracy%**	**Skill measure**	**Influence order**
All variables	62.04	0.2408	N/A
Distance from roads	61.08	0.2215	4
Distance from rivers	62.02	0.2414	8 (least influential)
Distance from oil fields	60.60	0.2121	2
Distance from pipelines	61.79	0.2358	6
Distance from settlements	61.16	0.2231	5
Population density	61.91	0.2382	7
Distance from oil spills	61.02	0.2203	3
Distance from oil wells	60.35	0.2070	1 (most influential)

4.5. Discussion

Understanding how the drivers of mangrove degradation interact through time and space is essential for the sustainable management of the ecosystem and the numerous ecosystem services it provides. The ‘remote sensing only’ approach where land cover classification outputs and land cover change maps are examined or the ‘speculative approach’ used to determine drivers of mangrove change in the NDR (James et al., 2007; Nwobi et al., 2020; Kuenzer et al., 2014a; Onyena and Sam, 2020; Numbere, 2014), are not reliable. Moreover, drivers of change can change rapid in type and speed, therefore need to be studied progressively.

The inherent difficulties in accessing the mangrove ecosystem (Carugati et al., 2018), data availability and accuracies issues associated with the sub-Saharan Africa tropical regions (Lambin, 1997), and particularly, the security instability in the NDR (Ayanlade and Howard, 2017), has been attributed to the scarce information on the driving forces of degradation in the largest mangrove forest of Africa and one of the most endangered ecosystems in the world (IUCN, 1992). This study, therefore, incorporates remote sensing and geographical information techniques, and artificial neutral networks (ANN) modelling algorithm to quantitively assess the driving forces of mangrove degradation in the NDR.

Despite the problems of data availability and accuracy, and security in NDR (Ayanlade and Howard, 2017; Lambin, 1997), an integrated approach was employed for the quantitative assessment of mangrove degradation drivers in the region. The study used six identical explanatory variables in doing so over two time periods. The model achieved an accuracy consistently above 60% in both periods, demonstrating its capacity as a good predictor of change. Results of the study compare favourably with few studies of the NDR (Omo-Irabor et al., 2011; Ayanlade and Howard, 2017; Fabiyi, 2011) and several others in tropical regions around the world (Olaniyi et al., 2012; Kamwi et al., 2018; Rideout et al., 2013; Shapiro et al., 2021; Newman et al., 2014; Hayashi et al., 2019). However, this is the first study attempting to empirically analyse mangrove degradation drivers in specific for the entire NDR. The only other mangrove-based study, analysed mangrove vulnerability (healthy and degraded) and its drivers (Omo-Irabor et al., 2011). However, it was only for a section of the Western NDR.

Similar to other land cover change studies in tropical coastal regions (Kamwi et al., 2018; Olaniyi et al., 2012; Newman et al., 2014), results in this study presented an interesting dynamic:

- Built up infrastructure related variables namely: distance to roads and distance to settlements had the highest strength of association in the first period; whilst oil and gas infrastructure variables were less important (table 4a-b).

- Built up infrastructure related variables were a lesser threat to mangrove degradation in the second period, whilst oil and gas infrastructure related variables were the most important drivers.
- Population density is the least important driver of mangrove degradation in both periods of the study.

Particularly, in the first period, findings reveal that distance from roads and distance from settlements were the most influential to mangrove degradation, whilst in the second period, the most important drivers were found to be distance from oil wells, distance from oil fields, and oil spills. In the first period, findings of this study is consistent with the studies of Ayanlade (2015) between 1987 to 2011 and Fabiyi (2011) between 2000 to 2006, who found distance from road network and distance from settlements respectively as primary causes of forest degradation and loss in the Delta. Interestingly, both studies used a near identical variables as this study and found similar results.

The difference between temporal period and the inclusion all forest types (mangrove swamps, freshwater swamps forests, and lowland rain forests) in their analysis makes adequate comparison difficult as this study is confined to mangrove forests. The study, therefore, recognises two things in-order to validate comparisons among results: firstly, the historical road developments and settlements effects and how they influence other drivers (e.g., socio-economic, cultural etc) in study area. Secondly, the fact that mangroves constitute one of the largest proportions of forest types in the study area and is most susceptible to degradation due to its confinement to the coast and the many natural resources it holds. Following these considerations, mangrove degradation in the region, if evaluated over a single long or short period as the studies Ayanlade and Howard (2017) and Fabiyi (2011) would put road networks and settlements variables as the leading drivers. Moreover, in the second period, results identify these variables sequentially just after the oil and gas infrastructure variables (major drivers) as drivers of mangrove degradation (Table 4.3b). However, two time periods used in the assessment of mangrove degradation drivers in this study allows for more appropriate and effective development and implementation of sustainable management measures of the ecosystem. Additionally, the findings are less biased as the data used are entirely spatially explicit and the model is validated.

In the Delta region, earlier studies have reported that mangroves are being greatly degraded through selective logging for fuel wood and housing construction, agriculture, dredging canals for navigable routes, sand mining for land reclamation for the tourism and human habitation purposes, dumping solid waste and defection, and nypa palm invasion (Ohimain, 2004; CEDA, 1997; Macintosh and Ashton, 2003; Mmom and Arokoyu, 2010; Okoye, 1991). These disturbances are human driven and are influenced by accessibility and proximity-based drivers such as road networks and settlements. Interestingly, in the almost identical study in the 80^s, dredging and sand mining activities for land reclamation were reported to have resulted to degradation and loss of ~ 4.2 million m^2 of mangrove forests in Buguma town, near Port-harcourt in the eastern NDR (Numbere, 2014). Furthermore, in the same identical study period (1988), 10 to 750 million m^3 of mangrove wood were reported to have been exploited for commercial activities (poles, pulp paper) (Macintosh and Ashton, 2003). These activities further confirm the study results in the first period. It is important to note that oil and gas activities were significant in driving mangrove degradation in this period, however not as significant as roads and settlements. Recent studies on forest degradation (Shapiro et al., 2021), and notably mangroves (Hayashi et al., 2019; Rideout et al., 2013) in the other tropical regions, found similar variables: built up area (within the 50 km) and road networks respectively as primary drivers leading forest disturbances.

In the second period, this study and the study by Omo-Irabor et al., (2011), found a similar greater influence of pollution from oil wells and pipelines. In their study, they assessed mangrove vulnerability into three categories in a section of the Western Delta: eastern, central, and western segment between 1987 and 2002 and found similar results across the central and west segment. Comparison remains difficult in the second period as the temporal period and spatial extent of study do not match. However, the western section of the delta has been identified as the highest with concentration of degraded mangroves resulting from oil pollution, and with notable increase through time (Nababa et al., 2020; James et al., 2007).

The temporal period (2000 -2013) been evaluated has been reported to be associated with major oil and gas pollution incidents that has directly affected mangroves in the Delta (Duke, 2016; UNEP, 2011), which may have influenced the results. Some of such incidents include: 117 incidents in the 2000 (Duke, 2016); 115 incidents estimated at 5,187.14 barrels spilled by the western operations of the Shell Petroleum Development Company (SPDC) in 2001, with only 14.2% total spilled oil recovered (Kadafa, 2012); and the three days straight burning of mangroves along Kala-Akama, Okrika resulting from pipeline leakage by the Nigerian Liquefied Natural Gas (NLNG) in 2004 (Kadafa, 2012). Furthermore, between 2012 and 2013, 3,778 illegal refineries were reported to have been destroyed by securities agencies in-order to curb illegal production and sell of crude oil by locals (Balogun, 2015). These illegal activities of local miners and destruction of their facilities by security agencies have cumulatively resulted to increased spills in within the mangrove systems where the illegal refineries are mostly situated. Duke et al., (2016), suggests that pollution had increased by five- fold around this period than previous decade.

Contrary to many forests change studies (Morakinyo and Tooze, 2007; Mmom and Mbee, 2013; Chima and Larinde, 2016), including mangroves in NDR (James et al., 2007; Omo-Irabor et al., 2011), population density is a less important driver influencing mangrove degradation in the NDR. Rather, other drivers identified in table 4.4 are more important. However, this study found similar results with the study by Ayanlade (2015). In his thesis, he used near identical variables to this study and used correlation analysis to identify causes of forest destruction including the mangrove forest for the entire NDR between 1987 to 2011. Forest areas have low population compared to near farmland and urban centres in NDR, which may explain the reason for the results found.

The model proved to be a good predictor of change in the hindcasting of mangrove degradation over the two-study period. However, in the first and second period, ~40% and ~38% respectively of change remains unexplained. The variation may be due to important variables such as soil type (Rideout et al., 2013), gross domestic (GDP) (Wang et al., 2021; Olaniyi et al., 2012), and climatic variables: sea level rise (SLR), temperature (Omo-Irabor et al., 2011; Olaniyi et al., 2012) and salinity (Osland et al., 2018; Villate Daza et al., 2020), identified in other mangrove studies but was left out here, as of particular interest to this study, are the human induced driver variables. Moreover, the study region has serious data availability and coarseness issues. Climate change, particularly SLR may have significant effects on Niger Delta's low-lying coastal region and can result to mangrove degradation through lowering of mangrove biomass density. Additionally, some of the variables used in the analysis were characterized by some uncertainties. Particularly, data for road networks sourced either contained incomplete or excess information (i.e the most recent data). This was pre- processed to form a composite data layer for the temporal periods of the analysis, which would inherently be associated with some errors. There was also a slight variation of settlement and population density data relative to the degraded mangrove data in the first period. Additionally, the differences in the spatial resolution (250m and $1km^2$) of some of driver variable data, despite been standardized mean that the capturing of local effects are unaccounted for. However, the MLP-ANN model has shown to perform adequately in prediction of strength of association of drivers of mangrove degradation in the NDR.

4.6. Conclusions

Mangrove forests are important resource on which millions of inhabitants depend on for means livelihood. In the NDR, mangroves continue to be degraded, however, the patterns and driving factors are rarely assessed, and poorly understood. The inherent difficulty in accessing mangrove forests, data availability and accuracy issues, and security situation in NDR makes it a challenging task.

Using a Multi-layer Perceptron, Artificial Neutral Networks (MLP- ANN) modelling algorithm a quantitative assessment of the spatial driving forces of mangrove degradation is presented over 25 years. Results reveal that the drivers of mangrove degradation vary over time between human infrastructure and oil and gas infrastructure induced variables. In the first period, distance from road networks and distance from settlements were identified as the major drivers of mangrove degradation; whilst in the second period, distance from oil wells, distance from oil fields, and distance from oil spills had greater influence. Results in this study also showed that population density is not a key driver of mangrove degradation in the NDR region as claimed by other mangrove studies for the region. This study provides the first ever spatial-temporal quantitative assessment of the driving forces of mangrove degradation drivers for the entire NDR.

Such assessments are vital for the appropriate development and implementation of sustainable management measures, where policy interventions are targeted to address the variation in mangrove degradation drivers both at the regional and sub-regional level. Overall, the assessment of mangrove degradation drivers is key to addressing global environmental policy frameworks such as a number of Sustainable Development Goals (SDGs) (Chow, 2018), the post-2020

Global Biodiversity Framework (CBD, 2019), and the UN System for Environmental Economic Accounting (SEEA, 2014).

Chapter 5

Future Land Cover Change and Mangrove Degradation in the Niger Delta Region

5.1. Introduction

River deltas are important socio-ecological systems (Moorhouse et al., 2021). They are one of the most populated areas in the world. Although, they account for less than 1% of the Earth’s surface, ~ 7% of the global population of inhabitants tap from its numerous locational benefits, including its low-lying nature, rivers and marine resources, eased waterways for transport, ice free harbours, and high biodiversity (Ericson et al., 2006; Claudia Kuenzer and Renaud, 2012). Some deltas are sources of sorted sand and gravel for construction and oil and gas and are key contributors to the nation economy (Loucks, 2019). However, they are highly dynamic and vulnerable due to a number of threats they face (Giosan et al., 2014).

The Niger River Delta (NRD) is the largest river delta in Africa (Goudie, 2005) and home to a rapidly increasing human population. It features the largest mangrove forest in Africa, estimated to be ~5% of the global mangrove coverage and the fifth largest mangrove forest in the world (Spalding, 2010). Substantial oil and gas deposits are found under the mangrove ecosystem of the NRD. It is considered as one of the most endangered ecosystems in the world and has been threatened over the past decades mainly due to oil and gas exploration activities, the overexploitation of the mangroves for fuelwood, urbanisation, and the invasion of the Nipa palm species (*Nypa fruticans*) (Numbere, 2014; Kadafa, 2012; Balogun, 2015; Onyena and Sam, 2020; Duke, 2016). Other threats to the Niger delta's mangrove forest include, climate change (World Bank, 1995b; Uyigue and Agho, 2007) sea level rise (Okali and Eleri, 2004), and coastal erosion (Awosika, 1995). Considerable land surface conversions have occurred on the Earth's surface resulting from these alterations (Meles, 2008), and are seen as important factors of environmental degradation in any landscape (Hamad et al., 2018).

In the tropical regions, forest degradation is the precursor to their loss (Vancutsem et al., 2021). Between 1996 and 2016, 1389km^2 area of mangrove were estimated to be in various stages of degradation globally (Worthington and Spalding, 2018). However, the present global rate of mangrove loss is estimated to be 0.13% (Goldberg et al., 2020). Accordingly, the current disturbance rates triggered the alarm that mangroves risk total disappearance by the end of the century given (FAO, 2007; Duke et al., 2007a). Furthermore, tropical coastal populations are estimated to grow by 45% by 2050 globally (Sale et al., 2014). Climate change related disturbances such as sea level rise, extreme floods, storm surges, erosion, subsidence, and salinity intrusion etc are also expected to increase with the climatic crisis (Szabo et al., 2016), which may cumulate to cause further alterations in the tropical coastal regions, including the river deltas. Therefore, the analysis of future land cover changes is essential for conservation, planning and sustainable management of these fragile ecosystems (Dezhkam et al., 2017; Regmi et al., 2014).

Land cover change (LCC) analysis assess change dynamics, can provide understanding of changes in relation to land use change drivers, and forecast future land cover change (Kamwi et al., 2018; Hakim et al., 2020). LCC change is influenced by variety of factors, including socio-economic, topographic, demographic, physical infrastructure, and planning constraints and policies which makes modelling LUC process challenging (Samardžić-Petrović et al., 2017; DeFries et al., 2010).

Remote sensing and geographical information systems are powerful and effective tools used for updating and managing spatial data in developing countries (Dong et al., 1997). They offer the opportunity for rapid and continuous coverage over large areas and provide data for numerous spatial bio-physical and socio-economic variables, especially data over scarce regions such as the NDR. Such data are important for land cover change analysis and robust simulation studies.

The sub-Saharan Africa tropical regions are data scarce environments mainly due to rapid economic development and political issues (Näschen et al., 2019; Xiao et al., 2022). Hence, modelling land cover in such environments has been done with the use of single modelling methods such as Markov model (Onojeghuo and Blackburn, 2011; Wali et al., 2018; Eyoh and Okeke, 2017; Dan-Jumbo et al., 2018; Abbas, 2012), cellular automata (Clarke and Gaydos, 1998), the SLEUTH cellular automata-based model (Clarke et al., 1997), Artificial neural networks (ANN) Model (Pijanowski et al., 2002), logistic regression (Linkie et al., 2004) and the Conversion of Land Use and its Effects (CLUE-s) model (Verburg et al., 2002). These models have demonstrated their capability as essential quantitative tools to aid decision making process related with the protection and conservation of forest ecosystems. However, many limitations have been identified with use of single models (Balzter, 2000; Araya and Cabral, 2010; Triantakonstantis and Mountrakis, 2012).

Data-driven models of spatial patterns of land cover enable the development of land change models which can be most useful to effectively support conservation and environmental planning at regional (Armenteras et al., 2019; Voight et al., 2019) and national level (Reddy et al., 2017; Verburg et al., 2011). They help find patterns and trends or to induce representative models of underlying processes using past data (Quigley et al., 2009; Tafazzoli Moghaddam, 2011). Land-use simulation models allow for the prediction of land use/ land cover (LULC) change through time and space (Lambin, 1997; Heidarlou et al., 2019).

Integrated modelling approaches (hybrid method) for simulation and projection of land cover such as Multi-layer perceptron, Artificial neural network and the Markov chain (MLP-ANN + MC) (Mishra and Rai, 2016; Voight et al., 2019; Shahi et al., 2020) and Cellular Automata - Markov chain model (CA-MC) (Hamad et al., 2018; Hasan et al., 2020; Musa et al., 2019), Dyna-CLUE (Verburg et al., 2009; Tizora et al., 2018), and logistic-CLUEs (Erdoğan et al., 2011; Lin et al., 2011) have been proven to produce better modelling outcomes than single-based model approach as they consider driver data. The MLP-ANN +MC model is one of the most widely used hybrid modelling methods and has been found to produce a considerably higher prediction accuracy compared to other hybrid modelling approaches combing two models (Roy et al., 2014; Ibrahim Mahmoud et al., 2016; Pérez-Vega et al., 2012; Ozturk, 2015). The model leverage on the combined MLP's capability to model transitions simultaneously and process complex non-linear relationships (Fuller et al., 2011;+ Eastman et al., 2005), and Markov's long-term prediction (Koko et al., 2020). Recently, a hybrid approach was developed incorporating three models, namely: cellular automata (CA), Markov chain (MC), and artificial neural networks (ANN) models to successfully predict different scenarios of LULC change on the Amazonian forest in Columbia (Armenteras et al., 2019) and to simulate LCC in Qeshm Island in southern Iran (Tajbakhsh et al., 2018)¸ and Upper Blue Nile Basin in Ethiopia (Leta et al., 2021).

There are very few simulation studies of land cover dynamics in the NDR (Eyoh and Okeke, 2017; Onojeghuo and Blackburn, 2011) most of which are covering a section of the region (Achionye et al., 2018; Wali et al., 2018; Abbas, 2012; Dan-Jumbo et al., 2018). The reason for the limited studies on the region is due to social unrest, security restrictions, and the inherent difficulty to access the mangrove ecosystem. With the exception of Musa et al., (2019), these studies have used the 'single model' approach which is considered to be weak and not reliable enough. Eyoh and Okeke (2017), used past trend of LULC change information (i.e., Markov chains) to predict LULC, including mangroves in the LCM for the NDR for the year 2046. Onojeghuo and Blackburn (2011), used Markov algorithm module to predict future forest conditions in the NDR for the 2027. Neither of these studies assessed the accuracy of their model.

However, simulation studies of land cover in a complex and dynamic ecosystem such as the NDR, require robust modelling approaches and tools. The combined MLP-ANN + MC modelling approach has been identified to be capable of providing a wide understanding of the complex mechanisms involved in the spatial patterns of land cover change and degradation in the NDR which is important for sustainable land management (Omar et al., 2014). The main objectives of the study are therefore to:

- Predict land cover change in the NDR for two business-as-usual scenarios in the short (2026) and longer-term (2038) using integrated spatial modelling and
- Assess mangrove degradation in the NDR short (2026) and longer-term (2038).

5.2. Study Area

The Niger Delta is located on the Gulf of Guinea along the Atlantic Ocean in the inner southern part of Nigeria (Figure 5.1). The Study area has a coastline of 470km bordered by a dense mangrove forest. It has a coverage area of slightly above 56, 000km^2, comprising of 7 administrative states (Abia, Akwa Ibom, Anambra, Bayelsa, Delta Imo, and Rivers) and a population of over 33 million (265 people per km^2) (NBS, 2018). Most of the populace live in the rural areas near the coast where they are deprived of basic amenities and infrastructure and depend on the natural environment for their livelihoods (Onyena and Sam, 2020).

The Niger Delta is a flat alluvial plain, where the climate is tropical monsoon with an average temperature of 27^{o}C throughout the year, and annual rainfall of 3000 to 4500 mm (World Bank, 1995b). It comprises of four ecological zones: mangrove swamps, freshwater swamps, forests, and lowland rain forests and considered a as hotspot for biodiversity in the world (IUCN, 1992). It is endowed with substantial oil and gas deposits (Ugochukwu and Ertel, 2008), rich alluvial soil for sustainable agriculture (Ukpaka, 2012), and abundant brackish/salt water that supports fisheries (Jemimah and Ike, 2015). About 11% of Nigeria's GDP is generated by the oil and gas sector and it accounts for the highest foreign revenue earnings (~ 95%) for the country (NNPC, 2019). However, the unsustainable practices resulting from the oil and gas extraction activities, amongst other land uses activities has led to a widespread degradation on the region's ecosystem. Land cover/use in the region includes built up areas, cultivated land, plantations, wetlands, mixed land use, grasslands, vegetation, and bare surfaces (Odunuga et al., 2015). Hence, the study models the main land cover/use in the region.

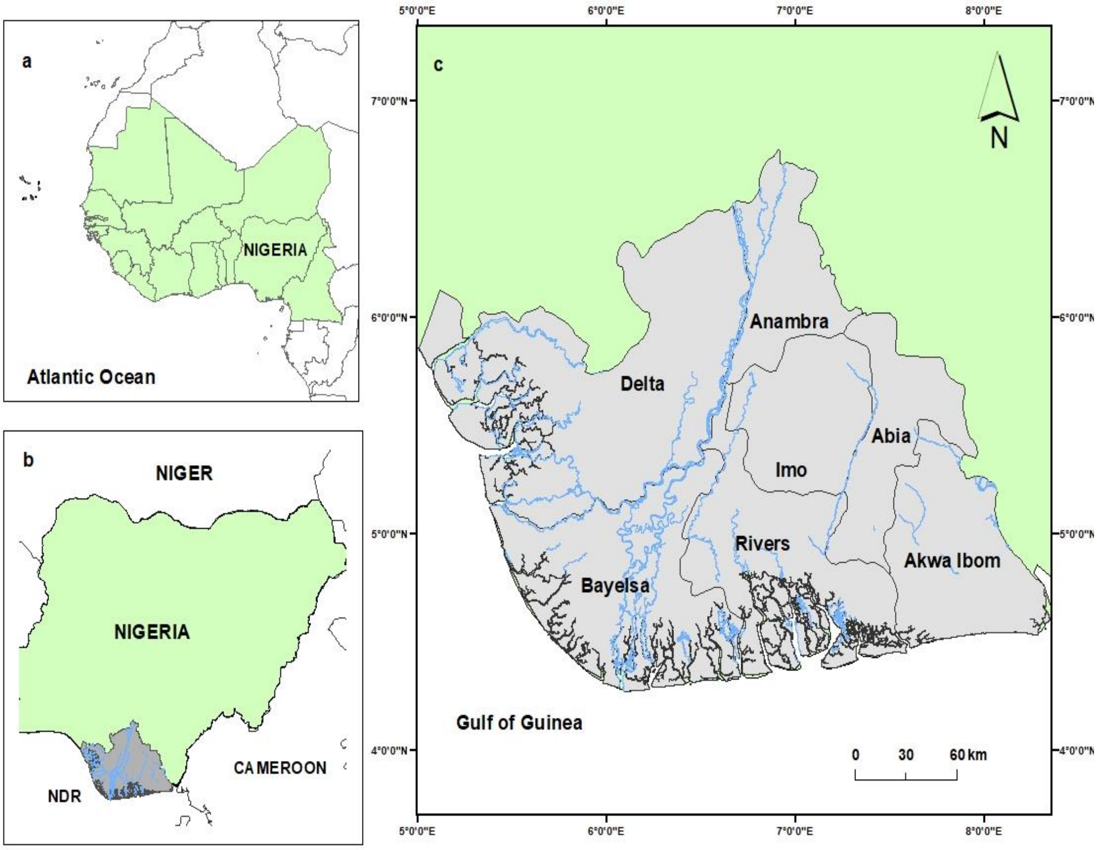


Figure 5.1: (a) West Africa and (b) Nigeria (a) Our delineation of the Niger Delta Region (comprising of the states of Abia, Akwa Ibom, Anambra, Bayelsa, Delta, Imo, and Rivers), and its location within (b).

5.3. Materials and methods

5.3.2. Overview of data and methods

In chapter 3, land cover was mapped for the periods: 1988, 2000 and 2013. Here, land cover maps of 1988 and 2000 were used to model 2013 map and then validated using the 'real' 2013 map from Chapter 3. Land cover was then projected under two business-as-usual scenarios: in the short term (2026) and long term (2038), representing regional drivers. Six sub models classes of land cover created for the undertaking of the task were: conversion to degraded mangroves (SM), conversions to agriculture (SM2), conversions to urban (SM3), conversions to grassland (SM4), conversions to water (SM5), and the regeneration sub-model. The familiarity with the study area greatly influenced the sub-model creation. The sub-models were created through selection and grouping of transitions (major or minor) perceived to have the same driving forces of change, whilst their explanatory power was evaluated. Transitional potential modelling was then implemented, and finally change prediction. Figure 5.2. is the flow chart of the methodological framework.

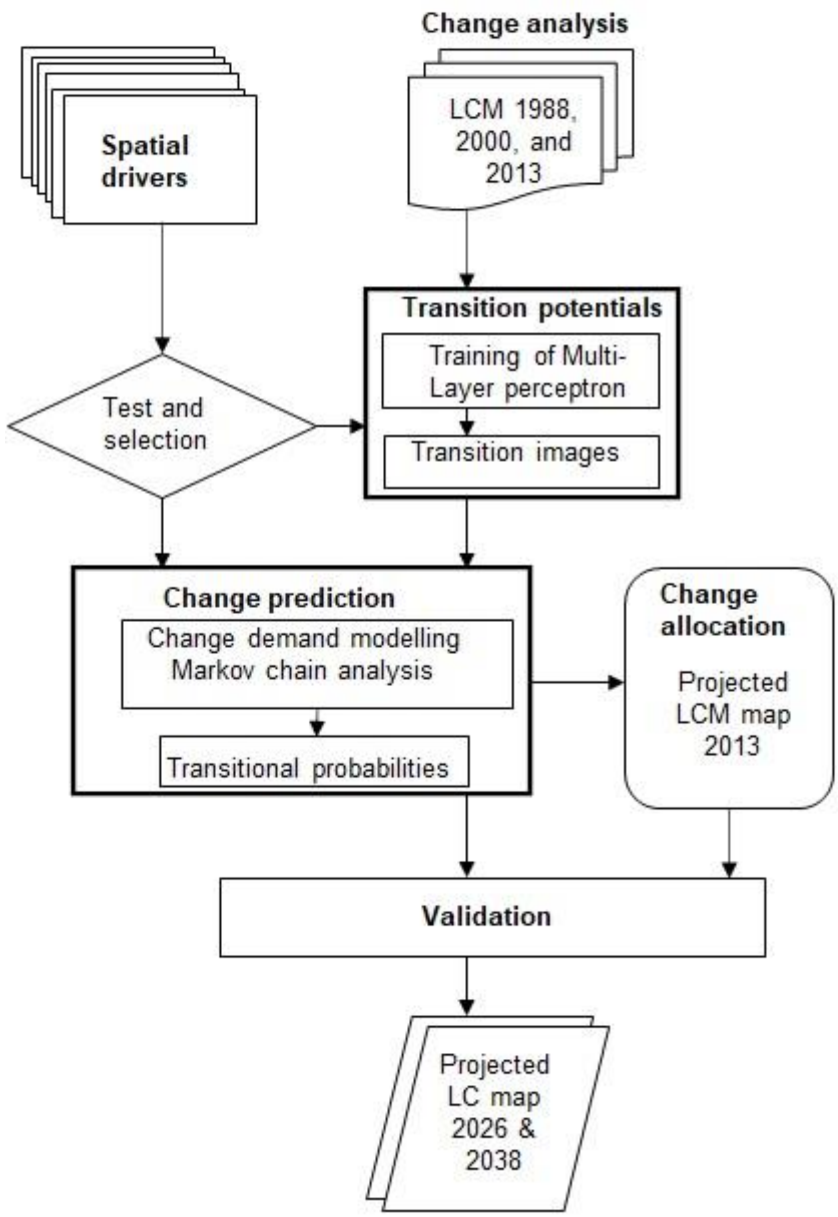


Figure 5. 2: Methodological flow chart

5.3.3. Data

5.3.3.1 Land cover

Land cover maps are essential to understanding the extent of change that occur among land cover categories, the spatial configuration of changes, as well as key to understanding the drivers of such changes and/or predicting future changes. Land cover maps centred around three epochs: 1988, 2000, and 2013 derived via remote sensing methods in Chapter 3 were used to model future land cover change under two business-as-usual scenarios in the short (2026) and long-term (2038).

5.3.3.2 Spatial variables

The study used eleven spatial data layers in total as explanatory variables to model land cover in the Niger Delta region. The spatial data layers include: distance from road, distance from rivers (major and minor), distance from coastline, distance from settlements, population density distribution, distance from pipeline network, distance from oilfields, distance from oilwells, distance from oil spills, slope, and aspect (Table 4. 2). The data layers were utilised as static and dynamic variables in the model. In this chapter, topography related parameters are described. Nine spatial datasets including roads, rivers (major and minor), coastline, settlements, population density, pipelines, oilfields, oilwells, oil spills were described in Chapter 4.

5.3.3.3 Digital elevation model (DEM)

Topographical data are an essential resource for land cover modelling and mapping, influencing hydrological processes such as the dynamics of water movement in rivers and wetland (Leta et al., 2021; Al-Khafaji and Al-Sweiti, 2017). The Shuttle Radar Topography Mission (SRTM) elevation data is arguably the most widely used freely accessible elevation data, with 85% global coverage (Musa et al., 2015). Acquired through SAR interferometry of C-band, it is available in ~30 and ~90m resolutions and has a vertical accuracy of ~3.7m (Syvitski et al., 2012). Other freely available DEMs exist such as Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (GDEM), Altimeter Corrected Elevations 2 (ACE2) GDEM, Global 30 Arc-Second Elevation (GTOPO30) and Global Multi-resolution Terrain Elevation Data 2010 (GMTED2010), however, they have a coarser resolution than the SRTM, and are argued to be less accurate due to their inherent pixel voids (Schumann et al., 2013; Weicai Wang et al., 2012; Bates et al., 2013). In low-lying floodplains such as the Niger Delta, the accuracy of SRTM data is less than 2m (Musa, 2018). Nevertheless, it is an indispensable source of elevation data for the area.

SRTM data was obtained from https://earthexplorer.usgs.gov/) with ~30m resolution. The data was used to generate slope and aspect using the Spatial Analyst Surface Toolbox in in ArcMap 10.7(ESRI, 2020). Slope and aspect control movement of hydrological flow path and flow accumulation (Kazakis et al., 2015; Sertel et al., 2019). These parameters were used to aid land cover modelling in the NDR, significantly, improving the accuracy of water sub-model class in the process.

5.3.4. Methods

5.3.4.1. Land cover change model

Land cover maps are essential to providing valuable land cover information such as land cover transitions and dynamics, their spatial patterns of change over time and space, and are key to explaining the changes in terms of explanatory variables (e.g.land use change drivers) and /or model spatial patterns of future (Kamwi et al., 2018; Armenteras et al., 2019).

Land cover maps of two periods were used to model two business-as-usual future (BAU) scenarios of land cover change in the short-term (2026) and long-term (2038) in the Land Change Modeller (LCM). The choice of the projection periods was driven by the need to achieve an accurate and reliable prediction of land cover in the study. Time scales have a significant impact on land cover simulation, with a general trend of short-term predictions producing better results (Roy et al., 2014; Pérez-Vega et al., 2012; Ahmed and Ahmed 2012). Therefore, in the long-term, a projection over 25 years (i.e., 2038) representing the study period was chosen in-order to limit simulation unreliability. The BAU scenario is a reference case scenario based on past and recent socio-economic or environmental trends (Samie et al., 2017).

The LCM is one of the most common LULC change tool used to detect and predict spatial patterns of land cover change (Hamad et al., 2018; Hakim et al., 2020), forest degradation (Hasan et al., 2020), and deforestation and fragmentation (Singh et al., 2017; Reddy et al., 2017), and so on. It is standalone tool embedded in the TerrSet IDRISI software used for change visualization and model constructions (Eastman, 2016). The LCM has four notable features and advantages: (a) flexible input data in pre-processing and the data collection process; (b) probability surface, exclusion layer, and regional stratification in the calibration process; (c) stochastic modelling to generate the model projections process; and (d) dynamic variables allowed and scenario analysis in extrapolating future scenarios (Pickard et al., 2017), which makes it a top choice amongst other LULC models (Mas et al., 2014; Shooshtari and Gholamalifard, 2015).

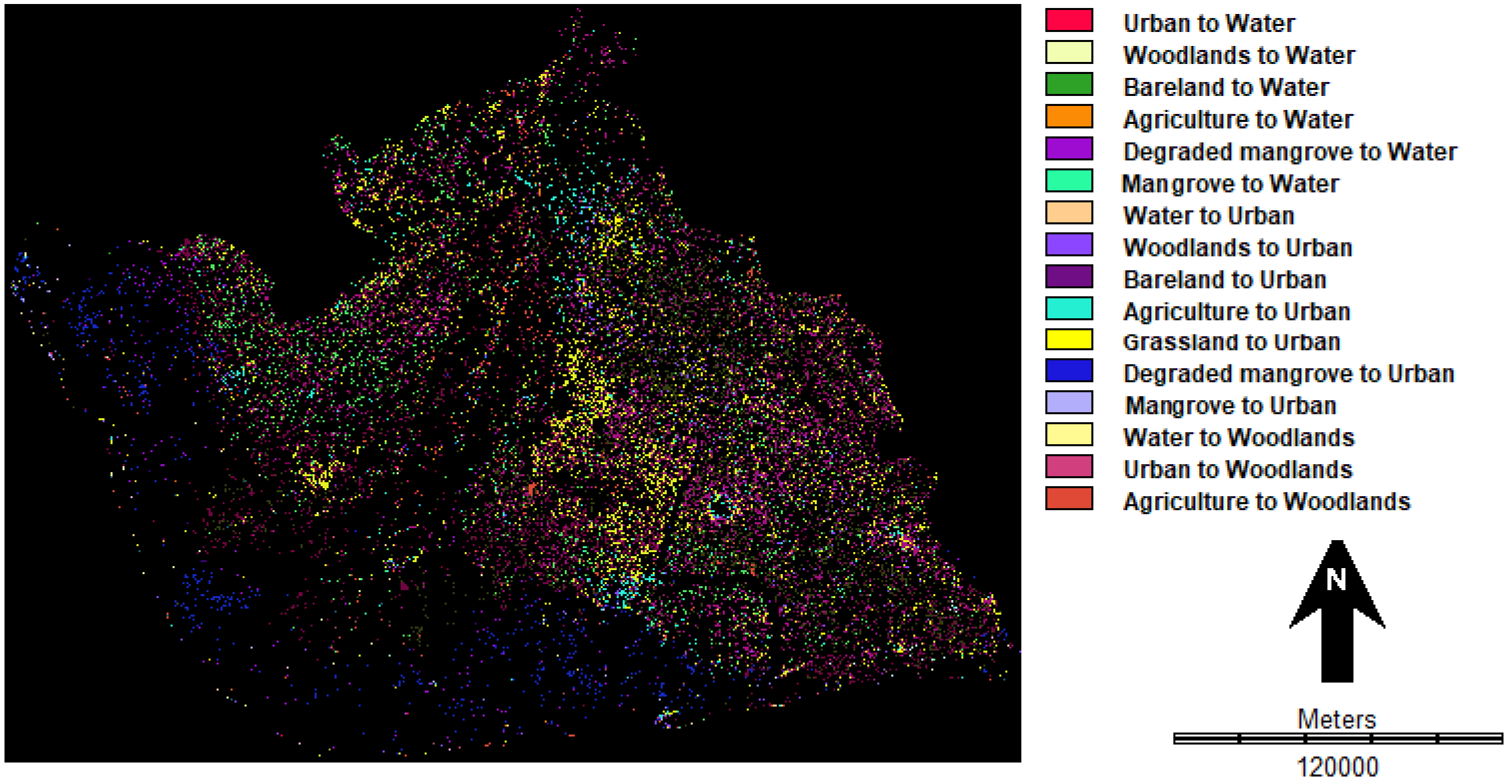
The LCM computes the following steps: Change analysis, evaluation and selection of spatial land cover change drivers (Table 5.1a-b), transition potential modelling, change demand modelling and validation. A review of the literature centred around land use simulation models revealed that LCM in the TerrSet software, incorporating Markov Chain-based neural networks to predict future LULC is effective (Kumar et al., 2014; Mas et al., 2014).

5.3.4.2. Change analysis in the LCM

Change analysis is most informative about the type and extent of changes occurring in LULC through time and can provide better understanding on the transitions therein.

In addition to the ‘Intensity analysis’ (Aldwaik and Pontius, 2012) carried out in Chapter 3, additional change analysis for the two periods between 1988 and 2000 and 2000 and 2013 was carried out here in order to identify focal areas of change (Voight et al., 2019) in the NDR using the ‘Change Analysis tool’ in the LCM. Given the complexity of land cover change in the study area, transitions less than 700 ha were ignored in-order to reduce the high combination of transitions, focus on major transitions, and at same time include minor transitions that are relevant to the study during implementation of the change analysis (Figure 5.3).

a. Land cover change map from 1988 to 2000



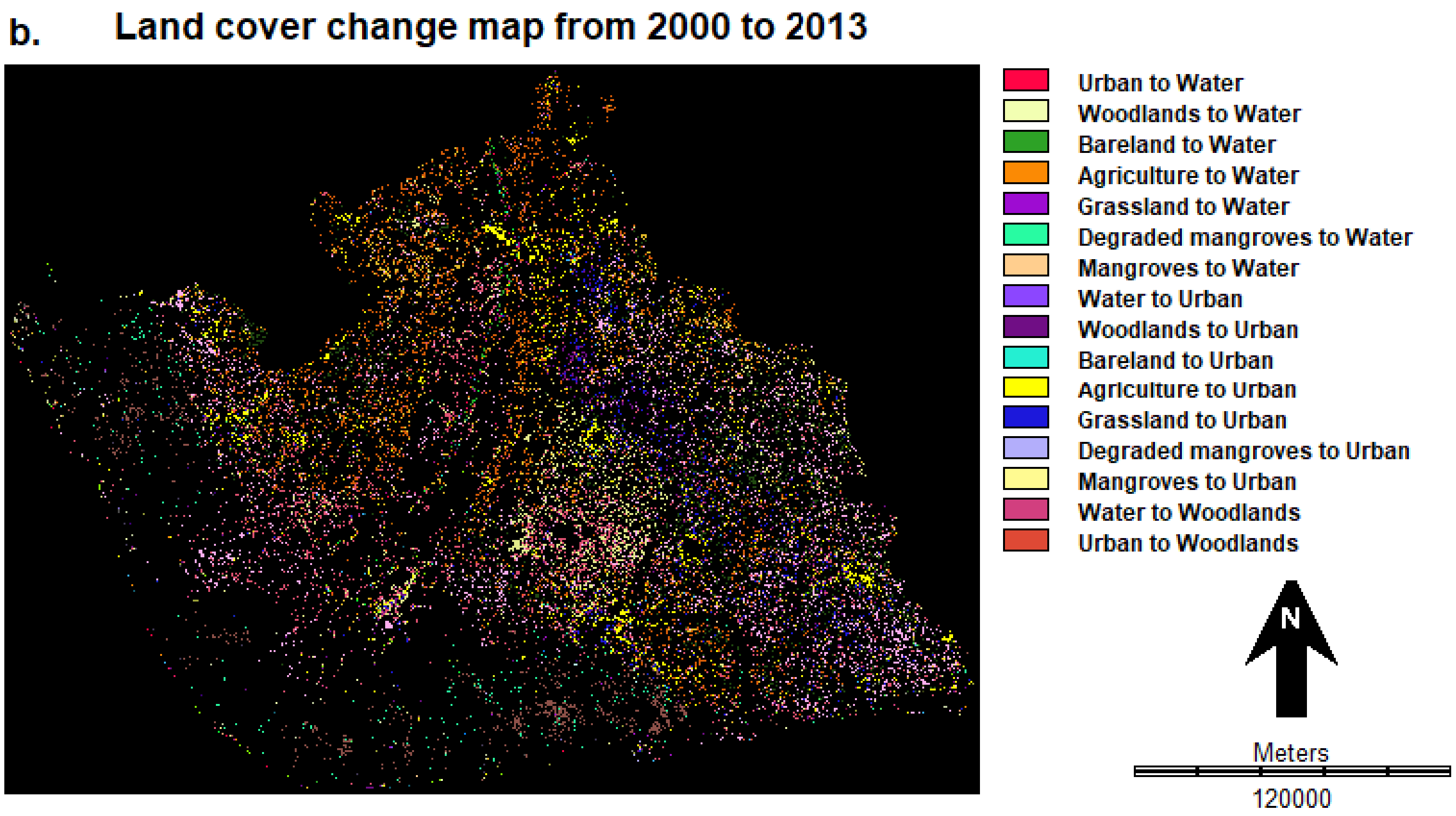


Figure 5. 3: Land cover conversions in the study region. (a) 1988 -2000; (b) 2000 -2013.

5.3.4.3. Transition potential modelling

Land cover categories with dominant transitions are influential to the dynamics and spatial configuration patterns in LULC modelling, in addition to boosting performance of Multi-Layer Perceptron, artificial neutral network (MLP-ANN) model (Armenteras et al., 2019; Mishra and Rai, 2016; Eastman, 2006). Due to the complexity of the study region and its high combination of transitions in terms of the change in land cover (Armenteras et al., 2019), both single and dominant transitions perceived with the same primary drivers of change were considered and selected for sub-model development (Geneletti, 2012; Armenteras et al., 2019; Mishra and Rai, 2016). Only very important minor transitions considered with the capacity of driving the objective of the study were considered in the sub-model creation. Thus, a single sub-model and five groups of sub-models were created. However, all sub-models were merged at the final change prediction stage (Armenteras et al., 2019). Selection of transitions in sub-model development help determine important transitions, and ultimately improves the overall performance of the models. A total of six sub-models were created:

- Conversions to degraded mangroves (SM1): Mangroves to Degraded mangroves. Changes in this sub-model are associated with changes with heathy mangroves to degraded. This transition is attributed to fragmentation of mangroves due to oil and gas extractive activities, selective logging activities, urbanisation as well as dredging and proliferation of the invasive Nipa Palm.
- Conversions to Agriculture (SM2): Grassland to Agriculture; Woodlands to Agriculture. Changes in this sub-model are associated with transitions that have occurred due to land clearing for the purpose of farming, settlement expansion, construction of roads, dredging and other developments.
- Conversion to Urban (SM3): Mangroves to Urban; Grassland to Urban; Woodland to Urban; and Agriculture to Urban. Changes in this sub-model are associated with transitions due to land clearing for development such as settlements, roads, and oil and gas infrastructural facilities.
- Conversion to Grassland (SM4): Woodland to Grassland and Agriculture to Grassland. These transitions are attributed to forest clearing for a number of

purposes: oil and gas facilities, settlements, logging activities, and agricultural land abandonment.

- Conversion to Water (SM5): Degraded mangrove to Water and Bare land to Water. These transitions are associated with forest and land clearing, climate change and sea level rise in the region.
- Regeneration sub-model (SM6): Degraded mangroves to Mangroves; Grassland to Woodland. Transitions in this sub-model are related to capability of the vegetative cover categories to bounce back to its healthier or natural state as a result of or restoration programs or land abandonment.

5.3.4.4. Evaluation and selection of spatial land cover change drivers

Driving forces for land cover may vary amongst or within sites and regions because of their distinct association with different land uses through time; hence their selection and evaluation is influential to modelling outcomes. Many studies assessing land use and degradation drivers in tropical forests have identified population pressure and agricultural expansion as the main drivers; and attributed proximity to roads, settlements, forest edges, and population density as strong spatial factors influencing changes in poorly protected or non- protected areas (Newman et al., 2014; Kamwi et al., 2018; Quezada et al., 2014; Poortinga et al., 2020; Hayashi et al., 2019; Reddy et al., 2017).

In the NDR, the main divers of land use change are rapid urbanisation, agricultural expansion, deforestation, and degradation of mangroves through oil and gas pollution (Onojeghuo and Blackburn, 2011; Ayanlade and Drake, 2015; Enaruvbe and Atafo, 2016; Dan-Jumbo et al., 2018), and these have been strongly linked to accessibility to roads, settlements, and coasts, and population density in the region; similar to other tropical regions of the world (Ayanlade and Howard, 2017; Omo-Irabor et al., 2011; Obida et al., 2018). Furthermore, DEMs have great influence on hydrological regimes, providing better understanding of physical processes underlying rivers and wetlands (Dwarakish and Ganasri, 2015).

Hence, a total of eleven spatial drivers of land cover selected as explanatory variables in the NDR. Eight static variables (distance from rivers, distance from oil wells, distance from pipelines, distance from oil spill, distance from oil fields, population density, slope and aspect) and three dynamic variables (distance to settlements, distance from roads, and population density) were used as input to the model (Table 5.1a-b). A static variable suppresses transition, and is unchanging over time (e.g., slope), whilst a dynamic variable is temporal-based, and is recalculated over time during the course of a model run (e.g., roads, settlements) (Reddy et al., 2017; Chim et al., 2019).

Other criteria that influenced the selection of spatial drivers are familiarity with the study area, spatial availability of datasets, as well as visual examination of land cover change maps over the study period. More importantly, a quick test of the potential explanatory power of the spatial variables conducted using a quantitative computation of association known as the Cramer's V coefficient for potential inclusion to the model. Each spatial variable was tested against predicted land cover change through the six sub-models (SM1 to SM6) over the two periods. Spatial drivers with a Cramer's V coefficient near 0.15 and above 0.4 are considered with strong predictive power (Eastman, 2009; Shooshtari and Gholamalifard, 2015). These drivers were selected for inclusion to the model for the creation of transition potential maps (Table 5.1a-b).

Table 5. 1. Explanatory variables used in the multi-perceptron layer model for the two study periods. Representing overall Cramer V's coefficient (in bold) and per class coefficient. (a) 1988–2000; (b) 2000–2013. SM1: Mangrove degradation sub-model; SM2: Agricultural sub-model; SM3: Urban sub-model; SM4: Grassland sub-model; SM5: Water sub-model; and SM6: Regeneration sub-model. X denotes variables not used for a given sub-model.

a.				1988-2000				Overall V
		SM 1	SM2	SM3	SM4	SM5	SM6	Cramer V
Explanatory variables	**Type of variable**							
Slope	static	x	x	x	x	0.2592	x	**0.1041**
Aspect	static	x	x	x	x	0.2564	x	**0.1013**
Population density	dynamic	0.0619	x	0.4128	x	0.0138	0.1428	**0.1709**
Distance from settlements	dynamic	0.1317	0.2295	0.1408	x	x	0.3487	**0.1678**
Distance from roads	dynamic	0.1238	0.1353	0.0454	0.0998	x	0.2217	**0.1094**
Distance from rivers	static	1306	0.3387	3387	0.1676	x	0.2737	**0.1867**
Distance from pipelines	static	0.1935	0.1639	0.1844	0.1639	0.1639	0.0852	**0.1357**
Distance from oilfields	static	0.1006	0.203	0.162	0.1676	x	0.1719	**0.1346**
Distance from oilwells	static	x	0.1727	0.1887	x	x	0.1442	**0.1031**
Distance from coast	static	x	0.2159		0.1966		0.1089	**0.0821**

				2000 - 2013				Overall
b.		SM 1	SM2	SM3	SM4	SM5	SM6	Cramer V
Explanatory variables	**Type of variable**							
Slope	static	x	x	x	x	0.2725	x	**0.1011**
Aspect	static	x	x	x	x	0.2696	x	**0.0984**
Population density	dynamic	0.0715	x	0.3753	x	0	0.453	**0.2203**
Distance from settlements	dynamic	0.0674	0.0234	x	0.1939	0	0.1421	**0.1496**
Distance from roads	dynamic	0.0255	0.0099	0.0016	0.0321	x	0.0108	**0.0322**
Distance from rivers	static	0.1384	0.0267	0.0893	0.3278	x	1591	**0.1709**
Distance from pipelines	static	0.1022	0.0142	x	0.1577	0	0.2134	**0.1248**
Distance from oilfields	static	0.079	0.019	0.0532	0.1932	0	0.1848	**0.1186**
Distance from oilwells	static	0.1123	0.0192	x	0.1631	0	0.1878	**0.1031**
Distance from oil spills	static	0.1001	x	x	0.1886	x	0.239	**0.1444**
Distance from coast	static	x	x	x	0.1966	0	x	**0.0717**

5.3.4.5. Transitional potential maps

In this modelling stage,13 transitional potential maps were created from empirically evaluated sub-models (i.e.SM1 to SM6) for the two periods of study. These were created from the land cover change analysis outputs (transitions grouped into sub-models) and spatial drivers that had been selected from the previous stage as driving factors of land cover in the NDR. Several methods can be used in developing transition potentials including logistic regressions (Pontius and Schneider, 2001), MLP- ANN (Pijanowski et al., 2002), and weights of evidence (Soares et al., 2006). Here, transition potentials were developed with an MLP- ANN model, as recent studies revealed that it is more robust than other methods (Fuller et al., 2011; Lin et al., 2011; Sangermano et al., 2012). In the model's implementation process, pixel samples were divided into two: half for training and half for validation.

The implementation of the sub-model was not straightforward due to complexity of the study area and determination to achieve the highest possible accuracy for each sub-model class. Hence, each sub-model was implemented multiples times with a combination of spatial variables and parameters being modified to make optimal use of the MLP-ANN method. The sub-models with the highest and lowest combination of spatial variables were Regeneration sub-model (8 variables) and Water sub-model (4 variables) respectively in the first period of the study (Table 5.1a). In the second period, Degraded mangrove sub-model (8 variables) and Grassland sub-models (8 variables) were the highest; and Urban sub-models (4 variables) as the lowest (Table 5.1b). Regarding the model parameters, the sub-models with less than 50% accuracy were trained through scaling up the hidden neurons and modifying the initial and final learning rate by half until a sustainable accuracy was achieved. The best performing sub-models were: Degraded mangroves (60.26%), Regeneration (59.8%), and Agriculture (72.79%) in the first period and Degraded mangroves (62.04%) and Regeneration (56.40%) in the second period of the study.

5.3.4.6. Change demand modelling

Change prediction serves as a guidance to dynamic land cover change modelling process (Reddy et al., 2017). In step 4, based on transitional potential maps created in the previous step for the first period, the quantity of change from each transition was predicted and probability matrix computed by using previous land cover maps and specifying the end prediction date (i.e.,2013), using the Markov chains analysis (MCA). This was then used to project land cover map for 2013 through the hard modelling process, which was the used to validate the model's accuracy.

Markov chains is a tool for simulating land change processes in a dynamic and complex landscape. It was developed by Andrei A. Rakov in 1970 and first utilised by Burnham for land use simulation by (Eastman, 2016; IPCC, 2018). It is arguably the most common model used in simulation studies over a large spatial scale owing to its predictive accuracy (Kumar et al., 2014; Jianping et al., 2005; Zhang et al., 2011). Based on prior information of the state of a system and probabilities of transitions amongst the states, the amount of change that will occur in the future is determined (Eastman, 2012). Markov model provided a simple methodology to which land cover alterations in any dynamic landscape can be deconstructed, analysed from one period to another, and future change can be predicted (Guan et al., 2008; Zhang et al., 2011; Dadhich and Hanaoka, 2010). The methodology is given as follows:

$S\,(t, t\ +1\,)\ = P_{ij}$ x S (t) (1)

where S (t) is the system status at time of $S\,(\,t\ +1\,)$ is the system status at time of t + 1; P_{ij} is the transition probability matrix in a state which is calculated as follows (Kumar et al., 2014; Hasan et al., 2020).

$$\mathrm{P} = P_{ij} = \begin{vmatrix} P_{11} & P_{12} & \dots & P_{1n} \\ P_{21} & P_{22} & \dots & P_{2n} \\ \dots & \dots & \dots & \dots \\ P_{n1} & P_{n2} & \dots & P_{nn} \end{vmatrix} \tag{2}$$

$$\left(0 \leq P_{ij} \leq\ 1\right) \tag{3}$$

P is the transition probability; P_{ij} stands for the probability of converting from current state *i* to another state *j* in next time; P_n is the state probability of any time. Low transition will have a probability near (0) and high transition have probabilities near (1) (Kumar et al., 2014; Hamad et al., 2018).

5.3.4.7. Validation

Validating the accuracy of the LULC change model is essential to assessing its predictive performance and reliability. The VALIDATE module in embedded in the LCM was implemented to evaluate the goodness of fit and the area under the curve (AUC) of the Receiver Operating Characteristic (ROC) was calculated (Pontius and Schneider, 2001; Pontius et al., 2004; Mishra and Rai, 2016; Voight et al., 2019; Gupta and Sharma, 2020). The AUC provides information about the accuracy of the model in relation to distinguishing land cover classes (Pontius and Schneider, 2001) The approach compares the “real” land cover map of 2013 produced in Chapter 3, with the predicted one, evaluating two propositions of areas: hits and null success and false alarm and misses (Voight et al., 2019; Hakim et al., 2020; Eastman, 2016) (Supplementary Figure 1). Then it generates the AUC figure denoting a perfect model with a value of 0.5 indicating accuracy comparable to a random fit (Voight et al., 2019). Hits and nulls denote the accuracy of the model, whilst false alarms and misses denote prediction errors of the model as disagreement between the “predicted” map and the “real“ map (Megahed et al., 2015). The projected map 2013 in the previous step was also used to assess the model’s accuracy as it was comparable with the “real” map of 2013 statistically (Figure 5.5).

5.3.4.7. Land cover change prediction under two BAU scenarios

Based on the validation conducted in the previous step, land cover under two BAU scenarios were projected through the “hard” and “soft” modelling processes. In hard projections, a simulated map is developed for the predicted year, in which each pixel is allocated to a specific land cover category (Ayele et al., 2019; Voight et al., 2019). Whilst the soft projection is a predicted map produced showing vulnerability in which each pixel is allocated a value from 0 to 1. It identifies locations that are susceptible to change with lower values indicating less vulnerability to change and high values indicating high vulnerability (Voight et al., 2019; Ayele et al., 2019). Given the absence of recent environmental policies, future land cover change follows past trends based on the identified driving variables in the NDR (Table 5.1a- b). Transition potentials created in step 3 using 2000 and 2013 land cover maps were used to compute the associated transition probability matrix using the Markov chain analysis (MCA). Based on the probability matrix, future land cover under two BAU scenarios for short-term (2026) and long-term (2038) were predicted using Markov chain model.

5.4. Results

5.4.1. Markov Chain Model Analysis

The method produces two important outputs of probability matrices: transitional probability matrix and the conditional probability images by analysing two land cover maps using the MCA. Transition probability matrix were computed between 1988 and 2000 for the prediction of 2013 map which was used for validation (Table 5. 2a). To predict future land cover for two BAU scenarios: short-term (2026) and long-term (2038), land cover maps for 2000 and 2013 and 1988 and 2013 were considered respectively, and MCA were used to compute transition probability matrixes required for the prediction (Table 5.2b-c).

Table 5.2 shows the outcome of the probability matrices of land cover transitions computed for the study. It summarises the area that remained unchanged, and the area and the type of change observed for each individual class. It also provides a summary of the area covered by each class in the beginning and the end of each period, as well as gains and losses they experienced. Gains were obtained by subtracting the probability that remained stable (in bold) from the total column, whilst losses were obtained by subtracting probability that remained stable (in bold) from the total row. The conditional probability images depict the spatial distribution of the MCA for the predicted years (Figure 5. 4).

Table 5. 2: Matrices for the predicted periods stable (in bold) and changed areas. (a) 1988–2000; (b) 2000–2013; (c) 1988–2013. Wa: Water; U: Urban; Wo: Woodland; B: Bareland; A: Agricultural: G: Grassland; DM: Degraded Mangrove; M: Mangrove.

	a			**2000**						
1988	**Wa**	**U**	**Wo**	**B**	**A**	**G**	**DM**	**M**	**Total**	**Loss**
Wa	**0.9211**	0.0198	0.0132	0.0064	0.0177	0.0011	0.011	0.0098	1	0.0789
U	0.0028	**0.9585**	0.0017	0.0021	0.0036	0.0232	0.0037	0.0044	1	0.0415
Wo	0.0005	0.0103	**0.7912**	0.0002	0.0721	0.1247	0.0003	0.0007	1	0.2088
B	0.0976	0.0853	0.001	**0.6418**	0.1727	0	0.0001	0.0013	1	0.3582
A	0.0022	0.0303	0.0277	0.0027	**0.8637**	0.0724	0.0006	0.0003	1	0.1363
G	0	0.0443	0.2087	0	0.2438	**0.5023**	0.0001	0.0009	1	0.4977
DM	0.0761	0.0054	0.0057	0.0001	0.0023	0.0005	**0.8944**	0.0155	1	0.1056
M	0.0001	0.0015	0.001	0.0001	0.001	0.0005	0.0494	**0.9463**	1	0.0562
Total	1.1004	1.1997	1.0502	0.6534	1.3769	0.7247	0.9438	1.0139	8	
Gain	0.1793	0.2412	0.259	0.0116	0.5132	0.2224	0.0494	0.0676		

	b			**2013**						
2000	**Wa**	**U**	**Wo**	**B**	**A**	**G**	**DM**	**M**	**Total**	**Loss**
Wa	**0.9179**	0.003	0.013	0.0129	0.0321	0.0007	0.006	0.0145	1	0.0821
U	0.0046	**0.9791**	0.0008	0.0035	0.0072	0.0001	0.0038	0.0009	1	0.0209
Wo	0.0003	0.0122	**0.8777**	0.001	0.041	0.0672	0.0002	0.0004	1	0.1223
B	0.2784	0.032	0.0157	**0.5736**	0.0976	0.0019	0.0004	0.0003	1	0.4264
A	0.0012	0.0508	0.0333	0.0009	**0.825**	0.0885	0.0003	0.0001	1	0.175
G	0.0001	0.038	0.1812	0.0005	0.1012	**0.6785**	0.0004	0.0001	1	0.3215
DM	0.0712	0.0021	0.0016	0.002	0.0019	0.0011	**0.9057**	0.0144	1	0.0943
M	0.0004	0.0011	0.0029	0.0004	0.0006	0.0009	0.0656	**0.9281**	1	0.0719
Total	1.2741	1.1282	1.1262	0.5948	1.1066	0.6805	0.9824	0.9588	8	
Gain	0.3562	0.1491	0.2485	0.0212	0.2816	0.002	0.0767	0.0307		

c				2013						
1988	**Wa**	**U**	**Wo**	**B**	**A**	**G**	**DM**	**M**	**Total**	**Loss**
Wa	**0.8411**	0.0084	0.0257	0.0196	0.0597	0.0053	0.0123	0.0279	1	0.1589
U	0.0105	**0.9575**	0.0019	0.0056	0.0139	0.001	0.0076	0.0019	1	0.0425
Wo	0.0011	0.0288	**0.7773**	0.0017	0.0795	0.1105	0.0005	0.0007	1	0.2227
B	0.4218	0.0575	0.0312	**0.3196**	0.1489	0.0133	0.0026	0.0051	1	0.6804
A	0.0028	0.099	0.0762	0.0015	**0.682**	0.1375	0.0007	0.0002	1	0.0318
G	0.0008	0.0728	0.2911	0.001	0.1632	**0.4699**	0.001	0.0003	1	0.5301
DM	0.1348	0.0047	0.0044	0.0041	0.0064	0.0021	**0.8151**	0.0285	1	0.1849
M	0.0062	0.0024	0.0057	0.0008	0.0015	0.0019	0.1244	**0.8571**	1	0.1429
Total	1.4191	1.2311	1.2135	0.3539	1.1551	0.7415	0.9642	0.9217	8	
Gain	0.578	0.2736	0.4362	0.0343	0.4731	0.2716	0.1491	0.0646		

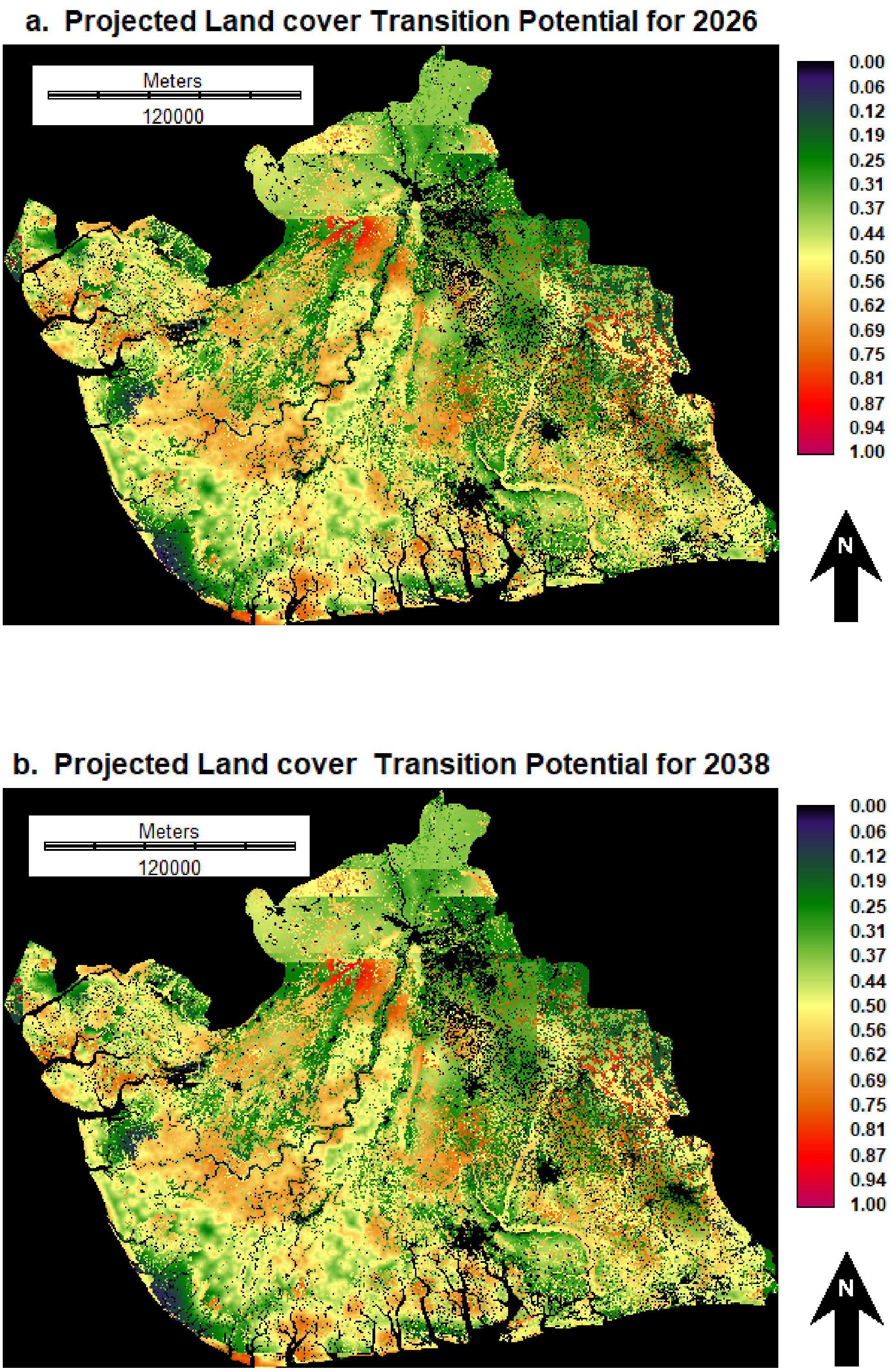


Figure 5.4: Projected land cover transition potentials over the NDR for (a) 2026 and (b) 2038.

5.4.2. Projected Land Cover Changes under Business-as-Usual Scenarios (BAU).

Figure 5. 5ab depicts projected land cover for the two BAU scenarios: short-term (2026) and long-term (2038) and are accompanied by a figure that summaries the proportion covered by each land cover category (Figure 5.5a-b).

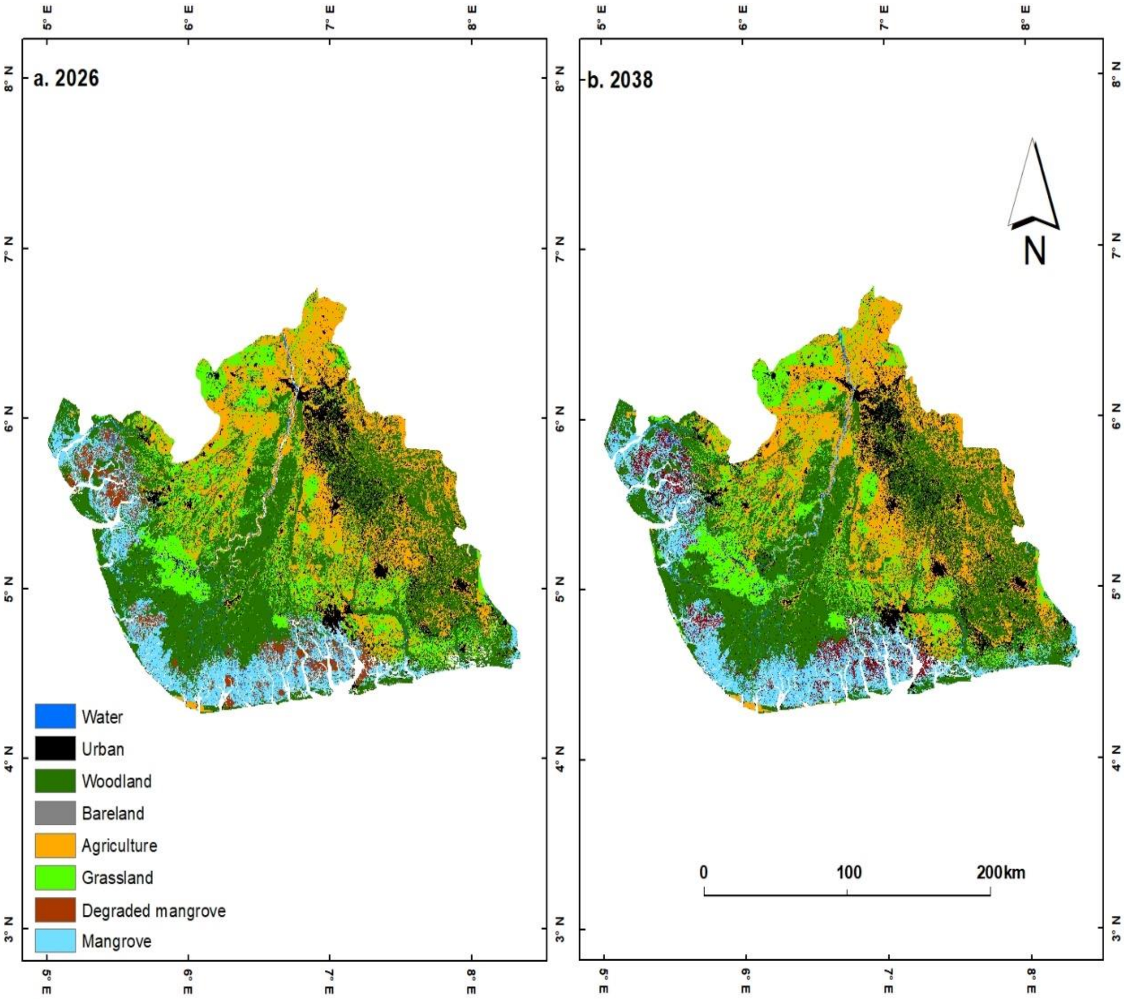


Figure 5. 5: Projected land cover over the Niger Delta Region in (a) 2026 and (b) 2038.

Table 5. 2b-c show the transition probability matrices that were used in the prediction of future land cover for the two BAU scenarios in the short (2026) and long term (2038). The projected land cover for the first BAU scenario (2026) indicate areas (km^2) and net percentage estimate for water, urban, woodland, bare-land, agriculture, grassland, degraded mangroves, and mangroves in Figure 5. 6a and Table 5. 3. For the second BAU (2038), results show net percentage estimate for

water, urban, woodland, bare-land, agriculture, grassland, degraded mangroves, and mangroves in Figure 5. 6b and Table 5.3.

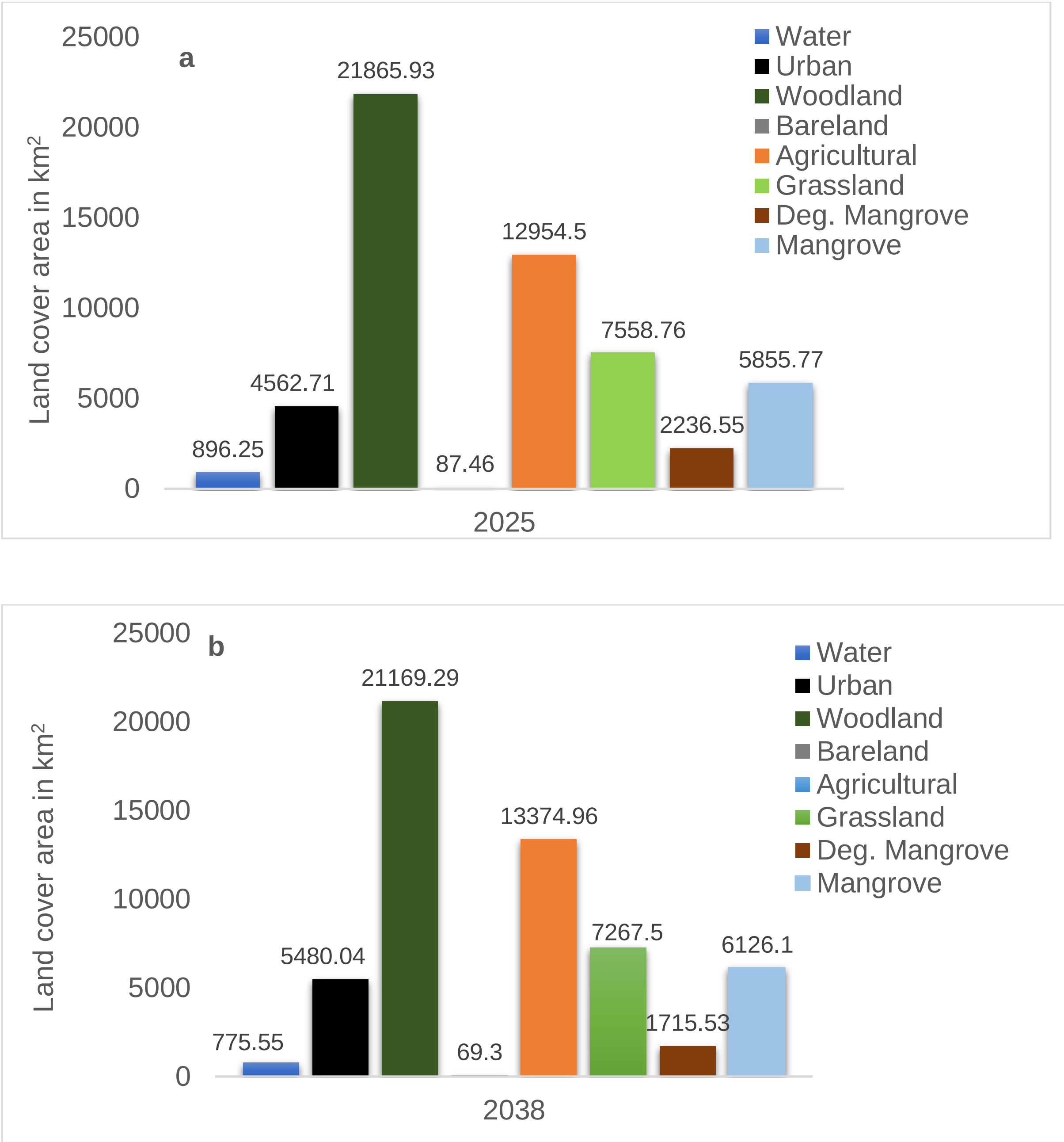


Figure 5.6: The predicted areas in km^2 of two BAU scenarios: (a) short-term (2026) and (b) long-term (2038).

5.4.3. Validation results

Figure 5. 7 show areas covered by each land cover class for real map and projected map of 2013 in the NDR. The "real" and "projected" maps were favourably comparable for three land cover classes in the study region: Mangroves; Degraded mangroves; and Water, whilst differences were observed for the rest of the land cover classes. A stronger agreement is indicated when the indices reach 100% (Hamad et al., 2018). A poor result for any class suggests that the class matrix is unable to forecast change for the corresponding class for 2013. The land cover map for 1988 was used as a reference map for predicting the land cover map for 2013 (simulated map) using a Multi-Layer Perceptron, artificial neutral network and Markov chain (MLP-ANN +MC) methods (Figure 5.8).

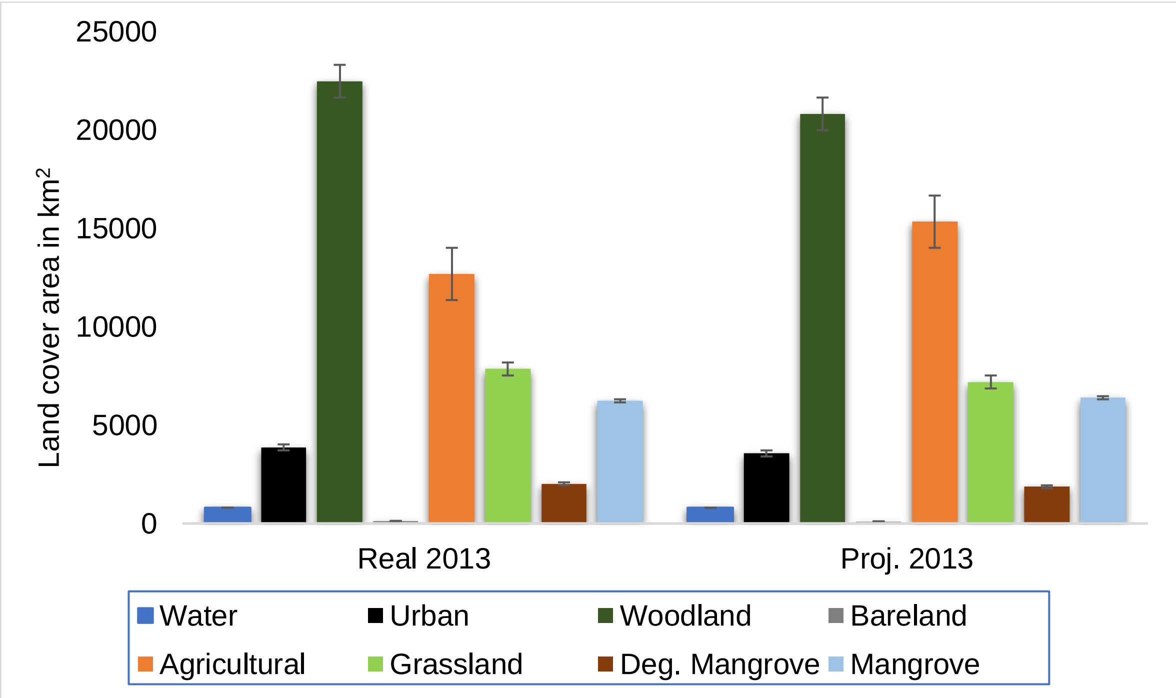


Figure 5. 7: Comparison between reference land cover map and projected map land cover map of 2013

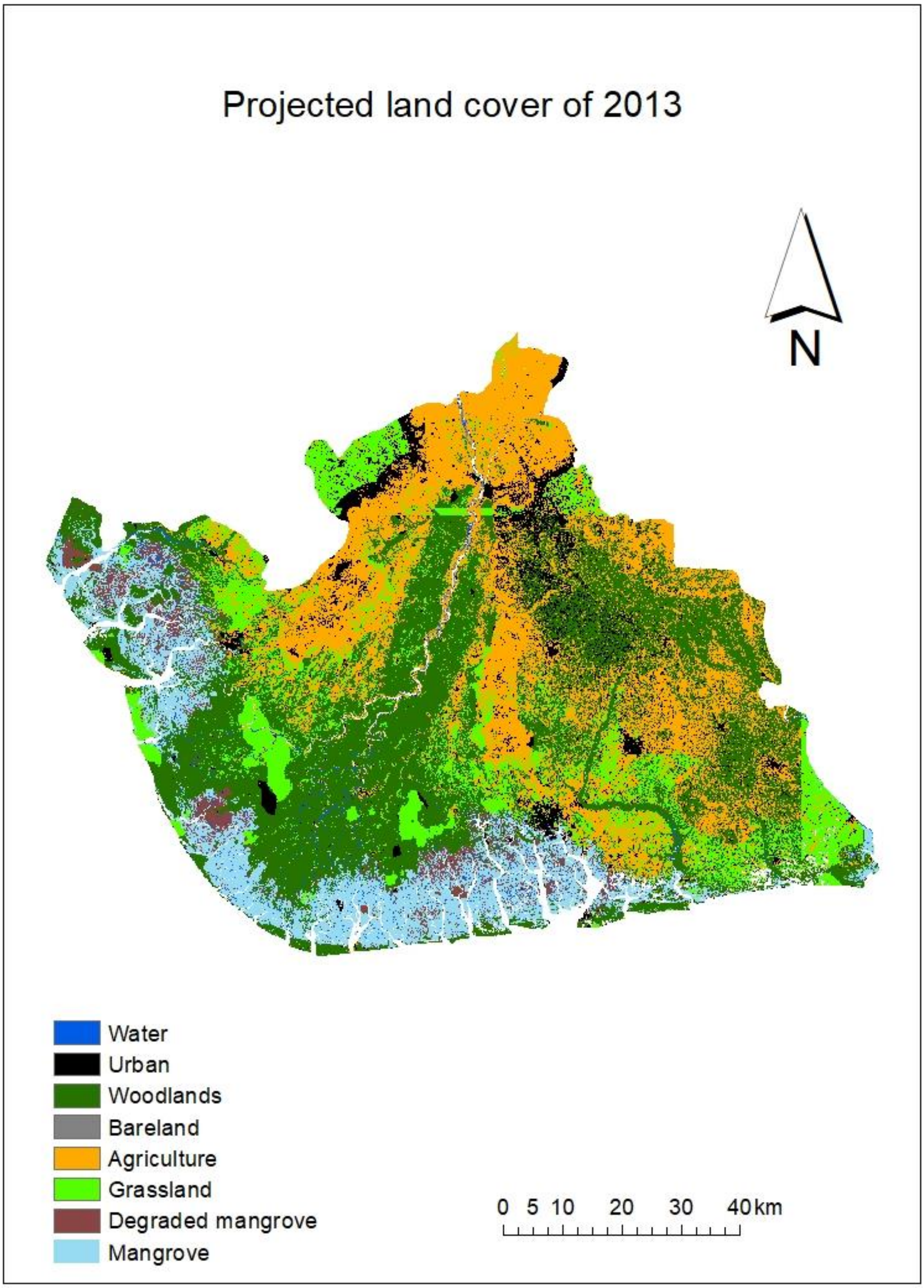


Figure 5.8: Projected land cover map of 2013 of the Niger Delta Region

5.4.3.1. Model validation

As shown in Chapter 3, the land cover maps (reference and real map) used for the validation purpose achieved an overall accuracy ~79%, for 1988 and ~82% both for 2000 and 2013, which is adequately within the threshold of 80% as suggested by Eastman (2006) and Aronoff (2004).Transition potential maps for the first period (1988 and 2000) generated based on transitions grouped into sub-models and to which the 2013 map was predicted achieved an accuracy of 72.79% for agricultural sub-model, 60.26% for degraded mangrove sub-model, 59.08% for regeneration sub-model, and water 53.02%.Transitions in these sub-model classes consist of major and important transitions of land cover categories which are of particular interest to the study. Other sub-models including, urban and grassland, have lower accuracies less than 50%. However, they constitute less important transitions and cover the least proportion of land cover classes in the study area. Regardless, a satisfactorily comparison was observed between the simulated and real map of 2013 (Figures 5.7 and 5.8). The model validation, importantly, provided an adequate output of goodness of fit from the AUC of the ROC. The model proved to be viable in adequately specifying location and quantity in the NDR.

5.5. Discussion

Reliable information of future land cover dynamics is vital for decision making related to the planning, conservation, and management (Parsa et al., 2016; Dezhkam et al., 2017), of tropical deltas and mangrove ecosystems. Data availability and accuracies, and insecurity problems has resulted to the limited simulation studies being conducted in the NDR. Moreover, the ‘single’ modelling approach which land cover is projected based on trend of change and transitions is not adequate and reliable in providing understanding and predicting a complex and dynamic ecosystem such as the NDR (Onojeghuo and Blackburn, 2011; Eyoh and Okeke, 2017; Achionye et al., 2018; Wali et al., 2018). This has resulted to fragmentary and lack of reliable information related to the future land cover change for the largest river delta in Africa and the failure to forecast the degradation of one of the most endangered ecosystems in the world (IUCN, 1992). The results in this study demonstrate that, integrated modelling techniques (MLPNN + MC) is truly a robust technique that can provide a reliable prediction of future change dynamics in the complex and dynamic ecosystem of the NDR.

5.5.1. Short and longer-term predictions of land cover

The study presents an MLP-ANN + MC approach to predict where changes of eight main land cover types are expected to occur based on human alterations of land cover in the NDR, using spatial variables that constitute regional drivers of change under two BAU scenarios. The short-term scenario (2026) represents historical land cover change observed between 2000 and 2013, whilst the second BAU (2038) scenario was based on long-term changes predicted using 1988 and 2013 as training (Table 5. 2a-b). Regarding mangrove degradation, results showed a variation between the two scenarios. In the first, an increased mangrove degradation trend was observed. However, in the longer-term scenario, results showed a notable decline in degradation.

The simulation results revealed some interesting dynamics based on past trends which were driven by the regional spatial drivers used in the study (Table 5.1a-b). More specifically, in the short-term scenario, the spatial patterns of the predicted land cover indicated there would be a sizeable decrease of healthy mangroves(~408km^2), a slight increase in the degraded (~220km^2) and decrease in the overall extent of mangroves (degraded and non-degraded mangroves; 157km^2) from 2013 to 2026 (Table 5. 3 & Figure 5. 9). A sizeable decrease in woodland (613 km^2), grasslands(~295km^2), and bareland (~36km^2) would occur between 2013 and 2026, accompanied by considerable increase in built areas (~694 km^2) and increase in agricultural land (272 km^2) in the NDR. Water is expected to increase (~90 km^2) in the region in the short-term scenario. The short-term change in mangrove class, including in its total area (degraded and non-degraded) would lead to the further reduction in the capability of the mangroves in providing ecosystem services and biodiversity loss due to a number of disturbance factors.

In the longer scenario, predicted land cover showed a different dynamic in the mangrove class compared to the short-term scenario. It indicated that there would be a slight increase in heathy mangroves (~270km^2) and a significant decrease in degraded mangroves(~521km^2) between 2026 and 2038. Although, there would be a similar slight decrease in the total area of mangroves (degraded and non-degraded) in the two scenarios, the rate of change is almost doubled in the second scenario (~250 km^2). Woodland (~717 km^2) and grassland (~321 km^2) would continue to experience a net a loss, although with a rate of change slightly higher; but lower in the bareland class in the second scenario compared to the first scenario (Table 5. 3 & Figure 5. 9). Similar to the first scenario, the expected trend in the change of woodland, grassland, and bare land, would be accompanied with an increase in bult up areas (~917 km^2) and agricultural land (~420 km^2), although, with a rate of change significantly higher in the second scenario (Table 5.3 & Figure 5.9). However, water would decrease (~121 km^2) considerably in the region in the second scenario (Table 5. 3 & Figure 5. 9).

The decrease in bare land in both scenarios suggest that it would be transitioning into the grassland, woodland and water class. The rate of change of net losses in all forests (woodland and total area of mangroves) expected to occur in the two scenarios in the NDR if summed together compares favourably with the report by IPCC; (2018). In their report, they predicted that predicted 30 to ~40% of coastal wetlands could be lost in the next 100 years given a scenario alike to this study.

Table 5.3: Land cover classes for 2013 and predicted area for the two BAU scenarios: 2025 and 2038 in km^2

	2013(km^2)		**2025(km^2)**		**2038(km^2)**	
Water	805.84	1.44%	896.25	1.60%	775.55	1.38%
Urban	3868.88	6.90%	4562.71	8.15%	5480.04	9.77%
Woodland	22478.87	40.09%	21865.93	39.08%	21169.29	37.81%
Bare land	123.92	0.22%	87.46	0.16%	69.3	0.12%
Agricultural	12682.9	22.62%	12954.5	23.15%	13374.96	23.89%
Grassland	7853.29	14%	7558.76	13.51%	7267.5	12.98%
Deg. Mangrove	2016.33	3.60%	2236.55	3.99%	1715.53	3.06%
Mangrove	6233.31	11.19%	5855.77	10.46%	6126.1	10.94%

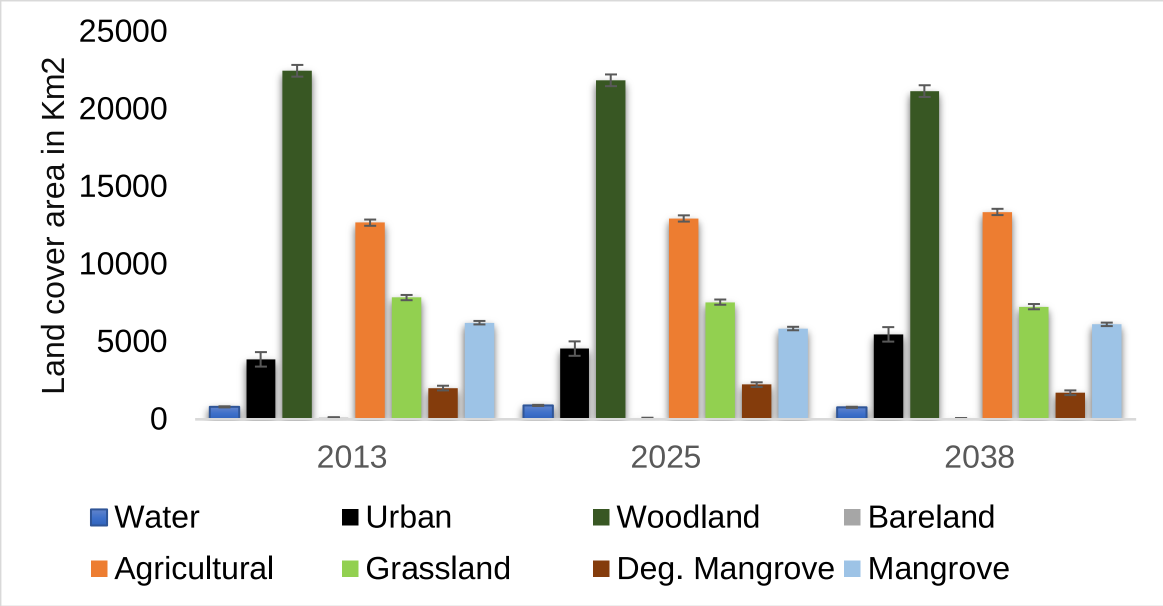


Figure 5. 9: Area changes in km^2 of land cover classes for 2013, predicted 2026 and 2038 of the NDR.

5.5.2. Degraded mangrove prediction and dynamics

Simulating and understanding mangrove degradation patterns is essential for several planning and sustainable management activities of the NDR to ensure continued ecosystem services provision and preservation of its high biodiversity. The results in this study show an interesting dynamic based on past trends and regional spatial drivers influencing mangrove degradation in the NDR:

- In the short-term scenario, degraded mangroves would experience a net increase of ~220km^2 by 2026.
- In the longer-term, between the proportion covered by degraded mangroves will decrease by ~521km^2, more than double the expected net gain from 2013 to 2026.

This future spatial pattern of change in degraded mangroves in the long-term scenario is further evidence that degraded mangroves in the NDR are capable of regenerating back to their healthier state as reported by Nababa et al. (2020). Moreover, results show that, as degraded mangroves would decrease, a portion of it is expected to revert back to its healthy state (~270 km^2), whilst the remaining proportion would be lost (~250 km^2; Table 5. 3). Several restoration activities and reforestation campaigns carried out by different entities have been reported in the literature, as well as existing legislations that could lead to reduced mangrove degradation in the NDR (Abere and Ekeke, 2011; UNDP and GEF., 2010; NFP, 2020; TRCC; 2020; Isebor, 2001; Zabbey and Tanee, 2016).

5.6. Limitations

Land cover change processes, particularly in tropical regions are notoriously known for their dynamics and complexity, hence they are difficult to capture in variables and model in algorithms (Gibson et al., 2018). This is because they are often controlled by dynamic, non-linear human-nature relationship (Olmedo et al., 2015). A Land-use simulation model must be capable of simulating quantity of change and the locational area of associated change (Pontius et al., 2004). The accuracy of output (e.g., transition potentials and land cover maps) produced by an inductive model is wholly dependent on the model's predictive capability and accuracy of input data.

The NDR, is one of the most affected globally with data paucity and accuracy issues, including remote sensing data and other geo-spatial data required for land cover simulation studies. This chapter is a follow up to Chapter 3 where land cover change analysis was carried out primarily using Landsat imagery. The study encountered confusion in the classification of certain land cover which resulted to mapping errors. The three land cover maps had an overall accuracy: 79% for 1988, and 82% for 2000 and 2013, which were utilised as dependent input data for the future prediction of land cover in this study. Although, the overall accuracies are high for the land cover changes analysis, the accuracy level become degraded when land cover modelling is carried out. Munch et al., (2017), provides an explanation of land cover map accuracies and their implication in land change analysis.

The LCM is an inductive approach where change is modelled empirically using past land cover maps. Therefore, errors in the individual input land cover maps are propagated by the model into the transitional potential maps, as well as the future scenario land cover maps which affected the acceptable established accuracy threshold to be achieved in this study. Although, mapping land cover with medium resolution imagery is inherently problematic, which often result to accuracy reliability issues. Furthermore, the study area is characterised with a number of peculiar remote sensing data issues, including data gaps and cloud contamination associated with Landsat data.

Regrading other geo-spatial data used in the simulation, a combination of physical, environmental and socio-economic factors as explanatory spatial variables was used in modelling two BAU scenarios in the short (2026) and long-term (2038). However, some of the spatial variables are characterized by some uncertainties. Particularly, data for road networks either contained incomplete or excess information (i.e the most recent data) which were pre- processed to form a composite data layer in-order to correspond to the temporal periods of the land cover maps. However, it would be inherently associated with some errors. There is slight overlap of settlement and population density data relative to land cover map of the earliest period (1988). Additionally, the differences in the spatial resolution (250m and $1km^2$) of some of the driver variable data, despite been standardized mean that the captured local effects are unaccounted for. Furthermore, it is important to recognise that climate variables such SLR, rainfall, and salinity and other spatial variables such as soil type and gross domestic (GDP) which can play a significant role in improving the accuracy in predicting future land cover dynamics in NDR was not included in the model due to data availability, coarseness and accuracy issues of the study area, and the time limit for submitting the thesis. Moreover, the study emphasises on human-induced changes to land cover in the NDR.

The limitations encountered have pushed the MLP-ANN + MC model accuracy lower than the threshold of 80% (Eastman, 2006; Aranoff, 2005), However, a comparison of the “predicted” and classified (i.e., the “real” map) of 2013, indicated an acceptable accuracy. Therefore, the MLP-ANN + MC approach has proven to be a robust approach for future scenario land cover change and mangrove prediction in the NDR.

It would be interesting to predict future land cover change further in the future e.g., for 2050 or even 2100, however, due to the limitations described above, it wouldn’t be reliable enough.

5.7. Conclusions

The Niger Delta region (NDR) is considered to be one of the most degraded ecosystems in the world (IUCN, 1992). Its mangrove forest particularly, has been consistently degraded over the past decades despite the huge role it plays in sustenance of livelihood of local communities (Nababa et al., 2020; Kuenzer et al., 2014a). Present global disturbance rate of the important resource put it at a risk of disappearance by the end of the century (Duke et al., 2007a; FAO, 2007). To prevent future degradation and depletion of mangroves, it is necessary to understand and predict future land cover change in the region. Data availability and accuracy issues together with the commonly used ‘single’ model approach have limited the understanding and reliability of future land cover change in the NDR.

In this chapter, an MLP-ANN +MC model was used to predict future land cover change and mangrove degradation under two BAU-scenarios for the short-term (2026) and longer-term (2038). A satisfactory accuracy model accuracy when comparing a “predicted” and “real” map for 2013. The prediction was carried out using land cover maps (1988, 2000, and 2013) produced in Chapter 3 and spatial explanatory variables which represent regional drivers of land cover change using the LCM in the TerrSet. Results showed that the mangrove forest and woodlands (lowland and freshwater forests) would demonstrate a net loss if past trends persist without any intervention, whilst the built-up areas and agriculture would a net increase in both scenarios. Results also showed that degraded mangroves would be reporting a net increase in the short-term, whilst in the longer-term, a portion of it, more than double the expected net gain in the short-term scenario would return to their healthier state. The MLP-ANN + MC has provided a valuable prediction of future land cover change in the NDR and the first ever degraded mangrove prediction in the region. This type of land cover predictions is useful for the planning, of several conservation actions and the sustainable management of the NDR resources.

Chapter 6

Conclusions

Mangroves are a highly important resource which millions of the inhabitants in the tropical coastal areas depend for their livelihoods. Over the past 50 years the rate of mangrove loss and the extent of their degradation(1389km^2; estimate between 1996 – 2016) has been an issue of global concern (Worthington and Spalding, 2018; Duke, 2016) as the ecosystem services they provide are reduced, including fisheries production, flood protection, carbon sequestration, fuelwood, and medicinal value (Numbere, 2014; Carugati et al., 2018; Onyena and Sam, 2020) Furthermore, the prediction that mangroves may vanish by the end of the century due to current disturbance rate from natural and anthropogenic sources has raised the alarm and further exemplified the need for the sustainable management of this important resource (Duke et al., 2007a; FAO, 2007; Worthington and Spalding, 2018). Reliable information on the past and present land cover, and particularly of the condition of mangroves is important for the decision-making process related with their sustainable management. To this end, satellite remote sensing has an important role to play. However, tropical regions, in general, and the sub-Saharan Africa region in particular, are associated with data availability issues and the extensive cloud contamination of optical remote sensing data, such as from Landsat satellites (Okoro et al., 2016; Kirui et al., 2013).

This study used state-of-the-art remote sensing approaches to reliably map land cover change over 25 years and model its short and long-term state under a business-as-usual scenario using integrated modelling techniques.

The main findings of the thesis are summarised into three analysis chapter as follows:

Chapter 3: Land cover dynamics and mangrove degradation in the Niger Delta region

- There are significant gaps in the Earth Observation data archive for western and eastern African regions and available data is often contaminated by clouds in the case of optical data (e.g., Landsat) which makes land cover mapping and modelling challenging. However, open access remote sensing together with the use state-of-the-art remote sensing techniques can be leveraged on to solve or significantly reduce data gaps and cloud contamination problems, as demonstrated in this study.
- The utilization of image mosaics or single images from single-sensor data to map and assess change should be avoided given the recent advancements in the technological developments which have given birth to new approaches that enable accurate mapping of land cover (Frantz, 2019; Griffiths et al., 2013). By using the cloud computing infrastructure of Google Earth Engine (GEE) and spectral temporal metrics from hundreds of Landsat images, the study overcame data gaps and cloud contamination problems and achieved high overall classification accuracies, User' and Producer's accuracies were achieved in the mapping of land cover, and degraded mangroves for the first time in the study region.
- Spatial-temporal Landsat-based metrics were sufficient in mapping land cover in the three epochs of the NDR, as combining Landsat and Radar data was only marginally beneficial, providing a slight improvement of user's accuracy of the Water and Urban land cover class by 4% in the latest time point.
- Land cover change results revealed that mangroves, the lowland rainforests, and the freshwater forests have demonstrated a net loss, while the built-up areas have almost doubled over the study period.
- Notable results of the intensity analysis showed mangroves losses were ~5 times more intense than gains, urban gains were ~10 times more intense than losses, and agricultural gains were ~2 times more intense than losses.
- The results of the fragmentation analysis showed that the 'number of patches' (NP) for the healthy mangrove consistently increased, which led to the increase of degraded mangroves observed in the more recent time points of the study.

Chapter 4: Assessing the spatial drivers of mangrove degradation in the Niger Delta

- Open geo-spatial data (e.g., roads, population, settlement) over certain areas of the sub-Saharan Africa (e.g., western Africa) are scarce and, when available, are characterised by limitations, such as spatial resolution and accuracy issues that result to uncertainties when they are utilised in the quantitative assessment of drivers of change. However, a number of GIS manipulations can be performed on the data to reduce uncertainties and enable their adequate use as demonstrated in the study.
- Assessing the drivers of change in mangroves needs to be carried out progressively, given that mangroves are highly dynamic. This is necessary so that the planning of conservation measures and development of policy interventions are targeted to tackle the variation of the drivers of degradation in mangroves. The results of the quantitative assessment of drivers showed a variation in the drivers of mangrove degradation, with built up and oil and gas infrastructure variables as major drivers of mangrove degradation in the first and second periods respectively. The model proved to be an adequate predictor of change, with a predictive accuracy above 60%. However, improved accuracy is suggested by mainly additional inclusion of a number of perceived mangrove degradation drivers.
- Interestingly, population density is the least important driver of mangrove degradation in the Niger Delta region

Chapter 5: Future land cover change and mangrove in the Niger Delta region

- Results of the business-as-usual scenario of future land cover for the short (2026) and longer-term (2038) reveal that if past trends persist without any intervention, mangrove forests, and woodlands (lowland and freshwater forests) would demonstrate a net loss, whilst the built-up areas and agriculture increase.
- Degraded mangroves would experience a net increase of ~220km^2 in the short-term (2026) but a net decrease(~521km^2), a net decrease in the longer-term (2038).
- A number of data issues limited the performance of the MLP-ANN + MC approach to be achieved in the land cover modelling outcomes. This included

the level of accuracy of the land cover maps and of the spatial drivers were used. Regardless, the integrated approach, being the first to be tested in the study region, was proven to be a robust approach. The model's accuracy (using 2013 map) was satisfactorily validated using the classified and predicted map of 2013.

6.1. Contribution to knowledge and significance of the study

This study leveraged on the benefits of open remote sensing to accurately assess land cover dynamics through the use of state-of-the-art remote sensing technologies and analytical techniques for the NDR in Chapter 3. This is an important contribution, providing advancement to the methodological approach to land cover change analyses in the NDR and adding to the existing body of literature. Apart from study by Nwobi et al., (2020), previous studies have used 'traditional' approaches to assess land cover change in the study region, and the results have been disputable (James et al., 2007; Kuenzer et al., 2014a; Ayanlade and Drake, 2016; Salami et al., 2010). The study is the first to utilize spectral-temporal metrics and machine learning algorithm on Landsat based images and explored the approach on the combination of optical/radar data to improve land cover classification accuracies in the study region at regional a scale. Notably, this enabled the first ever accurate estimates of degraded mangroves in the NDR and its fragmentation. These are significant contributions as the information could be used for improving the management of the mangrove forest in the NDR.

To support sustainable management activities of mangroves owing to past threats, spatial drivers of mangrove degradation were quantitively assessed using an Artificial Neural Networks (ANN) algorithm in Chapter 4. Prior to this study, driving forces of mangrove degradation and loss in the NDR were based on speculation, and therefore was un-reliable. Moreover, because information on the drivers was speculative, an understanding of how the drivers interact through time was un-known. Furthermore, globally, there is a very limited number of studies (e.g. Meng et al., 2016; Omo-Irabor et al., 2011) quantitively assessing mangrove degradation drivers in the literature. Therefore, this study provides a significant contribution to the assessment of mangrove degradation drivers in NDR as the first reliable assessment. Additionally, it provides an important contribution to the global literature on quantitative assessment of mangrove degradation drivers.

In Chapter 5, future land cover and mangrove degradation under two business-as-usual (BAU) scenarios were predicted using integrated modelling techniques. Most studies modelling future land change in the NDR utilized single modelling approaches which are considered to be limited in their robustness (Eyoh and Okeke, 2017; Dan-Jumbo et al., 2018; Onojeghuo and Blackburn, 2011; Wali et al., 2018; Achionye et al., 2018; Abbas, 2012). However, this study for the first time tested the capability of Multi-layered Perceptron neutral network and the Markov chains (MLPNN + MC) integrated modelling approach, representing spatial regional drivers, to provide a reliable information of future land cover dynamics and the first ever reliable prediction of mangrove degradation in the NDR. The MLPNN + MC method is arguably one of the best integrated modelling approaches for future land cover change mapping and assessment (Ozturk, 2015; Roy et al., 2014; Pérez-Vega et al., 2012). The approach used is an important contribution in the methodology utilized for modelling of land cover in the NDR. Also, another noteworthy contribution is the first ever future prediction of the extent of degraded mangrove which is important for planning, conservation and management of the Niger River Delta (NRD) and the mangrove ecosystem.

It is expected that the techniques applied in this thesis would stimulate similar studies to be conducted in other regions of Nigeria and Sub-Sharan-African regions where remote sensing and other geo-spatial data gaps dominate.

6.2. Policy implications

Although, there are no management policies that are exclusively targeted at protecting mangrove forests in Nigeria. However, laws and regulations that offer protection for mangroves are enshrined within general environmental and forest laws and policies of the country. Some of these policies have clearly defined objectives and action plans (Table 2. 3). Nevertheless, the continuous degradation in Niger Delta's ecosystem and its mangrove forest suggest that existing policies are ineffective and perhaps policy development targeted on mangroves should be formulated. Conflicting responsibilities that exist among MDAs related with the protection of forests are some of the problems that has been identified mitigating enforcement of forest and degradation laws in Nigeria (Adekola et al., 2012; Albert et al., 2018). Furthermore, data limitation issues including extensive cloud effects of optical remote sensing data, resolution and accuracies problems of other geo-spatial data, data paucity of fisheries NDR, and insecurity in the region have hampered the availability of reliable information that could drive policy making related with protection of mangrove and fisheries management.

The Global Mangrove Watch (GMW) project was initiated through a collaborative effort of the JAXA Kyoto and Carbon in 2011 aimed at providing information on mangrove extent and its change for sustainable management of mangroves through an effective monitoring system (Bunting et al., 2018). However, the GMW is limited to information about mangrove extent that emphasize loss between 1996 and 2016. Mangrove degradation is a predecessor to their loss, as such reliable information on the extent of degradation is a critical for risk assessment and effective management of the mangrove forest.

This thesis provides a holistic assessment of mangrove condition and, particularly of its extent of degradation. The methodologies used in addressing data limitation issues related with the optical remote sensing data and that of fisheries landings proved to be robust, providing reliable information which is important for sustainable mangrove and fisheries management in the NDR.

In chapter 4, the second period of the study (2000-2013) was a period characterised with serious oil and gas pollution resulting to considerable degradation of mangroves in the NDR (Duke, 2016; UNEP, 2011). This triggered the need for improved mangrove management and understanding of the driving factors of degradation in mangroves. In this chapter, the degradation scenario was recreated to an accuracy over 62%, suggesting that degradation could have been adequately managed if mitigation plans were put in place. Results revealed that oil and gas pollution were the major causes of mangrove degradation in this period as suggested in the literature (Kadafa, 2012; Balogun, 2015; Duke, 2016). This result presents the opportunity for prompt, appropriate, and effective intervention related with mangrove management.

6.3. Limitation and recommendations

Monitoring and modelling of land cover change and mangrove estimates using Earth Observation data and other geo-spatial information inherently comes with some limitations. Studies using optical data are particularly problematic as mapping and monitoring land cover over the tropics is compounded by gaps in satellite imagery and cloud cover contamination which limit the achievement of optimal land cover classification accuracies. These issues were identified and discussed in this study especially with regards to the modelling outputs in Chapters 4 and 5.

The complex processes of land cover dynamics are tricky to capture in variables, and model in algorithms, since they are shaped by dynamic and non-linear human-nature interactions (Olmedo et al., 2015). Human-induced variables were mainly used as regional drivers in the modelling of land cover and mangrove degradation, and assessment of mangrove degradation drivers, whilst climatic variables (e.g., salinity, pH etc) were ignored due to data challenges of the study area. Additionally, some of the driver variables were associated with resolution, accuracy and incompleteness issues that also affected the accuracy of the modelling outputs. Satellite images and other geo-spatial (i.e., data on spatial drivers) with higher spatial and spectral resolution and accuracies are required for an improved assessment of the drivers of mangrove degradation and modelling land cover change in a dynamic and complex region such as the NDR.

6.4. Future works

Recent studies have reported that the combination of metrics from different sensors and seasons enables optimal land cover mapping of savannah and woody vegetation (Symeonakis et al., 2018; Borges et al., 2020). Therefore, future works in the NDR could test the combination of Sentinel-1 and Sentinel-2 from different seasons for the potential improvement of land cover classification accuracies. Furthermore, future works could focus on forecasting land cover change effects on climate change (Pielke Sr et al., 2002; Bonan, 1997), carbon cycling and storage (Sudirman et al., 2018; Quijas et al., 2019; Boysen et al., 2014), nutrient loading (Boto, 2018; Hershey et al., 2021), biodiversity (Carugati et al., 2018; Polidoro et al., 2010), and other critical ecosystem services in the study area.

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Appendices

Appendix 1: Table S1: Mathematical notation for Intensity Analysis (Robert Gilmore Pontius et al., 2013) Table S2: Confusion matrix of the classification of the Landsat-based metrics centred around the year 1988, Table S3: Confusion matrix of the classification of the Landsat-based metrics centred around the year 2000, Table S4: Confusion matrix of the classification of the Landsat- and JERS-1-based metrics centred around the year 2000, Table S5: Confusion matrix of the classification of the Landsat-based metrics centred around the year 2013, Table S6: Confusion matrix of the classification of the Landsat-and ALOS PALSAR-2-based metrics centred around the year 2013, Table S7: Transition level intensity analysis FROM-class TO-class for 1988–2000 and 2000–2013 (all classes except Mangrove, which appears in Table 4), Table S8: Transition level intensity analysis TO-class FROM-class for 1988–2000 and 2000–2013.

Supplementary material

Table S1. Mathematical notation for intensity analysis (from Pontius et al. 2013).

Symbol	Meaning
J	number of categories, which equals 3 in our case study
i	index for a category at the interval's initial time point
j	index for a category at the interval's final time point
m	index for the losing category for the selected transition
n	index for the gaining category for the selected transition
Cij	number of pixels that transition from category i to category j
S	total change as percent of domain, which equals the uniform intensity for the category level
Gj	intensity of gain of category j relative to size of category j at final time
Li	intensity of loss of category i relative to size of category i at initial time
Rin	intensity of transition from category i to category n relative to size of category i at initial time where i≠n
Wn	uniform intensity of transition from all non-n categories to category n relative to size of all non-n categories at initial time
Qmj	intensity of transition from category m to category j relative to size of category j at final time where j≠m
Vm	uniform intensity of transition from all non-m categories to category j relative to size of all non-m categories at final time
EGj	hypothesized commission of category j error at final time
OGj	hypothesized omission of category j error at final time
ELi	hypothesized commission of category i error at initial time
OLi	hypothesized omission of category i error at initial time

Table S2. Confusion matrix of the classification of the Landsat-based metrics centred around the year 1988.

1988		Reference							
		Wa	**U**	**Wo**	**B**	**A**	**G**	**DM**	**M**
Prediction	**Wa**	319	5	17	15	33	0	15	8
	U	12	5684	106	9	372	119	3	5
	Wo	10	355	15,936	6	1583	1644	24	416
	B	11	8	0	210	61	0	0	0
	A	20	1448	934	102	16,765	1690	1	9
	G	0	629	1638	0	1878	8345	0	4
	DM	34	16	10	1	6	0	1262	219
	M	33	26	319	0	19	1	326	6476

Table S3. Confusion matrix of the classification of the Landsat-based metrics centred around the year 2000.

2000		Reference							
		Wa	**U**	**Wo**	**B**	**A**	**G**	**DM**	**M**
Prediction	**Wa**	270	1	3	6	8	0	23	12
	U	23	8800	88	36	550	120	2	6
	Wo	7	200	12,919	11	917	1047	6	381
	B	6	11	1	156	33	0	0	0
	A	6	1609	751	103	22,055	2295	1	2
	G	5	186	840	5	1548	3875	1	3
	DM	22	4	7	1	4	5	1090	150
	M	22	7	279	2	16	12	269	5236

Table S4. Confusion matrix of the classification of the Landsat- and JERS-1-based metrics centred around the year 2000.

2000		Reference							
		Wa	**U**	**Wo**	**B**	**A**	**G**	**DM**	**M**
Prediction	**Wa**	277	1	2	12	13	0	22	12
	U	10	8778	94	40	153	138	3	5
	Wo	8	218	12,920	10	827	1076	9	346
	B	5	21	0	157	40	0	0	0
	A	12	1560	743	98	22,153	2176	1	4
	G	3	200	869	5	1539	3957	0	9
	DM	34	4	10	1	3	2	1097	158
	M	20	7	272	2	11	12	264	5268

Table S5. Confusion matrix of the classification of the Landsat-based metrics centred around the year 2013.

2013		Reference							
		Wa	**U**	**Wo**	**B**	**A**	**G**	**DM**	**M**
Prediction	**Wa**	825	11	7	49	19	0	52	24
	U	10	9102	33	288	493	91	1	2
	Wo	28	54	14,634	36	795	1277	18	435
	B	58	102	6	934	101	2	5	2
	A	15	1461	1051	499	27,249	3484	0	0
	G	1	142	1358	41	2339	6260	0	26
	DM	114	1	8	8	0	0	1367	157
	M	61	0	280	14	1	0	151	5649

Table S6. Confusion matrix of the classification of the Landsat-and ALOS PALSAR-2-based metrics centred around the year 2013.

2013		Reference							
		Wa	**U**	**Wo**	**B**	**A**	**G**	**DM**	**M**
Prediction	**Wa**	866	10	10	46	15	0	48	18
	U	11	14,877	74	326	755	182	0	1
	Wo	27	119	14,629	32	749	1232	8	440
	B	51	120	9	938	73	2	2	1
	A	16	1544	1088	467	26,943	3395	1	0
	G	1	195	1312	32	2424	6285	0	23
	DM	89	3	13	13	3	0	1382	167
	M	45	0	253	12	2	0	154	5647

Table S7. Transition-level intensity analysis FROM-class TO-class for 1988–2000 and 2000–2013 (all classes except mangrove, which appears in Table 4).

Transitions FROM	Degraded Mangrove			
Time Interval	**1988–2000**		**2000–2013**	
TO Category	**Observed Annual Transition (km²)**	**Transition Intensity % of 2000 Category**	**Observed Annual Transition (km²)**	**Transition Intensity % of 2013 Category**
Water	7787	**1.32**	8937	**1.23**
Urban	566	**0.02**	272	0.01
Woodland	579	0.00	209	0.00
Bareland	19	0.02	255	**0.23**
Agricultural	243	0.00	255	0.00
Grassland	630	0.00	133	0.00
Mangrove	1595	**0.03**	1818	**0.03**
Transitions FROM	**Grassland**			
Time Interval	**1988–2000**		**2000–2013**	
TO Category	**Observed Annual Transition (km²)**	**Transition Intensity % of 2000 Category**	**Observed Annual Transition (km²)**	**Transition Intensity % of 2013 Category**
Water	42	0.03	82	0.01
Urban	27,872	0.01	22,895	**0.66**
Woodland	125,085	**1.19**	107,460	**0.53**
Bareland	48	0.05	2980	0.25
Agricultural	148,407	**1.22**	60,047	**0.53**
Degraded Mangrove	103	0.01	274	0.02
Mangrove	546	0.01	61	0.00
Transitions FROM	**Agricultural**			
Time Interval	**1988–2000**		**2000–2013**	
TO Category	**Observed Annual Transition (km²)**	**Transition Intensity % of 2000 Category**	**Observed Annual Transition (km²)**	**Transition Intensity % of 2013 Category**
Water	1745	0.30	1259	0.17
Urban	24,552	**1.05**	51,246	**1.47**
Woodland	23,369	0.11	34,306	0.17
Bareland	20,984	**2.04**	865	**0.78**
Grassland	54,602	**0.75**	87,124	**1.23**
Degraded Mangrove	483	0.03	263	0.01
Mangrove	263	0.00	67	0.00
Transitions FROM	**Bareland**			
Time Interval	**1988–2000**		**2000–2013**	

TO Category	Observed Annual Transition (km²)	Transition Intensity % of 2000 Category	Observed Annual Transition (km²)	Transition Intensity % of 2013 Category
Water	712	**0.12**	2309	**0.32**
Urban	633	0.03	270	**0.01**
Woodland	16	0.00	134	0.00
Agricultural	1248	**0.01**	180	**0.01**
Grassland	8	0.00	22	0.00
Degraded Mangrove	3	0.00	4	0.00
Mangrove	11	0.00	5	0.00

Transitions FROM	**Woodland**			
Time Interval	**1988–2000**		**2000–2013**	
TO Category	**Observed Annual Transition (km²)**	**Transition Intensity % of 2000 Category**	**Observed Annual Transition (km²)**	**Transition Intensity % of 2013 Category**
Water	623	0.11	468	0.06
Urban	14,159	0.60	16,151	0.46
Bareland	236	0.23	1325	**1.19**
Agricultural	95,219	0.78	53,121	0.47
Grassland	14,784	**2.03**	85,522	**1.21**
Degraded Mangrove	394	0.03	284	0.02
Mangrove	887	0.01	456	0.01

Transitions FROM	**Urban**			
Time Interval	**1988–2000**		**2000–2013**	
TO Category	**Observed Annual Transition (km²)**	**Transition Intensity % of 2000 Category**	**Observed Annual Transition (km²)**	**Transition Intensity % of 2013 Category**
Water	346	**0.06**	918	**0.13**
Woodland	281	0.00	155	0.00
Bareland	248	**0.24**	668	**0.60**
Agricultural	522	0.00	1389	**0.01**
Grassland	2647	**0.04**	31	0.00
Degraded Mangrove	444	**0.03**	746	**0.04**
Mangrove	535	0.01	171	0.00

Transitions FROM	**Water**			
Time Interval	**1988–2000**		**2000–2013**	
TO Category	**Observed Annual Transition (km²)**	**Transition Intensity % of 2000 Category**	**Observed Annual Transition (km²)**	**Transition Intensity % of 2013 Category**
Urban	747	**0.03**	150	0.00
Woodland	487	0.00	636	0.00
Bareland	228	**0.22**	616	**1.55**
Agricultural	667	0.01	1566	**0.01**
Grassland	54	0.00	45	0.00

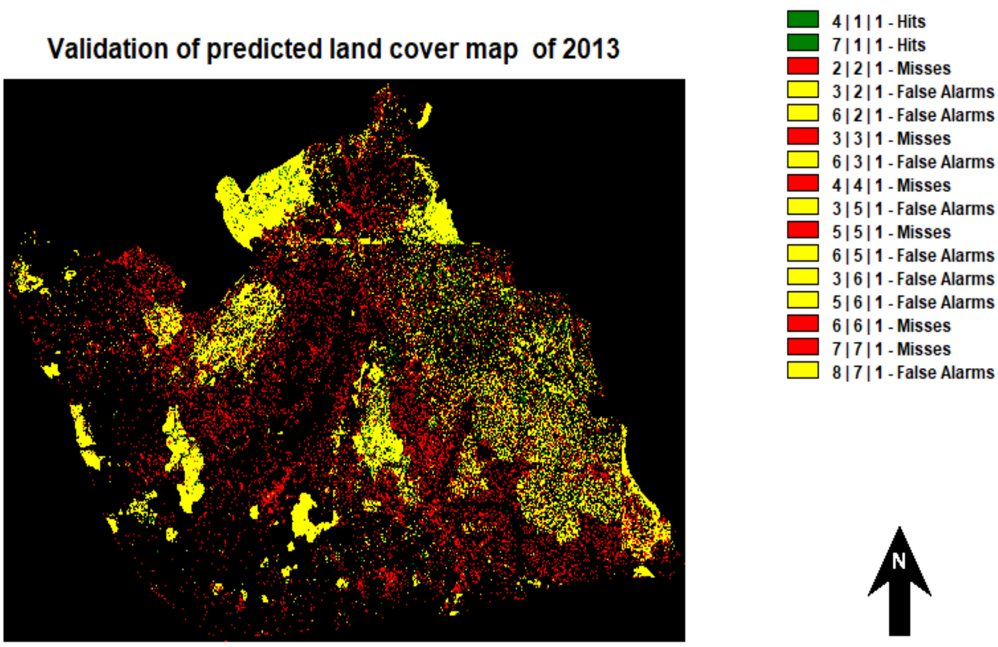
Table S8. Transition-level intensity analysis TO-class FROM-class for 1988–2000 and 2000–2013.

Transitions TO	**Mangrove**			
Time Interval	**1988–2000**		**2000–2013**	
FROM Category	**Observed Annual Transition (km²)**	**Transition Intensity % of 1988 Category**	**Observed Annual Transition (km²)**	**Transition Intensity % of 2000 Category**
Water	369	**0.08**	711	**0.12**
Urban	535	**0.03**	170	0.02
Woodland	887	0.00	456	0.00
Bareland	11	**0.01**	5	0.00
Agricultural	263	0.00	66	0.00
Grassland	546	0.01	61	0.00
Degraded Mangrove	1595	**0.12**	1818	**0.12**
Transitions TO	**Degraded Mangrove**			
Time Interval	**1988–2000**		**2000–2013**	
FROM Category	**Observed Annual Transition (km²)**	**Transition Intensity % of 1988 Category**	**Observed Annual Transition (km²)**	**Transition Intensity % of 2000 Category**
Water	411	**0.08**	294	0.05
Urban	444	0.03	746	0.03
Woodland	394	0.00	284	0.00
Bareland	263	0.00	4	0.00
Agriculture	483	0.00	263	0.00
Grassland	103	0.00	274	0.00
Mangrove	23,799	**0.38**	32,742	**0.54**
Transitions TO	**Grassland**			
Time Interval	**1988–2000**		**2000–2013**	
FROM Category	**Observed Annual Transition (km²)**	**Transition Intensity % of 1988 Category**	**Observed Annual Transition (km²)**	**Transition Intensity % of 2000 Category**
Water	54	0.01	45	0.01
Urban	2646	0.17	31	0.00
Woodland	147,840	**0.68**	85,522	**0.42**
Bareland	8	0.01	22	0.02
Agricultural	54,602	**0.52**	871,237	**0.72**
Degraded Mangrove	63	0.00	133	0.01
Mangrove	246	0.00	460	0.01
Transitions TO	**Agricultural**			
Time Interval	**1988–2000**		**2000–2013**	
FROM Category	**Observed Annual Transition (km²)**	**Transition Intensity % of 1988 Category**	**Observed Annual Transition (km²)**	**Transition Intensity % of 2000 Category**
Water	667	0.14	1566	0.26
Urban	522	1.03	1389	0.06
Woodland	95,219	0.44	53,121	0.26
Bareland	1248	**1.26**	810	**0.79**

Grassland	148,470	**1.75**	60,047	**0.82**
Degraded Mangrove	243	0.02	255	0.02
Mangrove	485	0.01	280	0.00
Transitions TO		**Bareland**		
Time Interval	**1988–2000**		**2000–2013**	
FROM Category	**Observed Annual Transition (km²)**	**Transition Intensity % of 1988 category**	**Observed Annual Transition (km²)**	**Transition Intensity % of 2000 Category**
Water	228	**0.05**	616	**0.10**
Urban	248	**0.02**	668	**0.03**
Woodland	237	0.00	1325	0.00
Agricultural	2098	**0.02**	865	0.01
Grassland	48	0.00	280	0.00
Degraded Mangrove	19	0.00	255	**0.02**
Mangrove	39	0.00	221	0.00
Transitions TO		**Woodland**		
Time Interval	**1988–2000**		**2000–2013**	
FROM Category	**Observed Annual Transition (km²)**	**Transition Intensity % of 1988 Category**	**Observed Annual Transition (km²)**	**Transition Intensity % of 2000 Category**
Water	487	0.10	636	0.11
Urban	281	0.02	15	0.01
Bareland	16	0.02	134	1.13
Agricultural	23,369	0.22	34,305	0.28
Grassland	125,085	**1.48**	107,460	**1.47**
Degraded Mangrove	579	0.04	208	0.0
Mangrove	505	0.01	1431	0.02
Transitions TO		**Urban**		
Time Interval	**1988–2000**		**2000–2013**	
FROM Category	**Observed Annual Transition (km²)**	**Transition Intensity % of 1988 Category**	**Observed Annual Transition (km²)**	**Transition Intensity % of 2000 Category**
Water	747	**0.15**	150	0.03
Woodland	14,159	0.07	16,151	0.08
Bareland	633	**0.64**	60	**0.21**
Agricultural	24,552	**0.23**	51,247	**0.42**
Grassland	27,872	**0.33**	22,895	**0.31**
Degraded Mangrove	566	0.04	272	0.02
Mangrove	717	0.01	540	0.01
Transitions TO		**Water**		
Time Interval	**1988–2000**		**2000–2013**	

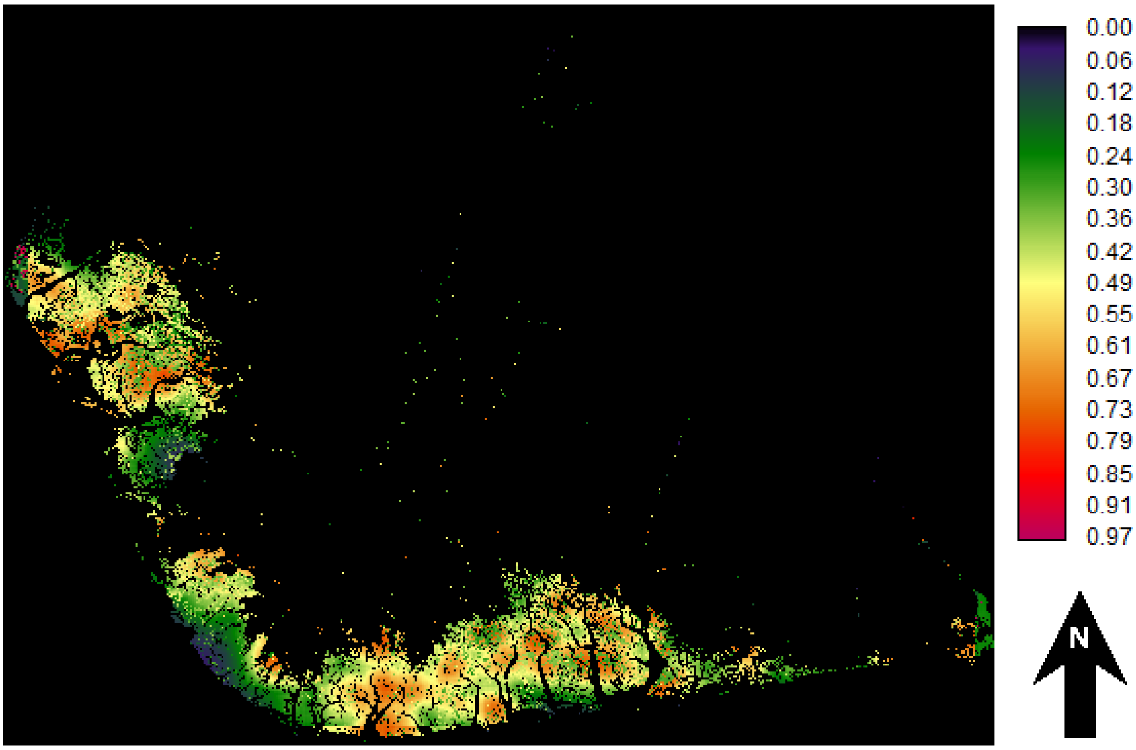
FROM Category	Observed Annual Transition (km²)	Transition Intensity % of 1988 Category	Observed Annual Transition (km²)	Transition Intensity % of 2000 Category
Urban	346	0.02	918	**0.04**
Woodland	623	0.00	468	0.00
Bareland	712	**0.72**	2309	**2.25**
Agricultural	1475	0.02	1259	0.01
Grassland	42	0.00	82	0.00
Degraded Mangrove	7789	**0.58**	894	**0.59**
Mangrove	206	0.00	355	0.01

Appendix 2. The area the curve (AUC) figure from The VALIDATE module.



Appendix 3: Projected mangrove transition potentials over the NDR for (a) 2026 and (b) 2038

a Mangrove Projected Transition Potential for 2026



b Mangrove Projected Transition Potential for 2038