An Assessment of the impacts of Land Use and Socioeconomic Changes on Flooding Risks in Nigeria

(ナイジェリアにおける土地利用と社会経済的変化が洪水リスクに与える影響の評価)

IGHILE, Eseosa Halima

(イヒレ　エソサ　ハリマ)

Doctor of Environmental Engineering

Graduate School of Environmental Studies, Nagoya University

2022

Summary

Flood is one of the most catastrophic natural disasters, posing a serious and immediate threat to people and the environment. Rapid urbanisation, socio-economic changes, and uncontrolled land utilisation have aggravated Nigeria's increased frequency of flooding disasters. With the expectations that Nigeria will continue to experience changes to the socio-economic landscape, the need to examine how these variations may impact the frequency and intensity of existing environmental problems such as flooding is now paramount. Furthermore, from the perspective of flood risk management and building resilience, innovative techniques emphasising the relevance of land use planning and flooding risk are still underrepresented in Nigeria's long-term growth and mitigation plans. Although several methodologies for assessing flood-prone sites have been established to lessen the total harmful effects on people and the environment, these approaches have not been highly successful in Nigeria. Since the frequency of floods and related disasters has increased, and the relationship between land use and socio-economic changes is still unknown, it has become necessary to investigate the interaction between land use changes and the impact on flooding risks to enable the development of effective long-term flood-prevention strategies.

The research proposed a new approach incorporating land use planning in flood risk assessment and management. First, the study attempts to identify the drivers of land use change and their implications on flooding risks while investigating the characteristic features of land use change and simulating potential land use demand by 2040. Then, following an understanding of how land use changes impact the risks of flooding, further investigation to predict the flood-prone locations based on historical flood data and the possible interaction between numerous conditioning factors. The result successfully gives insight into how socio-economic changes affect land use, which inevitably influences the probability of flood occurrence. It further highlights the need for long-term planning against existing flood hazards, which can aid in creating effective countermeasures for Nigeria's flood management and disaster risk reduction.

In the first chapter, the study provides an overview of the theoretical background, the current problems, motivation for the study and the research objectives. This chapter also provides information on the dissertation's scope, limitations and structure. The second chapter introduces the current status and challenges of Nigeria's land use and flood risk management. It provides information on the theoretical, prior and contemporary approaches to land use and flood risk management in Nigeria, highlighting current trends and techniques relevant to the study's objective. Finally, the chapter concludes with a comparison between the method proposed in this research, highlighting its advantage over existing methods in used flood risk assessment studies. The third chapter describes the general approach to the study. It highlights the tools and modelling approach and provides information on the data sources, method of collection, processing and analysis required.

The fourth chapter evaluates the natural and socio-economic drivers of land use change and flood risks. First, the Spatio-temporal trends were analysed to provide insights into the dynamics of land use changes between 1975 and 2013. Throughout the observed period, dynamic changes occurred across the different land use categories. First, agricultural land had expanded by about 21 per cent, forest area had experienced significant reductions estimated at about14 per cent, and settlement area had a nominal growth of about 0.57 per cent within 38 years. Following the understanding of the dynamics of land use change, a land use model is developed to assess the drivers of land use change and how the probability of each land use impacts the risk of flooding. The multinomial logistic regression model is adopted to highlight the factors influencing land use changes as a function of 13 selected independent variables. From the multinomial logistic model results, the drivers of land use change in Nigeria comprised demographic, economic, biophysical and accessibility factors, where population density, poverty ratio, the Gross domestic product (GDP), distance to road and migration were the most recurring among the land use categories. Similarly, further analysis on how land use change probability impacts the existing flood hazard areas shows that agriculture and settlement land changes significantly influenced the changes to existing flood hazard areas.

In the fifth chapter, based on the results from the drivers of land use change described in the previous section, the future land use demand under three developmental pathways was estimated based on varied socio-economic and land policy scenarios until 2040. In the first scenario, the goal is to maintain the existing growth trends' status quo regarding land use policies and socio-economic characteristics. As a result, the future land use demand for agriculture and related purposes grew to an estimated 58 per cent, forestry further declined to 20 per cent, and settlement areas rose to 1.8 per cent by 2040. However, the second scenario that promotes improvement in the current socio-economic characteristics saw a slight reduction in agriculture land expansion to about 52 per cent, forestry less depleted at 22 per cent, and settlement areas experienced a 2 per cent growth. The third and final scenario, which aims to promote biodiversity and forest conservation, shows a reduction in agriculture expansion at 44 per cent, forest cover at 23 per cent and settlement land at 1.7 per cent. From a comparison of the three scenarios, it can be observed how slight changes in socio-economic and land policy decisions can impact land use change patterns and indirectly influence the risk of floods.

In the sixth chapter, a flood risk assessment study is performed by integrating machine learning with selected natural and anthropogenic conditioning factors to predict areas with the risk of flooding in Nigeria. First, the geospatial flood database was developed using a collection of historical flood incident datasets from 1985 to 2020 and 15 conditioning factors to highlight what elements contribute to the probability of flood occurrence at a specific location. Then, two machine learning models were adopted: the artificial neural network and the logistic regression. Both models successfully showcased what areas had the highest probability of a flood occurrence ranked based on five scales from very low to very high; very low indicates a rarity of an incident, and very high indicates an almost certainty of flooding in the future. Several metrics such as AUC, ROC, accuracy, MSE, and RMSE helped gauge the modelling performances to test the validity of the machine learning results. The Artificial neural network performed significantly better than the Logistic regression with an overall accuracy in the validation samples having 88 per cent and 78 per cent, respectively.

In the seventh chapter, the results from the previous chapters are combined and utilised to estimate the population, land cover and the impacts of future land use changes on flood risks. The results show that 72 per cent of the urban population are exposed to flood risk irrespective of their socio-economic class compared to the rural population, which was significantly lower at about 42 per cent. Regarding land cover at risk of flooding, agricultural land exposure is at about 83 per cent, the forest at 53 per cent and settlement at 29 per cent. However, settlement land had the highest proportion of exposed land within the very high-risk zones at 1,102 km^2 about 67 % of the total high-risk area. Finally, in terms of the future land use change impacts on flood risk, a comparison between the three land use change scenarios shows that, under all three scenarios, the risk of flooding still exists. However, the market-oriented scenario had the potential to reduce the overall land area exposed to flood risks. In the final chapter 8, a summary of the research objectives, achievements and contribution to knowledge are highlighted. The concluding chapter also answers the research questions and highlights the strengths, limitations and future research for Nigeria and other sub-Saharan countries.

Keywords: Land use changes, Flooding, Flood risk assessment, socio-economic changes, Nigeria

Table of Contents

List of Figures

List of Tables

Chapter 1 Introduction

1.1 Research background

The frequency and intensity of natural disasters have become a significant concern in the last few years. Multiple scholars have argued that natural disasters such as flooding are a cumulative result of natural and anthropogenic factors. For example, Pelling (2003) emphasised that flooding incidents result from the interaction between the natural environment, human activities, and other societal processes. According to the Emergency events database (EM-DAT), in 2021, there were over 432 disasters, with floods being the dominant event with 223 occurrences, a rise from the previous annual average of 163 estimated between 2000 and 2020, which affected over 14.5 million people, 1,894 deaths and an economic loss of US$56.5 billion (EM-DAT, 2021). Nevertheless, the current approach to flood disaster mitigation involves the utilisation of advanced technological developments, which are usually in many regions independent of societal and environmental considerations (Pelling & Wisner, 2012). However, despite significant technological developments, flooding disasters continue to cause severe global damage.

In Nigeria, the impact of severe flood disaster occurrence follows a trend similar to regions such as China, India, and Bangladesh, evident in the massive damage to infrastructure and socio-economic systems, with its intensity and frequency increasing over the last 40 years. Based on the Center for Research on the epidemiology of Disasters (CRED) 2020 report, between 1969 and 2020, Nigeria has accumulated an economic loss averaging US$17 billion and 21,000 deaths due to flooding. In July 2012, Nigeria witnessed one of the most devastating flood disasters, affecting 30 of its 36 state districts. The flood disaster resulted from prolonged and continuous torrential rainfall spanning over 14 days, leading to an excess overflow, runoffs from water reservoirs, and a subsequent dam failure along the Niger-Benue axis. Between July and October, the incurred economic loss from the disaster was around US$500 million, 7.7 million persons affected, 2.1 million displaced and 363 deaths recorded as of September 2012.

Nigeria is not new to frequent flood incidents (Figure 1). However, in most flood incidents, the landscape and climatic changes have been the main driver of increased levels of water runoffs, especially in urban metropolia like Lagos, Kano and Anambra, which are densely populated, and possess multiple informal and uncontrolled developments, especially along flood plains or within proximity to known flood hazards (Ajayi et al., 2012; Orunoye, 2012, Coker et al., 2008). Aside from the natural and climatic conditions that influence flood incidents in Nigeria, demographic changes, land tenure practices, and other anthropogenic factors resulting from socio-economic development have also played a role in the frequency of flood disasters. In the last 40 years, however, due to other issues such as the continuous rapid population growth, overexploitation of land resources and uncontrolled development, many poor urban residents have been forced to live in unideal situations and substandard structures in hazardous and flood-risk zones.

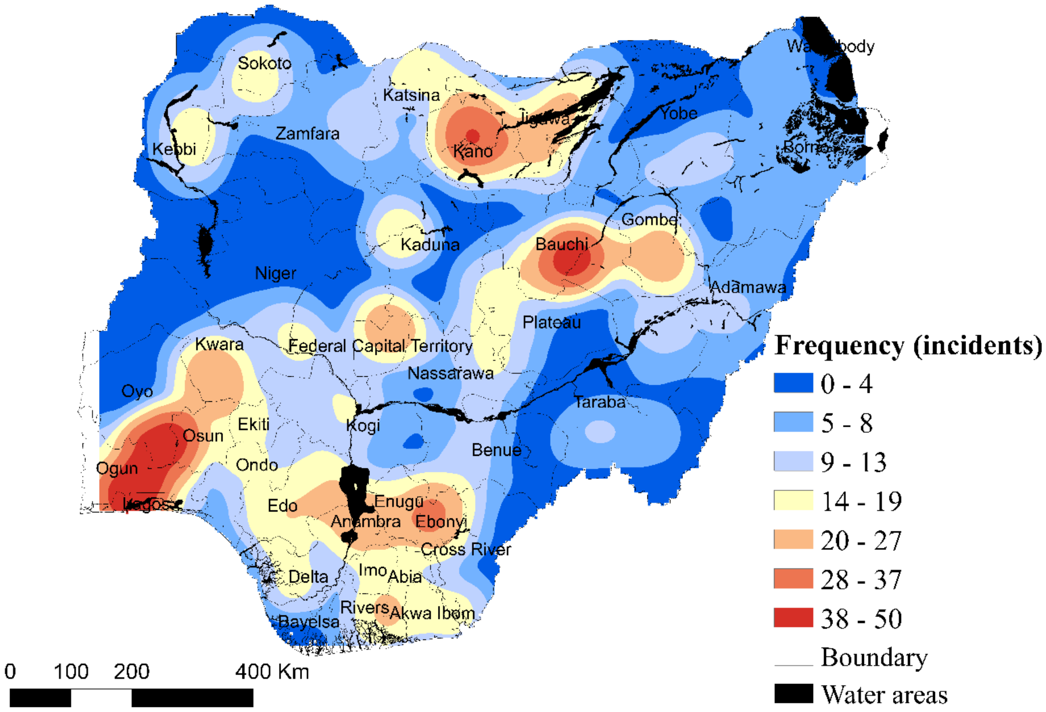


Figure 1 Flood-prone cities in Nigeria (source: Dartmouth Flood Observatory (DFO); Graphics by: Ighile)

1.2 History of Nigerias' vulnerability to flooding

Nigeria has had a long history of flooding incidents and is considered one of the top countries prone to the adverse effects of floods in sub-Saharan Africa (UNECA, 2015). Since the inception of tracking flood incidents on a national scale in 1985 (EM-DAT, 2020), unprecedented flooding has affected thousands of Nigerians and destroyed properties valued at millions of dollars. For example, one of Nigeria's first recorded high-profile flooding incidents occurred on September 11th 1994, affecting about 580,000 persons and estimated infrastructural damage of US$66.5 million (Table 1). However, modern history's most devastating flooding incidents occurred between July and October 2012, with a duration of 123 days, affecting over 7 million Nigerians and estimated damage of US$500 million, which led to a significant setback in the socio-economic growth and development of Nigeria. Table 1 highlights a brief history of flooding disasters in Nigeria, the duration, total affected and estimated economic damage between 1985 and 2020.

Table 1 History of flooding disasters in Nigeria: duration, estimated damage and total affected (1985 – 2020)

Year	Disaster Subtype	Origin	Displaced (km2)	Duration (Days)	Total Affected	Total in Damages ('000 US$)
1985	Riverine flood	Heavy rain	74,620	1	6,000	8,000
1988	Riverine flood	Heavy rain	-	1	300,000	-
1994	Riverine flood	Heavy rain	270	4	580,000	66,500
1998	Riverine flood	Heavy rain	-	2	107,000	-
1999	Riverine flood	Heavy rain	-	37	117,000	-
2000	Flash flood	Heavy rain	-	1	5,500	6,705
2001	Flash flood	Heavy rain	15,360	1	89,917	3,000
2002	Flash flood	Heavy rain	-	1	200	-
2003	Riverine flood	Heavy rain	134,900	53	210,000	2,570
2004	Riverine flood	Heavy rain	35,830	12	29,900	-
2005	Riverine flood	Heavy rain	159,500	41	4,004	147
2006	Riverine flood	Heavy rain	724	72	13,000	-
2007	Riverine flood	Heavy rain	635,370	78	55,000	-
2009	Riverine flood	Heavy rain	64,200	14	150,000	-
2010	Riverine flood	Heavy rain	8,694	17	1,500,200	30,000
2011	Riverine flood	Heavy rain	123,013	26	30,915	4,500
2012	Riverine flood	Torrential	-	123	7,000,867	500,000
2013	Riverine flood	Heavy rain	-	125	81,506	-
2014	Riverine flood	Torrential	-	1	10,000	-
2015	Riverine flood	Torrential	186,816	19	100,420	25,000
2016	Riverine flood	Heavy rain	-	19	12,000	-
2017	Flash flood	Torrential	86,947	36	10,500	-
2018	Flash flood	Heavy rain	257,477	15	1,938,204	275,000
2019	Flash flood	Heavy rain	-	16	123,640	-
2020	Riverine flood	Torrential	-	39	25,114	-

Nigeria consists of multiple densely populated metropolitan areas; the influx of economic activities attracts rapid population growth, urban expansion, and indiscriminate land use, leading to many urban and suburban dwellings along floodplains. In addition, the poor land use management practices and slightly deficient land urban planning policies have contributed significantly to flooding across major Nigerian cities. Similarly, changes in the natural landscape are some of the contributors to increased flooding episodes. For example, the increased replacement of original cover and absorptive soil cover with impervious materials like concrete due to urbanisation and city expansion and deforestation along hillslopes for land cultivation for agriculture-related purposes has resulted in an increase in the quantity and rate of runoffs in human settlement areas (USGS, 2018). Furthermore, social behaviours around land usage are a significant contributor. Poor governance, poorly planned and managed urbanisation processes, a lack of proper drainage, inadequate infrastructures, mismanagement, and ineptitude in implementing existing laws and policies have contributed to increased flooding events (Oladokun & Proverbs, 2016).

1.3 Research Motivation

Since the 1960s, demographic and economic changes, spatial land development, and a rise in flood occurrences have all resulted in significant socio-economic and environmental challenges (Adelekan, 2016). Apart from demographic and economic changes, the perceived impact of climate change also affects human settlements and existing infrastructure because of increasing variability in climatic variables such as precipitation and temperature in various regions of the country and leading to more flooding occurrences (IPCC, 2013). Consequently, the frequent flooding would further impoverish the poor (Wisner, 2015) through displacements and loss of assets, further exacerbating their vulnerabilities and wreaking havoc on communities (Pelling & Wisner, 2012). Furthermore, given the lack of comprehensive disaster management plans centred around the social and natural environment and the ever-increasing possibility that each alteration in the existing land use will affect the ecological system's ability to function and combat impending disasters (Khan et al., 2014). Therefore, attempts to understand the role of land use, its drivers, and their connection to flooding risks are now required.

Although the research on flood risk assessment in Nigeria and other African cities is relatively minimal, and the government of Nigeria has adopted multiple methods for combating flood risk, these strategies have been unsatisfactory and limited. As a result, the difficulties of frequent floods have yet to be solved. The Nigerian government's approach to flood assessment and management has been microscale (city-level), depending mainly on traditional methodologies (hydrological modelling and structural defences) without much thought for a thoroughly integrated framework examining land use, socio-economic changes, and flood mitigation. Similarly, the rapid urbanisation in major cities and a lack of long-term plans for flood risk management and research have resulted in ineffective strategies that can address flooding risk and manage the vulnerabilities of inhabitants.

For Nigeria's long-term growth and development, understanding what drives land use changes and impacts flooding risk is critical. Similarly, determining the influence of each land use class on variations in flooding catastrophe risk levels is critical for land resource management and disaster mitigation. In light of this, the study proposes a new approach to flood risk management that integrates land use change modelling with a flood risk assessment model that focuses on highlighting and minimising the consequences of each environmental stressor on disaster risks. As such, the applied method focusing on flood risk assessment utilising land cover dynamics and modelling would aid in assessing the potential influence of existing spatial planning policies on future land use change (Lavelle et al., 2004) and assist in evaluating flood risk reduction planning policies and initiatives. As a result, this research fills a void in the existing literature by utilising land use modelling techniques as a critical tool for flood risk assessment in Nigeria and other African cities and expanding the knowledge on the effects of socio-economic and land use interactions in flood risk management.

1.4 Research Objectives

Understanding how land use changes driven by socio-economic changes affect flood risks and vulnerabilities would enable institutions and government agencies to design policies and programmes to mitigate the negative consequences. Furthermore, accurately anticipating future land-use patterns and their implications on disasters necessitates a thorough understanding of land use changes' past and current impacts on disaster risks. In addition to having the proper knowledge of the contributions of overall changes to land use, having an awareness of the contributions of the individual land cover changes on disaster risks and impacted areas would enable the design of appropriate land use plans that focus on mitigating the effects of each environmental stressor on disaster risks.

Furthermore, the rapid urbanisation and climatic changes are predicted to increase the frequency and intensity of flooding occurrences, affecting population growth and, as a result, land use changes if left unchecked (Pelling, 2011). The amount of social, economic, and environmental sensitivity to flooding impacts is not solely due to proximity to a flood hazard or socio-economic status; the failure of governments at all levels to recognise and address hazards is one of the critical drivers of the root cause and a contributor to catastrophe risk generation. Finally, assist in providing accurate and timely flood risk management solutions and ensuring prioritisation of regions in desperate need of action by analysing how land use changes affect flood vulnerability.

The objectives are;

i. Examine the association between changes in land use types and their drivers and the risks of flood disasters in Nigeria;
ii. Understand land use dynamics and predict future land use changes under varying socio-economic changes;
iii. Develop flood susceptibility maps that highlight the areas prone to flooding disasters based on natural and anthropogenic factors;
iv. Estimate the effects of future land use changes under diverse growth scenarios and the impact on flood susceptibility and exposure;
v. Finally, estimate the distribution of persons and land cover vulnerable to flood hazards.

1.5 Scope and Limitations

This research is focused on assessing how land use change resulting from various socio-economic drivers impacts the risk of flooding in Nigeria. Therefore, the extent of the research is based solely o modelling the effects of land use changes and the implication on flooding risk in Nigeria until 2040 based on varied land development patterns. Here, the study mainly assesses the drivers of land use change, predicts future land use patterns, and simulates possible flood risk areas by integrating Statistical modelling, System Dynamics, GIS and Machine learning to highlight how land use changes under varied socio-economic characteristics impact flood risks in Nigeria.

The limitations of the research are the availability of locally sourced statistical and GIS data, which made it challenging and forced the reliance on numerous global data warehouses, that required in-depth cleaning, processing and validation before they could be used in the research. Another limitation is that the study focused solely on Nigeria and made no comparison with other sub-Saharan African or developing countries with similar land use and socio-economic characteristics. Finally, the research utilised cross-checking and triangulation to decrease bias, which led to a review of relevant literature to understand how to limit scientific data disparity.

1.6 Structure of the dissertation

The research contents are as follows; Chapter 2 focuses on existing literature, where it reviews previous works, studies and methodologies on land use, flooding and flood disaster risk management in Nigeria. In addition, the section provides information on the past, current and future trends in the selected research and methods. Chapter 3 discusses the general methodology for the research, including data acquisition, processing and analysis. Chapter 4 evaluates land use change's natural and socio-economic factors and their implication on flood risks. Finally, chapter 5 highlights future land use patterns based on the drivers of land use change based on a proposed system dynamic model under multiple socio-economic growth pathways. Chapter 6 follows the assessment of flood-prone areas based on various natural and socio-economic factors. The section evaluates flood-prone areas using machine learning models and highlights the factors responsible for increasing flood risk probability. Chapter 7 estimates the effects of flood risks and land use changes on the exposure and vulnerability of people and infrastructure. Finally, the last chapter summarises the initial objectives and results of proposed research questions and makes recommendations for future research and development.

Chapter 2 Current Status and Challenges of Flood Management in Nigeria

2.1 Disasters and the Nigerian Society

Advocacy for disaster risk reduction has become a significant concern in Nigeria. Although Nigeria continues to develop and implement innovative strategies to combat the existing disasters, the effects of disaster reoccurrence have threatened the country's social, economic, and overall sustainable development. Moreover, the frequent disasters in the decade have significantly impacted Nigeria's capital assets and harmed the country's overall economic performance. For example, following the 2012 flood disaster in Nigeria, an estimated economic loss of approximately N2.6 trillion Nigerian naira (US$ 17billion), 1.4 per cent of the nominal Gross Domestic Product (GDP) of 2012 (UNECA,2015).

As a result of the frequency of disaster incidents, most natural surroundings become contaminated and toxic during and soon after, and the natural and artificial resources become unfit for consumption and utilisation. Similarly, agricultural land and adjacent natural resources are polluted, drowned and destroyed, diminishing food yield and making it unfit for vegetative growth and human relocation. Aside from the effects of disasters on Nigeria's economy and environment, the effects on the country's social setting are tremendous. Therefore, when considering disasters in Nigeria, the effects on housing, education, population, and people's health should not be neglected.

2.1.1 History of policies and measures for Disaster Risk Management in Nigeria

In order to address the growing dangers of disasters in the country, the Nigerian government created legislation in 1999 that established a non-governmental organisation entrusted with dealing with disasters and hazard-related events around the country. The organisation was known as the National Emergency Management Agency (NEMA). However, NEMA concentrates primarily on disaster assistance rather than developing action plans for mitigating, preventing, or minimising disaster risks. Since the agency's mode of operation is focused on recovery rather than preparedness or mitigation, most disasters and emergencies in Nigerian communities have become repeated and inadequately addressed, posing a considerable drain on national development (Ojo 2004, Abubakar et al. 2015).

Following the failure to fulfil the first goal, the Nigerian government improved its disaster risk management (DRM) plans, establishing a new directorate designated the National Disaster Management Framework (NDMF) in 2011. This law and framework address existing policies focusing on risk response and recovery. The new set of priorities aims to establish a fully functioning Disaster risk management institution at all tiers of government, as well as to ensure coordination among all government agencies in order to address the risks and growing exposure to hazards and disasters, as well as to promote the future building of community resilience and coping capacity in Nigeria.

2.1.2 Challenges of Disaster Management in Nigeria

Nigeria is subject to numerous natural disasters, especially annual flooding. These disasters have not been well managed over time, which has increased casualties, exposure levels, and frequency. One of the critical challenges noted from prior disaster occurrences in handling and managing disasters in Nigeria is the incapacity of numerous agencies to effectively perform their tasks owing to redundancy in the efforts of various authorities. Another issue is a lack of coordination and cooperation among individual agencies, which reduces the impact of emergency response (Lamidi and Benson, 2014). The absence of an integrated system that considers both the urban growth process and catastrophe risk management has produced a mismatch between disaster management and the entire urbanisation process, evident in existing disaster management methods, which rely only on structural measures and imported expertise than localised solutions.

Furthermore, the absence of comprehensive disaster mitigation education, information, and participation by all stakeholders present a problem for efficient disaster management in the Nigerian community (Bashir et al., 2012). In the case of disaster recovery, which involves restoring impacted areas to their original state, the inability to preserve accurate data on the affected population impedes the restoration and relocation process. Another typical characteristic in Nigeria in the aftermath of most disasters is that the number of people who can fully recover is relatively negligible. The difficulty in fully recovering is due to the displaced persons being compelled to live in more dangerous conditions during the tragedy (Wisner & Luce, 1993). The more affluent individuals in society are more likely to enjoy better living conditions than those with fewer financial resources (Cosgrave & Herson, 2008). As a result, the most vulnerable individuals are likely to live in disaster-prone areas, which typically lack access to the essential infrastructure to mitigate disasters.

2.2 Flood Risk Assessment

The word "flood risk" refers to the potential of significant economic, social, and environmental damage and loss resulting from flooding. Flood risk may result from a chain reaction of risk and feedback, decreasing society's well-being and causing poverty and hardship (Balica et al., 2013, Rayhan, 2010).

Similarly, age groups, population density, income distribution, and the inability to access essential services can all be used to measure a town's flooding risk.

For decades, there has been an increasing worry about flood losses. As a result, flood risk assessment requires mapping and predicting existing threats. The nature of the flood, its severity and the frequency can be better understood by modelling and mapping the past and future flood dangers (Komolafe et al., 2015). In addition crucial for ascertaining the number of people and buildings impacted, providing early warning in case of recurrence and design purposes, particularly for flood control and disaster risk reduction. Some scholars have also developed different methodologies to assess flood losses (Kellens et al., 2013). For example, field analyses combined with physical and socio-economic methods of flood assessment have received increasing attention since the 1990s. In addition, the growth of geospatial technology, such as remote sensing, and the availability of multispectral data, have given us an advantage in assessing flood risk at a spatial scale.

As part of performing flood risk assessment studies, reducing the vulnerability of people and infrastructure are essential indicators for a successful flood mitigation plan. Flood risk and hazard vulnerability modelling has evolved during the last decades. For example, poverty, land resources, and access to infrastructure are being addressed as social and economic components of flood risk assessment. In addition, other factors, such as the cultural systems and economic drivers, can now be used to investigate a society's exposure, susceptibility, and resilience to flooding. Another commonly used term in flood risk assessment studies is Flood vulnerability. Flood vulnerability is a multidimensional concept incorporating risk, exposure, and sensitivity components. Various methodologies have successfully evaluated all aspects of vulnerability from environmental, economic, and social dimensions (Rehman et al., 2018). Several scholars have sought to quantify flood vulnerability in their studies. For example, according to the United Nations Educational, Scientific, and Cultural Organization (UNESCO), the flood vulnerability of a place can be assessed using the equation below.

$$Vulnerability = Exposure + Susceptibility - Resilience \tag{1}$$

where: exposure refers to the elements and assets within the flood hazard zones, susceptibility indicates the lack of ability to resist extraneous agents (flood), and resilience is the capability to recover after a disastrous event. According to Scheuer et al. (2011), consideration should be placed on environmental and socio-economic factors when addressing flood vulnerability. Therefore, flood vulnerability could be environmental, economic, or social (Figure 5).

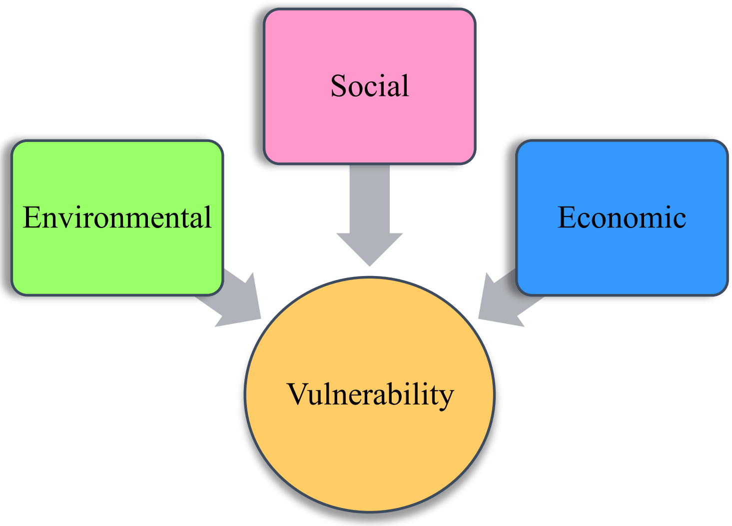


Figure 2 The three forms of vulnerability.

Environmental vulnerability in flood risk assessment can be understood at numerous levels, including an organism's nature, population size, species group, ecosystem characteristics, and landscape. As the ecosystem plays a vital role in the sustenance of human lives, evaluating the adaptation of various species following a disaster can reduce the overall environmental vulnerability (Adger et al.,2005; Brown, 2009; De Lange et al., 2010; Cai et al., 2011).

Adaptation and resilience within societies are intrinsically connected to the degree to which societies are vulnerable to the effects of climate change and catastrophic disasters. Vulnerability in society has a significant influence on an individual's ability to make a living for themselves and is linked to insecurity in a wide variety of social groups. Consequently, vulnerable groups may experience financial hardship and restricted access to essential resources. There are growing concerns about the rapid increase in people vulnerable to flood risk, especially in developing countries. For example, the top 10 countries with the highest social vulnerability to flood risk are the developing nations, including Nigeria, with about one-third of all vulnerable populations residing in China and India. Figure 6 shows an aggregation of the number of persons vulnerable to floods per country headcount of the total population.

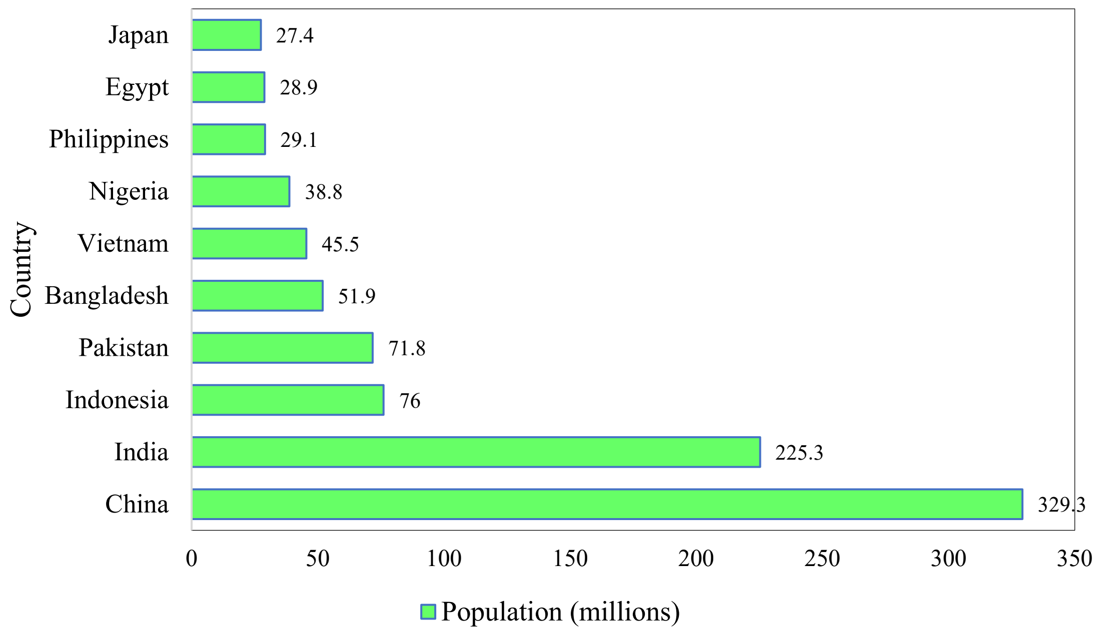


Figure 3 Countries with the highest share of vulnerable populations globally (source: Rentschler & Salhab, 2020. Modified by: Ighile)

One of the most common aspects of flood risk assessment studies is the aspect of economic risks or vulnerability. Developing countries have demonstrated to be most vulnerable or at risk to natural disasters due to their inability to establish high-quality infrastructure, exposing structures and livelihoods to significant destruction. Using global flood economic vulnerability estimates as an example, approximately one hundred thirty-two million (132) people living in severe poverty (less than $1.90 per day) are at risk of flooding, with 72.5 million (55%) living in Sub-Saharan Africa (Figure 7). Rentschler & Salhab (2020) estimates that globally, two out of 10 individuals vulnerable to flood risks live in extreme poverty, with the highest concentration in three nations: India, Nigeria, and the Democratic Republic of Congo. The top ten nations for poor people at risk of flooding (Figure 7) account for 65 per cent of all poor people globally.

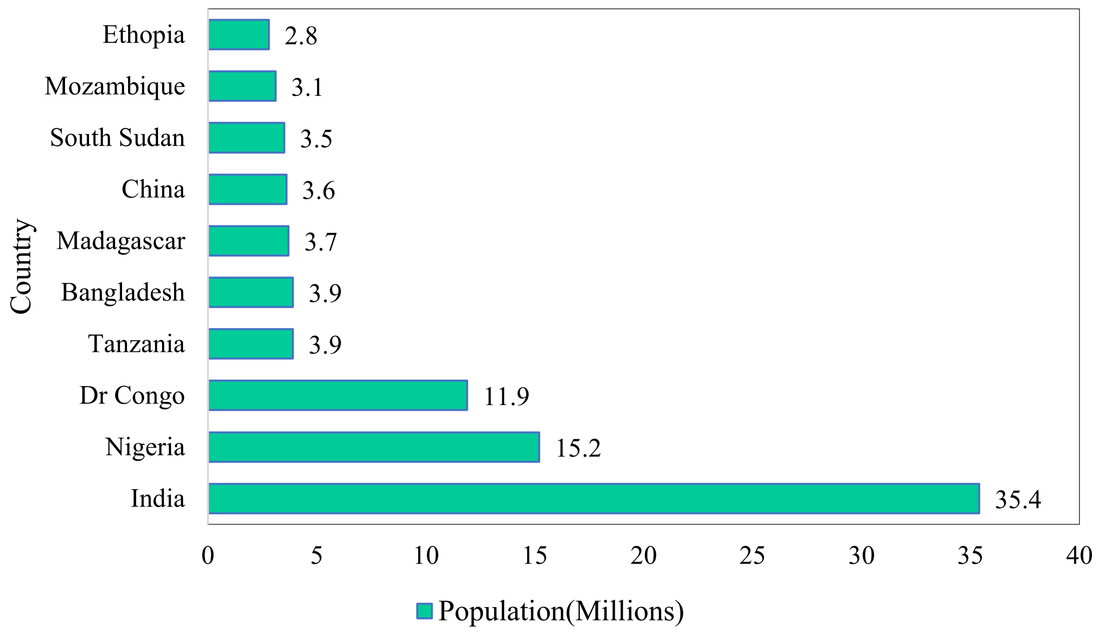


Figure 4 Top 10 countries with the highest proportion of economically vulnerable groups (source: Jun Rentschler and Melda Salhab, 2020. Modified by: Ighile)

2.3 Methods for flood risk assessment and their limitations

Flood assessments are essential in estimating flood risks and managing extreme events. Implementing accurate and timely flood assessment methods can aid disaster risk management and help prioritise solutions to existing hazards. As a result, comprehensive flood assessment systems capable of predicting short and long-term floods (Panahi et al., 2021) and other hydrological occurrences are crucial for disaster damage mitigation. Several hydrological, statistical and spatial methods have been employed to assess and predict flood-prone areas. Among the most popular flood assessment methodologies, the rainfall and runoff models are the most generally used approaches (Lin et al., 2019). However, they require detailed topography and precipitation measurements, which are sometimes not readily available or accessible. Another method standard in flood risk assessment is the statistical method. Most current flood prediction research relies on data-specific models with various simplification assumptions. There are three main statistical flood assessment models: physical, data-driven, and machine learning models (ML).

2.3.1 Physical Models

Physical-based models are the most commonly used flood assessment and forecasting tools, and they can mimic the runoff processes of river channels (Zhao et al., 2009). A typical example of the physical model is the Hydrological Engineering Centers' River Analysis System (HEC-RAS), frequently used by hydraulics and hydrology for estimating potential flood damage. However, one disadvantage of these models is the reliance on extensive hydrological and climatic knowledge. In addition, the data requirements to successfully compute short- and long-term flood prediction are sometimes challenging in scarce data regions (Mosavi et al., 2018).

2.3.2 Data-driven models (DDM)

The second type of flood assessment model is the Data-driven model (DDM). This modelling approach emphasises the interconnectivity between complex variables without previous expertise in the structure's natural performance. They typically depend on extensive hydrological and meteorological data to achieve a precise conclusion. The DDM models are helpful in situations with inadequate hydrological data. Typical examples of the DDM models are the Autoregressive Integrated Moving Average (ARIMA) and the Frequency Ratio analytic (Valipour et al., 2013). However, the shortcomings of these models are comparable to those of physical models in that they necessitate the collection and analysis of massive volumes of data over time.

2.3.3 Machine learning models

In flood risk modelling, the algorithms of machine learning (ML) models are relatively new. As a result, they are advertised as faster modelling tools that require less data than physical and DDM models. As a result, machine-learning systems' predictive skills have significantly improved for flood risk assessment and can outperform conventional modelling approaches, especially considering the cost development and estimation time (Mekanik et al., 2013; Xu et al., 2002).

Machine learning is a branch of artificial intelligence (AI) that uses mathematics and computerised algorithms to identify data patterns without requiring complicated or advanced coding functions. For example, machine learning is becoming increasingly popular for diving into non-linear systems and anticipating floods. Traditional flood forecasting systems typically include many hydrologic and hydraulic models that simulate physical processes. While these models can help with system knowledge, they typically have high computational and data requirements, swift training and validation, less difficulty, and higher performance than physical models (Kim et al., 2016; Wagenaar et al., 2020). In addition, machine learning models can be supervised, unsupervised, or reinforced.

a. Supervised learning algorithms teach themselves to perform functions that can generate predictions (Gareth et al., 2013). A typical example of a supervised learning algorithm is the linear regression model (Liu et al., 2012).
b. Unsupervised learning occurs when each data sample contains a set of predictors but no associated responses. Unsupervised learning can help discover patterns in sample data and establish correlations between variables.
c. Reinforcement-based learning is a branch of machine learning that studies how intelligent agents should operate in a given environment to maximise the concept of cumulative reward. Reinforcement learning is unlike supervised learning, as it does not need the presence of labelled input or output pairings or the explicit correction of suboptimal behaviours. Instead, the focus is on striking a balance between exploration (new terrain) and utilising existing information (Kaelbling et al., 1996). Some typical applications of reinforced learning include autonomous driving and robotics.

2.4 Flood Risk Assessment in Nigeria

Researchers have long been concerned about flood's impact and associated susceptibility in developing countries. In developing long-lasting solutions to existing flood hazards and reducing disaster impacts, the physical, economic, and social vulnerability must be assessed jointly, especially in countries where poverty is apparent and resources are few. Nigeria at present has high-level dangers of flooding due to various natural and anthropogenic forces, which influence extreme weather and climatic events and increase the risk of flooding disasters.

Many Nigerian researchers performed flood risk assessment and mapping, primarily applying remote sensing and Geographic Information Systems (GIS). Other studies have also combined satellite imagery and hydrological models to map the effects of climate change on flooding. For example, Ojigi et al. (2013) delineated and mapped the 2012 floods in some parts of central Nigeria using RADARSAT and Shuttle Radar Topography Mission dataset.

Similarly, in Makurdi, Nigeria, Mayomi et al. (2013) proved the efficacy of geo-information approaches in analysing the 2012 floods. They combined GIS and field surveys to assess all 120 settlements in the region and classified flood-prone areas based on their susceptibility and vulnerability levels. Ezemonye & Emeribe (2014) also assessed the factors that impacted practical flood risk assessment in Benin City, Nigeria. The study discovered that religious belief and a lack of finance were the variables that explained the variation in the application of flood disaster preparation measures.

2.5 Land use and Land Cover Changes

The "Food and Agriculture Organization of the United Nations" (FAO) defines land use as the characteristic arrangement of various anthropogenic activities within human societies (FAO, 2000). By definition, the land use pattern of a society reflects the activities carried out on the existing land cover. Nagamani and Ramachandran (2003) also defined land use as "a product of the interaction between human society, its physical needs, and the natural environment". They expressed that the shifts in land utilisation might take the form of conversion or modification. An example includes forest land converted into agricultural areas or vice versa. On the other hand, modification suggests that the separate components of an existing land use class transform—for example, expanding an existing road network to accommodate a greater volume of vehicle traffic (Khan et al., 2014; Baulies, 1997; Quentin et al., 2006).

2.5.1 Studies on land use and land cover changes in Nigeria

Since significant shifts in land use and land cover are occurring worldwide (Wu, Shen, Liu, & Ding, 2008), investigating the dynamics of each land use is essential to have a proper understanding of the factors driving changes in the global environment over the next few decades (Baulies, 1997). The FAO's initial research on the shifting patterns of land use in Nigeria aimed to determine the forest base of the country to improve forestry management. It entailed the creation of land use maps with a primary emphasis on the use of vegetative cover to address existing trends in environmental deterioration.

Similarly, the United States Geological Survey (USGS) researched the West African region, including Nigeria. The research endeavour began with monitoring land resources and land cover patterns, primarily for agricultural development, settlement growth, and landscape changes brought on by deforestation, restoration, or re-greening. However, the study was restricted to the influence of climate change on land use conversion, the growth of agricultural and urban land expansion, the nature of human activities, and the implications for the tropical forest reserves in Nigeria. Other similar studies by independent researchers have focused on urban and regional centres (Braimoh & Onishi, 2007) using statistical models. The primary purpose of the research was to understand the elements that impact land development in Lagos and make predictions on the nature of land conversion for residential, commercial, and industrial development. The study contributed to a better understanding of the reasons that drove urbanisation in Lagos, Nigeria, between 1984 and 2000 (Braimoh & Onishi, 2007). The shortcomings of all the existing studies for Nigeria are that; there was little emphasis on understanding the factors that drive land use change based on its natural, social and economic characteristics.

2.5.2 Detecting land use and land cover changes

Land use patterns provide valuable information on human activities, environmental conditions, and probable future development patterns (Zhou & Kockelman, 2008). In addition, weather patterns and geographical locations, as well as prior regulations on land use and land allocation systems, may also be significant drivers of LULC change (Veldkamp E.F and Lambin 2001; Lambin, Geist, & Lepers, 2003; Zhou & Kockelman, 2008; Agarwal et al., 2010). A popular approach to detecting land cover change and its drivers is using land use change models.

The fundamental goal of developing land-use change models is to investigate the origins and dynamics of land use and provide meaningful information that aids in creating policy that attempts to affect change. There are numerous land modelling techniques, each with its advantages and disadvantages. According to Parker et al. (2003), despite the multiple land use change models developed, there is no more superior approach to land use change modelling due to the complexity and variety of data available, development style or region.

Veldkamp & Fresco (1996) identified four components as the major contributors to land use change dynamics. These variables are the interactions between the location, time, biophysical processes, and human activities. Land use change modelling can take various shapes, but they all use these dimensions. Some examples include; time-series statistical models without human dimensions; time-series statistical models with human dimensions; classic GIS applications; GIS-based modelling with temporal components; econometric theoretical models; and spatial modelling.

2.6 Land use Change Assessment and Simulation Models

Most land use evaluation models concentrate on agricultural intensification, the extent of geographical explicitness, and the economic basis for classification (Han et al., 2015). Studies on land use modelling have successfully identified different modelling approaches. These modelling systems include machine learning models, cellular models, sector-based economic models, spatially disaggregated economic models, and agent-based models (Pei et al., 2015; Arsanjani et al., 2013). However, the geographic, economic, and integrated models are the primary forms of land use models utilised locally and globally (Parker et al., 2003).

a. Geographic

The geographic models represent the biophysical and socio-economic characteristics of the land, its circumstances, and its suitability for a particular use (Arima et al., 2016). The most common model types are empirical-statistical, rule-based, and land-system models. One well-known example is the conversion of land use and its effects (CLUE) model, which requires logistic regression and land demand values estimated exogenously to determine the relationship between observed land use and other spatial parameters.

b. Economic

The economic models focus on the demand and supply functions of products that cause changes in land use. One example of an economic model is the "International *Model* for Policy Analysis of Agricultural Commodities and Trade" (IMPACT) (Feng et al., 2018). In order to investigate the effects that potential future growth trajectories might have on food security, the "International Food Policy Research Institute" (IFPRI) developed a global partial equilibrium model (PE) with an emphasis on the agricultural sector to track the supply and demand of agricultural products and their trade prices.

c. Integrated models

The integrated model combines elements of the geographical and economic models. In addition, the integrated models often include several economic, process, and environmental aspects investigating land use change. Integrated assessment models, sometimes referred to as Integrated Assessment Models (IAMs) (Lin et al., 2020), are large-scale models that incorporate both natural and human subsystems. They illustrate consumption patterns, industrial growth, agricultural progress, land use or land cover alterations, and potential future development scenarios (Lambin et al. 2000).

2.6.1 The Discrete Choice Models

The discrete choice theory is a concept used in economics to describe or predict a choice between available options. The model makes projections about how a decision or choice will shift in response to changes in the characteristics of the demography. The most common varieties of discrete choice models can be categorised by the number of options at a participant's disposal. They are of two forms; binomial (dichotomous) and multinomial (polytomous). According to the discrete choice theory, a choice is binary if there are only two possible outcomes (yes, no; 0,1), whereas a discrete choice model with more than two outcomes (yes, no or maybe) is multinomial. For example, the discrete choice theory can be used to understand whether one should drive to work or take public transportation and the elements that influence that decision under various circumstances. An advantage of the discrete choice model is its ability to quantify the relationship between the driving factors and land use change patterns (Veldkamp & Fresco, 1996; Peppler-Lisbach, 2003). For example, Landis and Zhang (1998) included the discrete choice theory in the research of land use types using probabilistic equations to identify the drivers of land use. Other applications of discrete choice theory for developing land use models include the logistic regression models (LR).

2.6.2 System dynamic models

System Dynamics (SD) modelling is a technique for deciphering complicated system interactions involving dynamic procedures and feedback (Paterson et al., 2021). The SD can forecast complicated system changes under various situations, making it a valuable tool in various domains, including natural science, social science, and engineering technology (Rasmussen et al., 2012). When dealing with complicated problems, SD strongly emphasises explicit modelling and simulation of non-linear feedback (Siregar et al., 2018), which aids in the identification of different influential factors (demographic or economic) and future forecastings of land use changes, climate variability and flooding. The derived results help understand how a system changes over time and provide a method for studying complex systems based on nonlinearity and feedback control (Liu et al., 2017). As a result, SD is a powerful tool for exploring how land systems work and, more importantly, assessing the drivers of environmental degradation and their contribution to flood risks (Josephat, 2018).

2.7 Land use changes and the impacts on flood risks

How land use changes occur typically affects disaster management services. As a result of human development and the natural endowment having an existing relationship that is both dynamic and contextual, a few repeating themes can play significant roles in the evolution of the physical landscape (Barbedo, Miguez, van der Horst, & Marins, 2014). For example, the European Water Framework Directive (2011) emphasises disaster mitigation adapted towards and not against the natural environment, in contrast to traditional approaches, which act against the natural ecosystem. Furthermore, their strategy emphasises that reducing the risk of flooding disasters through implementing adaptation measures for land use is the most environmentally responsible alternative. However, patterns of land use that change over time can bring about a situation in which existing risks become critical. According to the "Forensic Investigators of Disaster" (FORIN), changes in land use are significant elements contributing to recent natural disasters. In addition, alterations to the preexisting land use patterns have increased the likelihood of a catastrophe. These land-use changes may result from an increase in the rate at which the urbanisation process occurs, disruptions to the natural ecosystems due to resource extraction, and infrastructure construction. It is common knowledge that natural habitats and ecosystems are essential in providing services that mitigate the effects of imminent natural disasters.

An interesting case study on how land use change impacts flooding risks was conducted in Thailand, highlighting how recent changes in land use due to agricultural cultivation in some areas led to increased exposure and vulnerability to disasters (Backman et al., 2015). According to the report, the primary reason for the rise in the risk of natural disasters is not necessarily the hazards themselves but rather the policies regarding land use and other socio-economic variables affecting lives and property. Another example of land use change impacts on flood risks is highlighted in a recent flooding incident in India, where land use changes played a significant role in flood-impacted areas. Here, the existing mangrove ecology that ran along the Mithi River in Mumbai was destroyed because of the rapid development and land reclamation in the surrounding swampy areas to make way for construction. These ongoing transformations and reclamations of land along the Mithi River contributed to an increase in the total damage caused by a flooding disaster. Other prominent examples of changes in land use and unplanned or poorly planned development practices show that these factors can increase the severity of risks at the micro and macro levels.

In Nigeria, land use changes have played a significant role in the extent and frequency of flood incidents. Poor land use planning, inadequate drainage system maintenance, and rapid development along flood plains have increased flooding incidents (Figure 8). In addition, the high rate of deforestation and agricultural land expansion has increased exposure to flooding, as highlighted by current studies on flood risk management in Nigeria. In light of this, it is of the utmost importance to emphasise that returning land to its original condition may be taxing, time-consuming, and costly. However, to effectively mitigate the effects of natural disasters, it is necessary to make concerted efforts to enhance existing land use, spatial policies, and human behavioural patterns.

Figure 5 Examples of Flood impacted areas in Nigeria resulting from land use changes. (source: PunchNg, The GuardianNg and the BBC pidgin news)

2.8 Land use simulation and flood risk assessment

A wide variety of modelling tools, ranging from straightforward to complex systems that combine a variety of attributes, can anticipate or simulate land use changes and flood risks (Irwin et al., 2001; Heistermann et al., 2021; Rosa et al., 2014). In addition, the land use simulation approach encourages the consideration of various factors that impact disaster risks (Brown et al., 2013; Rosegrant et al., 2001; Van Socsbergen, 2016) and allows for the easy identification of exposed and vulnerable locations (Moss et al., 2010; Harfoot et al., 2021). Several studies have shown that this method is feasible by including land use models in flood risk assessment. They allow the calculation of vulnerable zones and can demonstrate what actions need to be taken to provide better disaster mitigation. For instance, Weibin et al. (2020) employed the future land use simulation (FLUS) model to study how future land use changes help predict flood danger zones in Guangzhou's urbanising deltas. They did this by investigating how the Future Land Use Simulation (FLUS) model simulates land use changes by combining a flood ensemble model for flood risk assessment. According to the study's findings, the critical factor contributing to an increased risk of flooding is the development of new metropolitan centres in regions prone to flooding (Szwagrzuk et al., 2018). Similarly, simulating land use and flood risk changes makes it easier to understand and highlight areas with the highest vulnerability and develop appropriate mitigation plans to reduce long-term damage.

2.8.1 An overview of the comparison between the land use and traditional flood assessment models

There are numerous approaches to performing a flood risk assessment. As earlier mentioned in section 2.3. Although these methods have been utilized in many flood risk assessment studies, they have advantages and disadvantages, especially in developing countries, where data is scarce. In addition, depending on the scale and coverage, some of the existing not methods may be inadequate. Therefore, the study developed an approach that integrates land use dynamics analysis to assess flooding risk in Nigeria. Although the goal of any flood risk assessment is to understand the probability of a flood occurrence and develop appropriate measures to combat future losses, in this case, we compare two differences between the conventional and traditional approach with the proposed land-use change integrated assessment models (Table 2), further highlighting the advantages and effectiveness, especially in data-scarce regions.

Table 2 Comparison between the Conventional and Proposed Land use modelling approach for flood risk assessment

	Land use modelling	Traditional modelling
1	The approach of utilising land use model techniques for flood risk assessment aids in determining the expected effects of current and spatial planning policies on future land use development.	Traditional techniques often underestimate the likelihood of susceptibility in flood-prone locations, even though the degree of vulnerability within a community dictates the effects of any particular hazard.
2	Combines flood assessment modelling with land use change models, which aids in evaluating existing spatial planning policies and developing measures for natural risk reduction at both local and national scales.	Sometimes ignores the interplay between the natural and human environments and the variables that impact them as a cause of flooding.
3	Another benefit of the land use model approach to flood risk assessment over traditional models is its capacity to be used in	Requires a comprehensive understanding of flood modelling methodologies and datasets

	the study of natural hazards such as landslides and droughts.	accumulated throughout time and requires expertise in hazard modelling.
4	It can be implemented at both the micro and macro scales, enhancing the capacity to transfer across time and space, and may analyse past, present, and future patterns in land use, spatial strategies, and flood mitigation using historical data.	Most traditional flood modelling methodologies have been restricted to a small city or coverage region, and because this research is focused on a nationwide scale evaluation, the traditional approach to flood risk assessment is not possible.

Chapter 3 General Methodology

The research methodology is presented in this chapter, beginning with the data acquisition, processing, land use and flood database development, land use drivers' analysis, future land use demand estimation, flood risk analysis, and estimating the exposed groups in the following subsections.

3.1 Data acquisition and processing

The first step is to gather the relevant data, analyse and process it for land use change, flood risk and damage assessment, which usually depends on the spatial scale, goals, accessible data, and other resources. Information on the interaction between socio-economic characteristics and land use and how this impacts flood risks was required for a more detailed study evaluation.

- Land use change modelling was estimated using metrics that included demographic, biophysical, economic, and accessibility data obtained from multiple sources.
- A total of seven hundred and sixty-five (765) flood occurrences and historical flood hazard maps were considered in the computation of flood vulnerable areas, exposed population, and average economic damage estimation.
- The databases also include aggregated land use data and more comprehensive information on anticipated infrastructure value.
- Due to data availability restrictions, the study combined multiple data sources, formats, and geographic resolutions as an alternative to addressing the shortage in a data point. As a result, obtained spatial datasets were reclassified to the closest forms to maintain spatial distribution and uniformity in resolution and scale to fulfil the most relevant needs in the study.

The data obtained from multiple sources (official or open source) and formats (quantitative or qualitative) were rectified and normalised during the data collection process. Nigeria's National Bureau of Statistics (NBS) data sharing website provides statistical information on most demographic and socioeconomic indicators, while other geospatial data was obtained from multiple global data storage platforms. The geospatial data described all necessary components (environmental, socio-economic, demographic, hydrological and meteorological, land use, and economic value of infrastructure) in vector (points, polygons) and raster formats or informal illustrations with attribute tables.

ArcGIS, QGIS and R studio tools helped clean and categorise these datasets for ease of use, storage, management, and accessibility. Table 3 gives a brief overview of the datasets and their sources. A more detailed explanation of the data implementation is described in each research section.

Table 3 Sources of the data used in the study

Data	Source	Resolution	Period
Administrative maps	GADM	Vector	-
Land cover	United States Geological Survey (USGS)	1-km	1975; 2000; 2013
	Globeland30	30-m	2000; 2010; 2020
Annual mean temperature	Global Climate data: Worldclim; Nimet	1-km	1975-2015
Annual mean precipitation	Global Climate data: Worldclim; Nimet	1-km	1975-2015
Poverty ratio at $2/day	SEDAC	1-km	2005; 2010
Gross Domestic Product	SEDAC	1-km	2005; 2010
Internal Migration	WorldPop	1-km	2005; 2010
Population density	WorldPop	1-km	2000~2020
Elevation	USGS, Earthexplorer	30-m	-
Soil information	The Harmonised World Soil Database v1.2	1-km	2009
	ISRIC: World Soil Information Service	1-km	2019
	Global Hydrological Soil Group- ORNL DAAC	250-m	2020
Road network	NASA, Socioeconomic Data and Applications Center; Global Roads Open Access Dataset v1	vector	-
Water network	OCHA, Nigeria	vector	-
Railway network	OCHA, Nigeria	vector	-
Flood risk map	UNEP-GRID	100-m	2010
Flood incidents data	EM-DAT, CRED; Dartmouth Flood Observatory (DFO)	vector	1985 ~ 2020

Promotion and commodities (imports and exports)	National Bureau of Statistics, Nigeria; Knoema Data portal	Statistics	1960 ~ 2020
Socio-economic (consumption, revenue and expenditure)	National Bureau of Statistics, Nigeria; Knoema Data portal	Statistics	1981 ~ 2017

3.2 Methodology selection

The research methodology is in 4 phases (Figure 6). First, begin with evaluating the drivers of land use change. Then based on the results in phase two: simulate the future land use patterns under diverse socio-economic pathways using the System Dynamics and FLUS models under three scenarios until 2040. In the third phase: a flood risk assessment study is performed using machine learning algorithms and developing a flood susceptibility map. The final phase involves using the results from Phases 2 and 3 to estimate the effects of land use changes on flood risks.

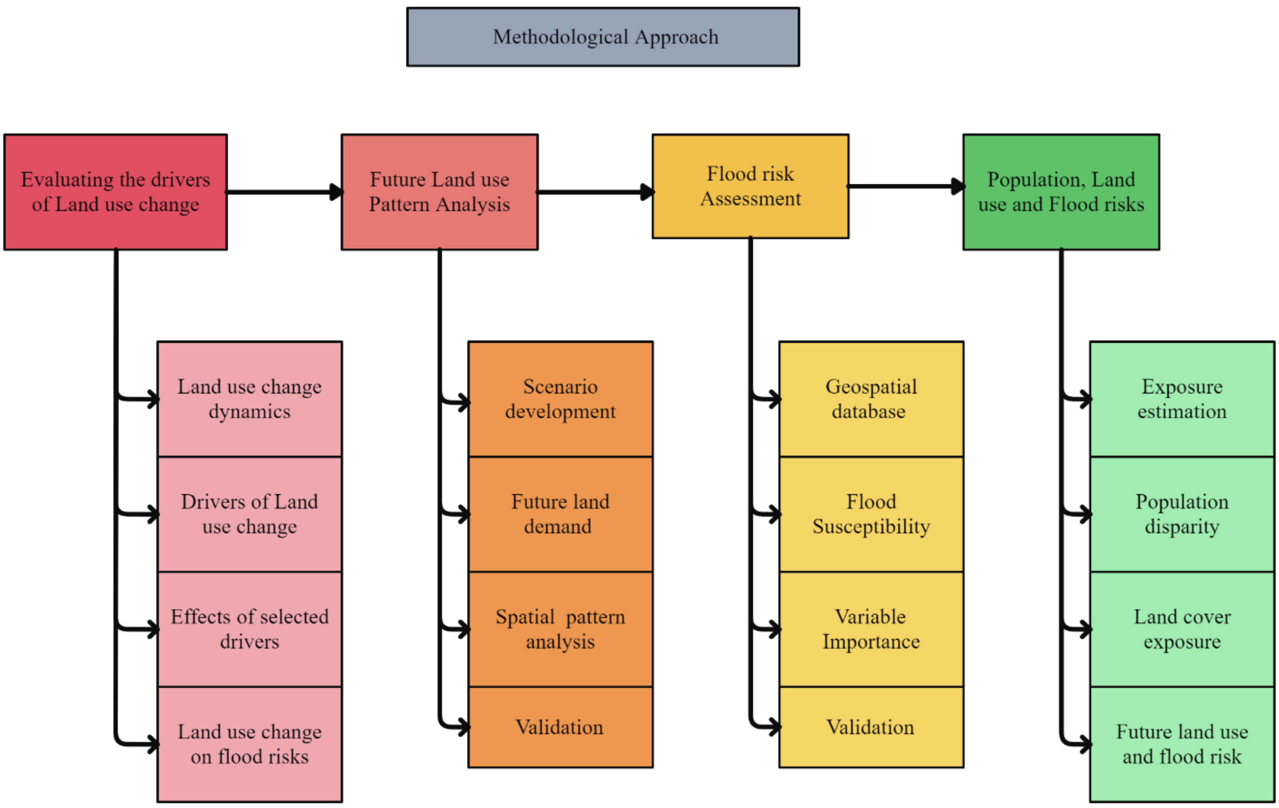


Figure 6 Methodological approach to the study

The spatial scales, modelling approach, and risk assessment methods were all considered when developing the methodology and tools used in the study. Choosing the right analytical approach and spatial scale ensures accurate results. Aside from spatial scale, the land use and flood assessment models were chosen during each stage based on the available data resources.

3.2.1 Evaluating the natural and socio-economic factors of land use change and flood risk

Several factors ranging from biophysical, climatic, demographic, accessibility, and economic characteristics were considered to assess the drivers of land use change (Figure 7 and Table 4). Before deciding on the independent variables for the land use model, a few questions needed to be answered. They include;

- What changes have happened in the study area's social, economic, and environmental characteristics?.
- What are the causes of change?.
- Who and what stands to gain and what ends up losing from the change?.

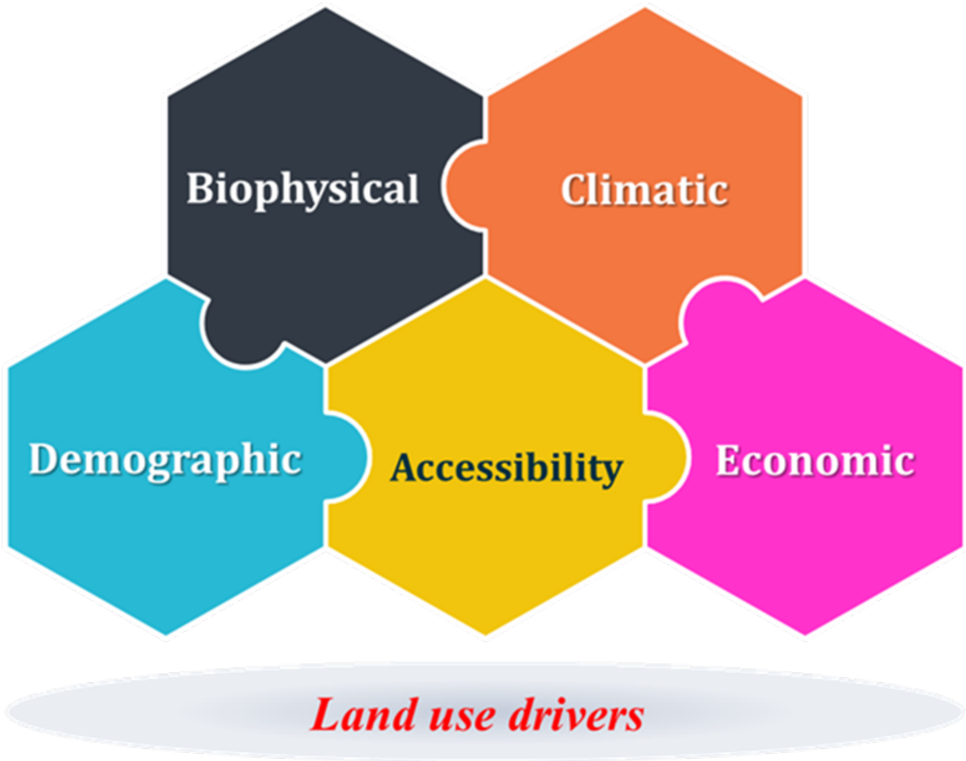


Figure 7 selected factors for estimating the drivers of land use change.

Table 4 parameters for examining the drivers of land use change

Groups	Factors
Demographic factors	Population density
	Internal migration
Economic factors	Gross Domestic Product (GDP)
	Poverty Ratio
Biophysical factors	Temperature
	Precipitation
	Elevation
	Soil Quality
	Slope
	Soil type
Accessibility factors	Distance to water
	Distance to Road
	Distance to Railway

3.2.2 Flood risk assessment

The flood risk assessment database is developed by

- Collection of required data (Flood incidents report data)
- Construction of the Grid Unit model in QGIS to develop the Flood geospatial database.
- Flood susceptibility assessment using machine learning models in R studio software.

Building the database required collecting Seven hundred sixty-five (765) flood incidents reports for Nigeria between 1985 and 2020 from the Emergency Events Database (EM-DAT) and Dartmouth Flood Observatory (DFO) websites to build a comprehensive geodatabase for flooding in Nigeria. After collecting all the required data, the QGIS software helped construct the geospatial database. In constructing the geospatial database for flood risk assessment, six (6) phases were involved. These steps are highlighted below (Figure 8).

(a) Extraction of the study area using the compiled flood inventory and elevation data.
(b) Extracting the slope values for the actual flood inventory: The study area elevation and flood inventory are applied to calculate the slope values.

(c) Extraction of flood-free inventory: Utilising the slope and its values and the areas without flood incidents are extracted.

(d) Extract training and testing samples: The training and testing samples extraction is done using the model builder in QGIS, dividing the data samples into training (70 per cent) and testing (30 per cent) datasets, using the flood-free points information, slope values and inventory data as shown below. Where 1 represents presence and 0 represents an absence of flooding.

(e) Extract conditioning factors values: After splitting the flood inventory samples into two sets for training and testing (including presence and absence), the next step is to extract the flood conditioning values using the model builder.

The model process for developing the geospatial flood database is shown below (Figure 8).

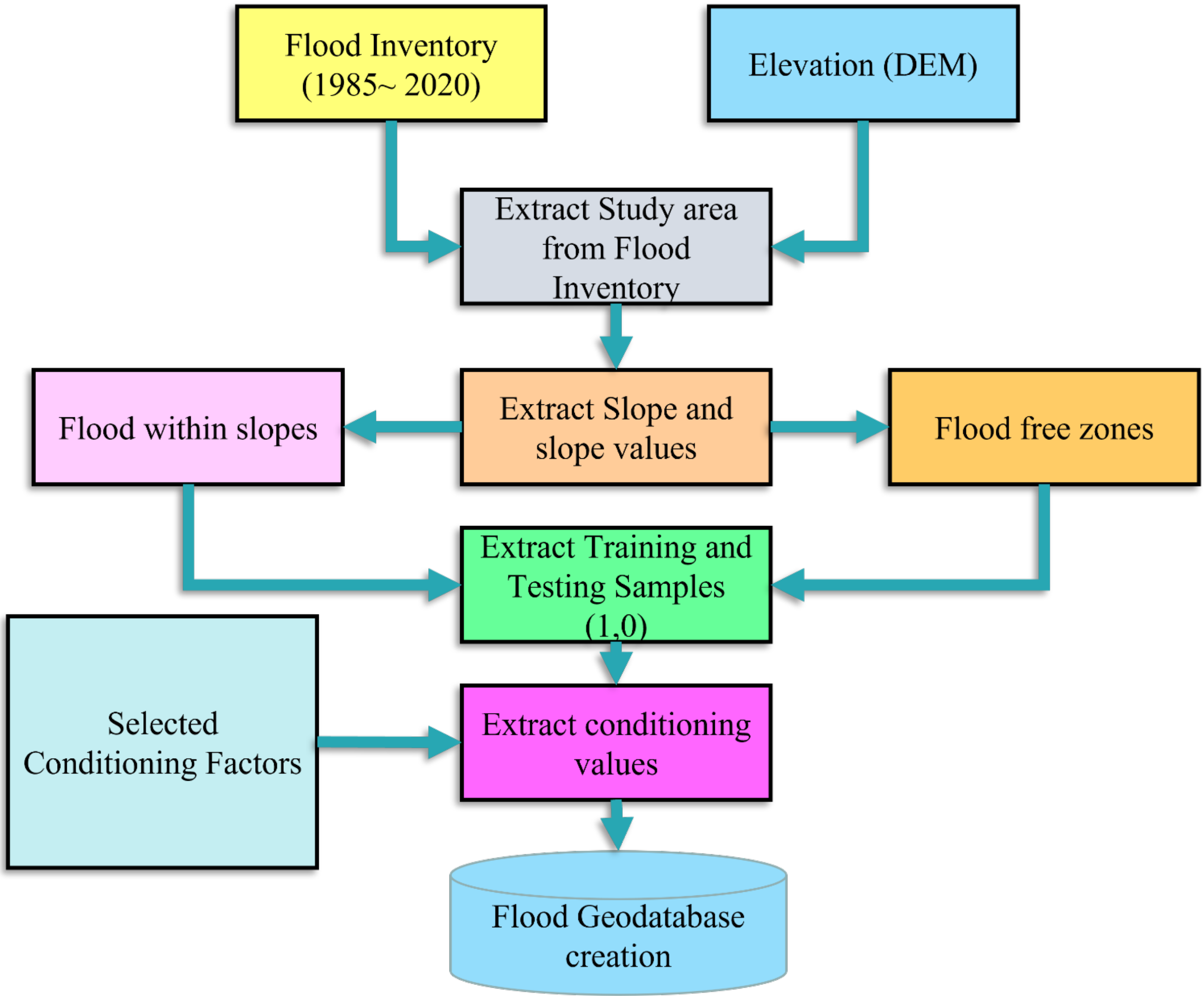


Figure 8 Flowchart for creating a geospatial flood database

3.2.3 Estimating the population exposed to flood hazards

This step integrates the population density map with the hazard areas maps to estimate the population exposed to flood risk and then reassigns the values to each administrative district to derive the final result. The method of estimation using the QGIS software is outlined below.

(a) Creating the flood intensity levels based on the flood hazard map

The flood risk raster data is reclassified from 5 to 2 classes (low and high risk) to simplify the analytical results. The UNEP-GRID file and the simulated flood risk maps in their original state contain five levels of risk intensity, from a minimum value (1) to the maximum (5). The simplified two classes for this study are Low (1, 2) and High (3,4,5).

(b) Applying the QGIS function to reclassify the flood risk map

Part 1: QGIS processing Toolbox →SAGA→Raster calculus→Raster calculator

- Main input layer: Flood_risk.tif (The flood risk map)
- Formula: ifelse(lt(a,3),1,0) (using raster calculator function, where lt = less than the specified value)
- Rasterised: Flood_risk_Levels_1_2.tif

Part 2: QGIS processing Toolbox →SAGA→Raster calculus→Raster calculator

- Main input layer: Flood_risk.tif
- Formula: ifelse(gt(a,3),1,0) (where gt = less than the specified value)
- Rasterised: Flood_risk_Levels_3_4_5.tif

(c) Estimating the population distribution risk areas

Part 1: QGIS processing Toolbox →SAGA→Raster calculus→Raster calculator

- Low risk (1_2) / High risk (3_4_5)
- Main input layer: Population density (2000~2020)
- Additional layer : raster (Flood_risk_Levels_1_2 / Flood_risk_Levels_3_4_5)
- Formula: a*b
- Calculated result: Population in flood low_risk (year).tif / Population in flood high_risk (year).tif

(d) Extraction of statistics per administrative district

Following the extraction of the population (2000~2020) exposed to flood risk per level, the next step involves the production of the exposed values per administrative district. Finally, an aggregated sum of each pixel value is assigned to each region.

- QGIS processing Toolbox →SAGA→ Vector−Raster→Raster statistics for polygons

Chapter 4 Evaluation of natural and socio-economic factors of land use change and flood risk

4.1 An overview of the drivers of land use change

Many factors operating at various spatial and temporal scales and acting in different time-specific interactions can affect land use change. Many theories can describe the changes in land use through natural, social and interdisciplinary scientific research. However, changes in land utilisation begin at the micro-level when land users believe that a shift to a new land use type is appropriate, usually prompted by increased demand for goods, services and other factors acting independently. Depending on the source, the elements driving land use and land cover change can be biophysical or socio-economic, intricately linked and interdependent. For example, changes in weather patterns can impact the climate on a regional and global scale. In the same way, soil and ecosystem changes can determine the quality of soils and the ecosystem of a given place.

Aside from the biophysical factors influencing large-scale changes, decisions by individuals on land management practices from an environmental or socio-economic standpoint can considerably impact land use change (Figure 9). Some of these drivers could be population changes, technological advancement, cultural practices, and climatic and economic changes.

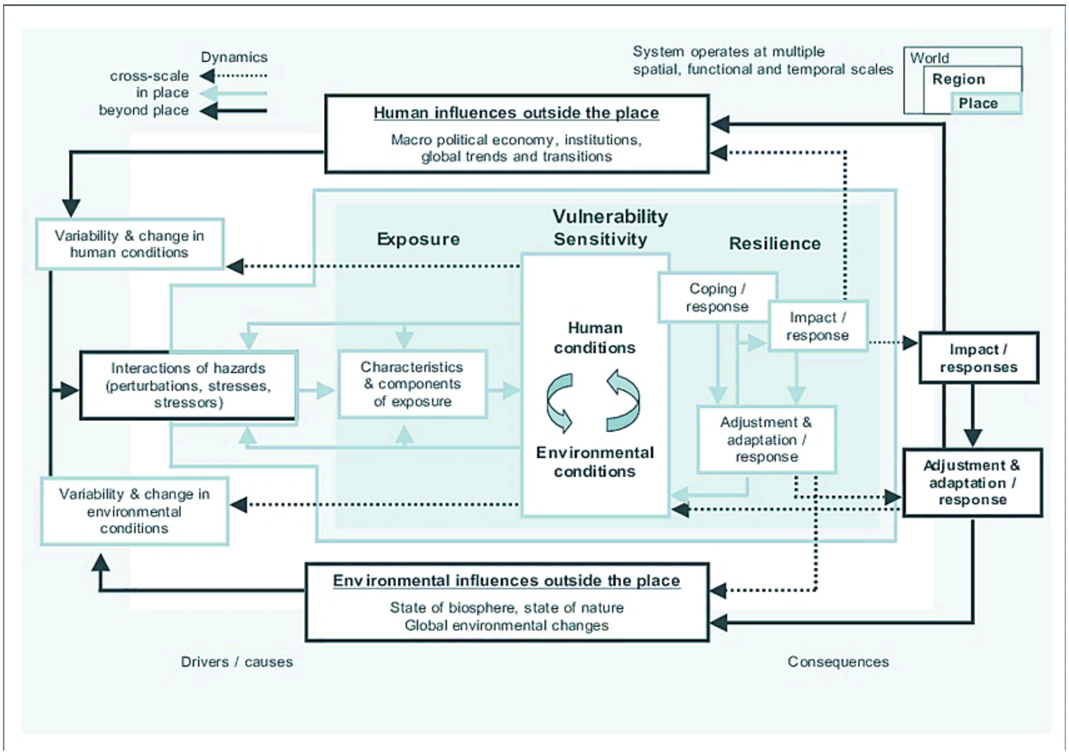


Figure 9 Deciding factors of land use change and the socio-ecological vulnerability (Turner et al., 2003).

4.2 Selection of the factors influencing land use change

Land use choice, irrespective of ownership, may be influenced by its current use and geographic location. In addition, several elements can impact land-use change based on the interactions between the immediate environments. For example, population growth changes and industries' demand for agricultural land to produce goods and services may impact the rate of expansion of farmlands solely to meet existing demand. Furthermore, one of the deciding factors in land use change depends on the biophysical environment since it can measure the suitability for the proposed range of use. For example, climatic conditions, topography, soil type and water resources may be favourable to a particular land use type and unfavourable to another. Another factor influencing land use change is accessibility elements such as access to road networks and other transportation infrastructure (airports, railway stations and seaports) and the suppliers of necessary inputs such as labour (skill migrants) and capital. For example, when considering settlement land expansion, areas with higher economic growth tend to be more attractive for development due to increased demand and available capital needed for expansion.

Similarly, many interconnected demographic, economic, socio-cultural, and technological factors influence land use decisions about continuing with their current state or requiring change. Some of the selected factors influencing land use change are highlighted in the following subsections.

4.2.1 Demographic factors.

The demographic factors selected include population density (age, gender and household size) and migration (immigration and emigration). As a general rule, the distribution of demographic characteristics influences the level of resistance to change. For example, if the distribution within a population group consists of older generations (above 65 years), there is a higher likelihood of resistance to change concerning existing practices than their younger counterparts. Similarly, regarding gender disparities, the attitudes on the life of single heads of families are vastly different from those of married couples with a significant number of children in their households.

These factors combined have diverse implications on land use change, as demographic characteristics influence the perceptions to change and the adoption of new technological or otherwise approaches. In this study, migration rate and population density are selected as the demographic drivers of land use change as they encompass all the requirements needed to address the influence of demography on land use change.

4.2.2 Economic factors

Economic concerns are also significant land-use elements to consider, as demonstrated by von Thunen's "land rent theory". The demand for goods and services can be linked with a specific land use category. To a certain extent, the variations in demands are responsible for the shifts in land use since they impact revenues linked with that piece of land. For example, if agriculture production is very lucrative, the tendency for agricultural expansion may increase. Similarly, if the economic situation is sluggish, residents in an area may be prompted to depend on agricultural production to meet their needs leading to agricultural land expansion or a booming economy promoting infrastructure development, thereby expanding settlement areas. For example, an economic boom would likely trigger industry and infrastructure development, while an economic slump may increase poverty, and natural production processes may become more agrarian. For Nigeria, incentives around agriculture production are high, especially for export and industrial processes. Therefore, landowners who engage in large-scale agricultural production would probably expand agriculture production due to the benefits derived and cheap labour. The study's selected economic factors are the poverty ratio and the gross domestic product (GDP).

4.2.3 Technological and accessibility factors

Briassoulis (2011) showed that the number of new technologies and how easily they can be used on land significantly affect the economy's productive labour and capital. For example, in hilly terrains where automating processes is complicated, the amount of land use modifications that may occur is limited. Similarly, if the distance between the land process and the raw materials or consumer markets is relatively large, the attraction to the specified land parcel may be significantly diminished. For instance, land developments that are easily accessible would attract more patronage than their more distant counterparts. The same theory can be applied to the existence of advanced technological elements. For land users, if an access road, railway and water network that promotes easy distribution of goods and services from one place to the other exists, such land parcels are more likely to be lucrative than non-accessible parcels.

4.2.4 Biophysical factors

A variety of biophysical factors influence land use and cover change. Climate, soil, topography, and other natural environmental features are the biophysical factors influencing land use. The changes in the biophysical environment due to climatic or manufactured actions can lead to environmental degradation, which may directly or indirectly affect land use change. Generally, the existing land cover and the biophysical environment are interlinked, and a unit change in one can potentially trigger the other change. For example, for agriculture to thrive, it requires a favourable biophysical environment to produce the highest possible yields, which are essential for ensuring food security and improving lives. Available arable land, fertile soils, sufficient water, favourable climatic conditions, and a diverse range of flora and fauna are all characteristics of a productive biophysical environment. Therefore, it is vital to investigate how the biophysical environment impacts land use change. The biophysical factors selected in the study are temperature, precipitation, soil type, slope and soil quality.

4.3 Modelling land use changes drivers

The multinomial logistic regression model helped investigate the drivers of land use change. The multinomial logistic model is an extended version of the binomial logistic regression (Figure 10). Using the multinomial logistic regression model, one can take advantage of multiple categories as dependent variables, reflecting various patterns, and the independent variables as determinant factors (Lesschen et al.,2005).

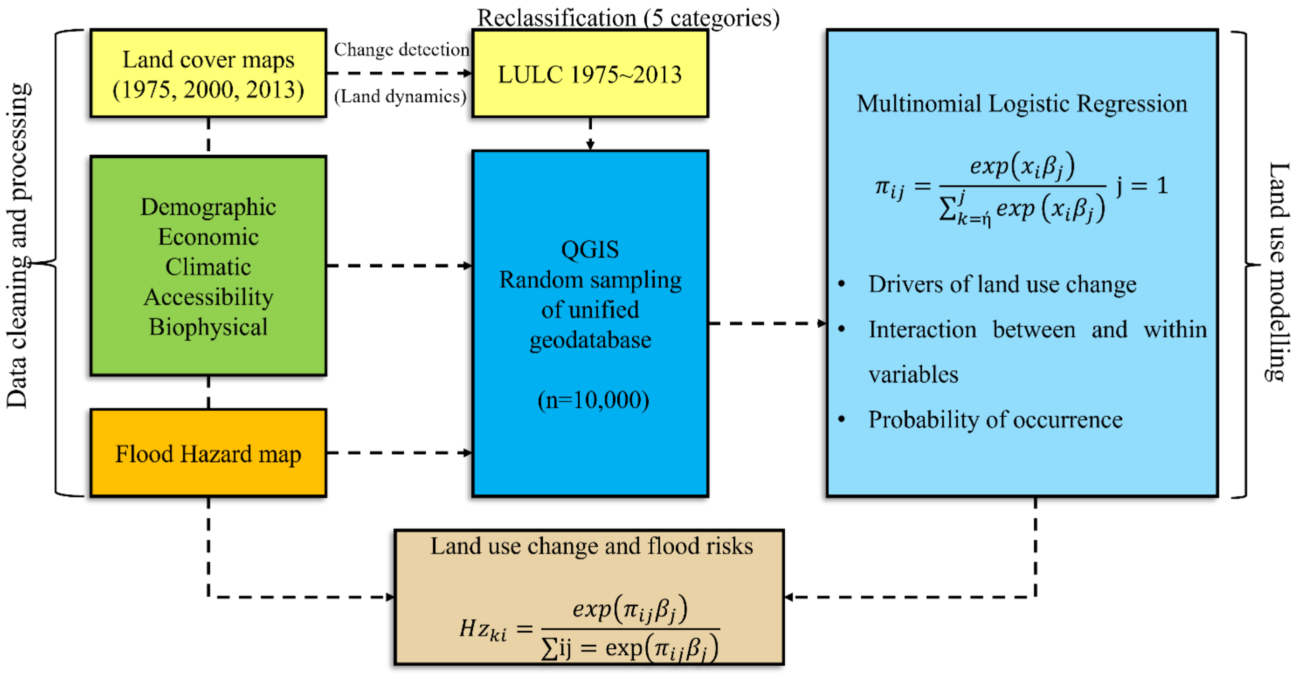


Figure 10 Flowchart for assessing the drivers of land use change

This research's multinomial logistic regression model choice is based on the need to identify patterns and factors responsible for each land use change based on the interactions between the selected factors mentioned in section 4.2. The land use probability (πij) is;

$$\pi_{ij} = \frac{exp(x_i\beta_j)}{\sum_{k=ή}^{j} exp\,(x_i\beta_j)} \; \mathrm{j} = 1, \dots \dots \mathrm{J} \qquad (2)$$

where i represents the index of the location;

J is the total number of land use types;

π_{ij} denotes the probability of j at i ;

β is the vector of parameters;

x the vector of variables;

j the land use type;

k the index of the hazard risk level and;

ή the risk level.

The statistical significance of each variable was verified using the p-value reported in the output result tables.

4.4 Estimation of the effects on flood hazard risk levels by LULC and land use drivers

The flood risk data (Figure 11) were reclassified into three main groups: low, medium, and high, to assess the impacts of land use on flooding risks at different levels. A multinomial model was used to quantify the link and impact of land use probability on flood risk levels. This model included the previous land use model results and the reclassified flood risk map (Figure 19). Three land use categories (agricultural, settlement and forest) experiencing the most variations over the years were utilised as the predictors for assessing the impacts on flood risk levels. The dependent variables were the flood risk levels calculated as the probability of change from equation (2).

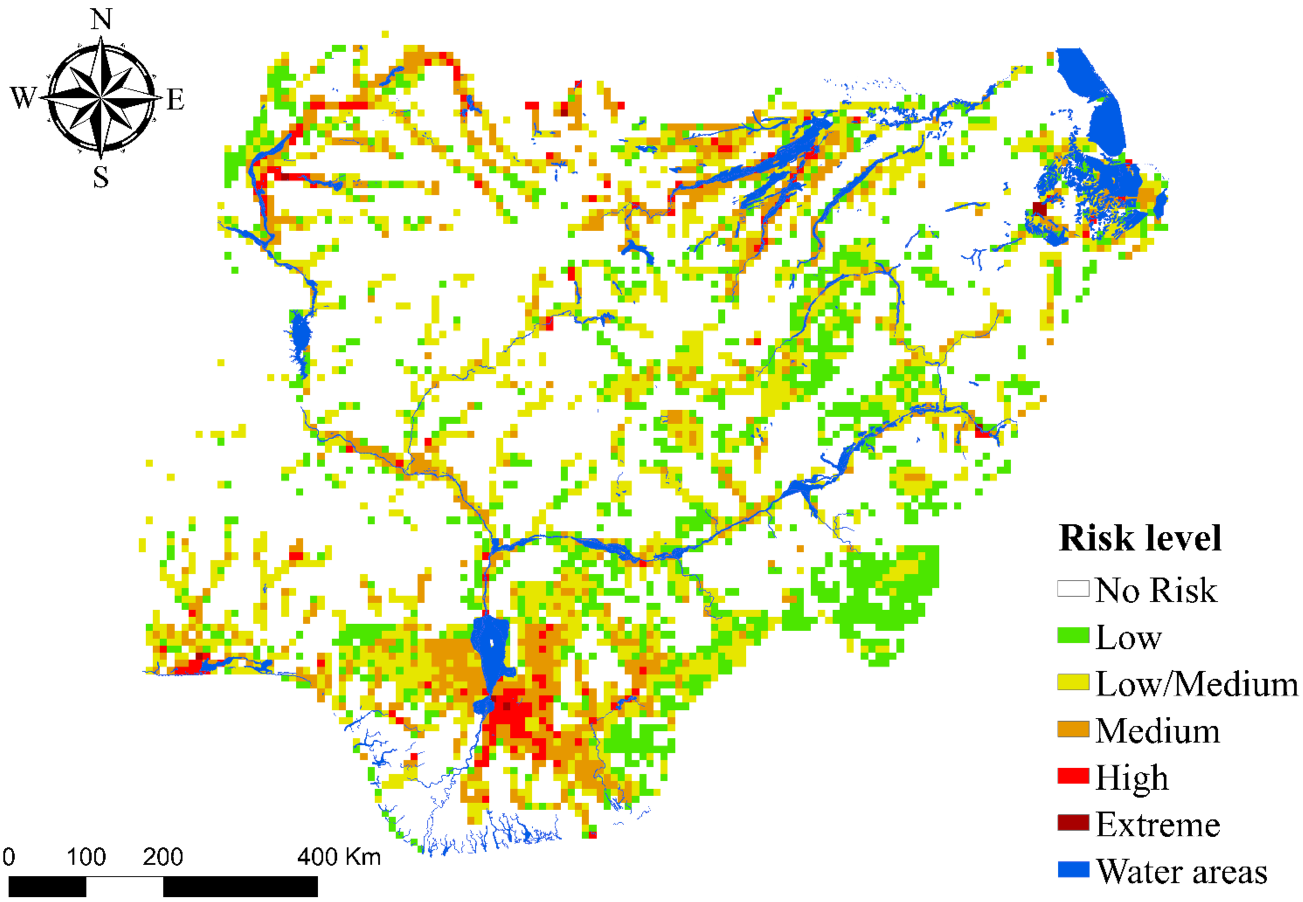


Figure 11 Estimated global risk index for Nigeria (Source: UNEP,2011)

The objective is to estimate the probability of change in the individual LULC on the likelihood of a disaster. The resulting outcome would enable city planners to simulate and build a scenario of land alteration and examine the potential consequences of hazard risks. The multinomial logistic regression model for the land use effect analysis is;

$$Hz_{ki} = \frac{exp(\pi_{ij}\beta_j)}{\sum ij = \exp(\pi_{ij}\beta_j)} \tag{3}$$

The changes in the LUCC classes (agriculture, settlements, and forest) were used to calculate the probability of displacement, and the responses were the existing risk levels (low, medium, and high) to calculate Hz_{ki}: the probability of displacement in each class.

For the logistic model analysis, 10000 randomly generated points within the Nigeria administrative boundary map. Each point represents a sample of the independent and dependent variables. All computations are performed in the R environment. The data used in the analysis are in Table 5.

Table 5 Source of data used in the analysis

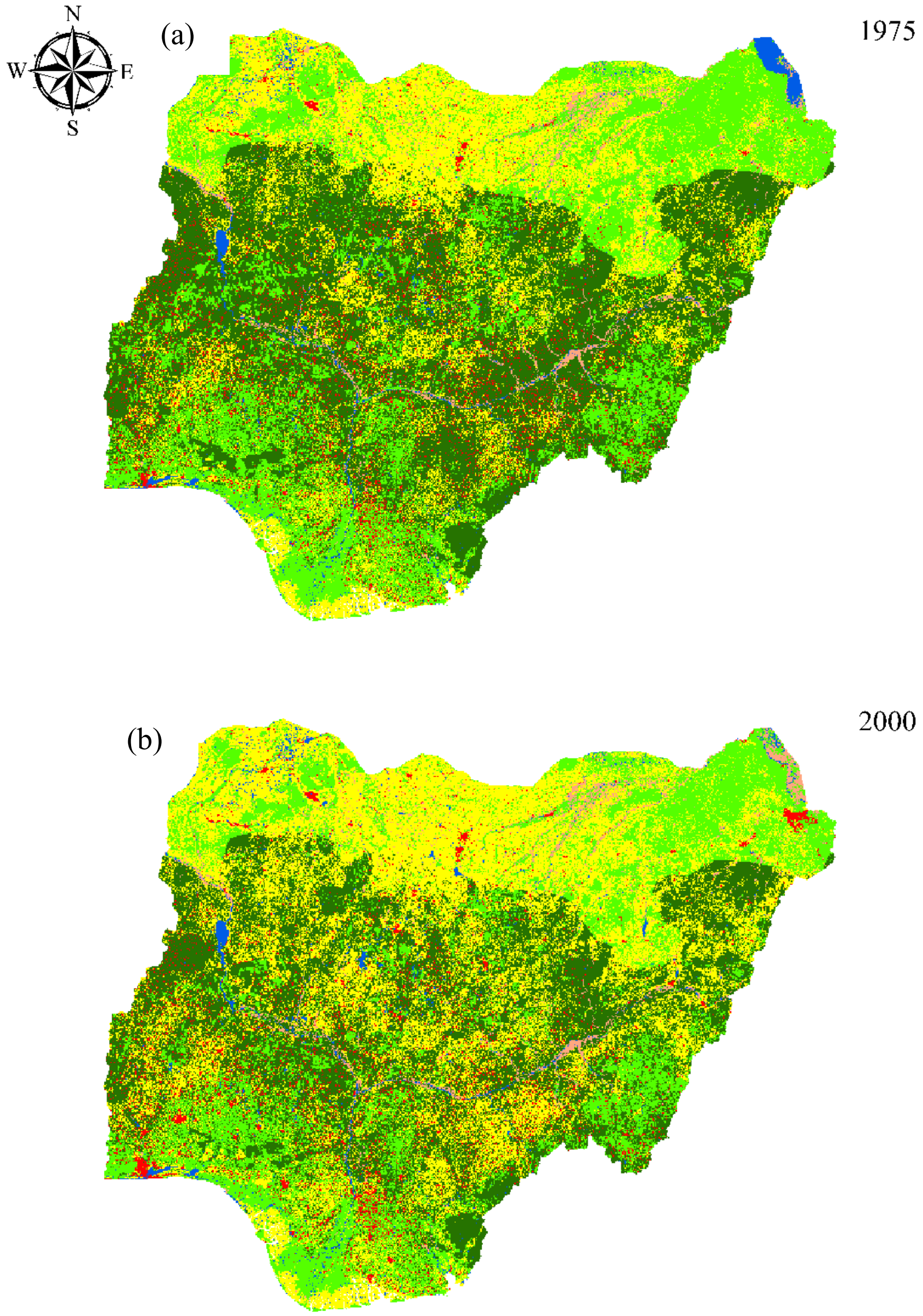
Data	Source	Resolution	Period
Administrative maps	GADM	Vector	-
Land cover	United States Geological Survey (USGS)	1-km	1975; 2000; 2013
Soil information	The Harmonised World Soil Database v1.2	1-km	2009
Elevation	USGS, Earthexplorer	30-m	-
Poverty ratio at $2/day	NASA, Socioeconomic Data and Applications Center (SEDAC)	1-km	2005; 2010
Gross Domestic Product	NASA, Socioeconomic Data and Applications Center (SEDAC)	1-km	2005; 2010
Internal Migration	WorldPop	1-km	2005; 2010
Population density	WorldPop	1-km	2000~2020
Railway network	The United Nations Office for the Coordination of Humanitarian Affairs (OCHA), Nigeria	vector	-
Road network	NASA, Socioeconomic Data and Applications Center; Global Roads Open Access Dataset v1	vector	-
Water network	The United Nations Office for the Coordination of Humanitarian Affairs (OCHA), Nigeria	vector	-

4.5 Results of land use change analysis

4.5.1 Spatio-temporal variation of land use change

Figure 12 and Tables 6 and 7 depict the trends in land use change over the last 38 years (1975 ~2013) in Nigeria. Agricultural land, which constitutes the majority of the land use class and includes plantations, cropland, and irrigated agriculture, has increased by 218,319 km2 in the last 38 years, representing a significant increase from the previous 38 years (20.74 per cent). The forest area, which includes evergreen forest, woodland, mangroves, swamp forest, and degraded forests, has decreased by 149,463 km2, a significant decrease from the previous year (14.20 per cent). The area covered by shrubs decreased from 24,306 km2 (2.31 per cent) in 1975 to 23,018 km2 (2.19 per cent) in 2013, implying a decrease of 0.12 per cent, while the miscellaneous area, which is primarily comprised of grassland and other land areas, decreased by 6.98 per cent. Conversely, settlement land increased from 45,352 km2

(4.31 per cent) to 51,364 km2 (4.88 per cent) between 1975 and 2013. The water area, which includes the Niger and Benue rivers and their tributaries, decreased by less than 0.0001 per cent from 14,975 km2 in 1975 to 14,925 km2 in 2013 (Table 7).



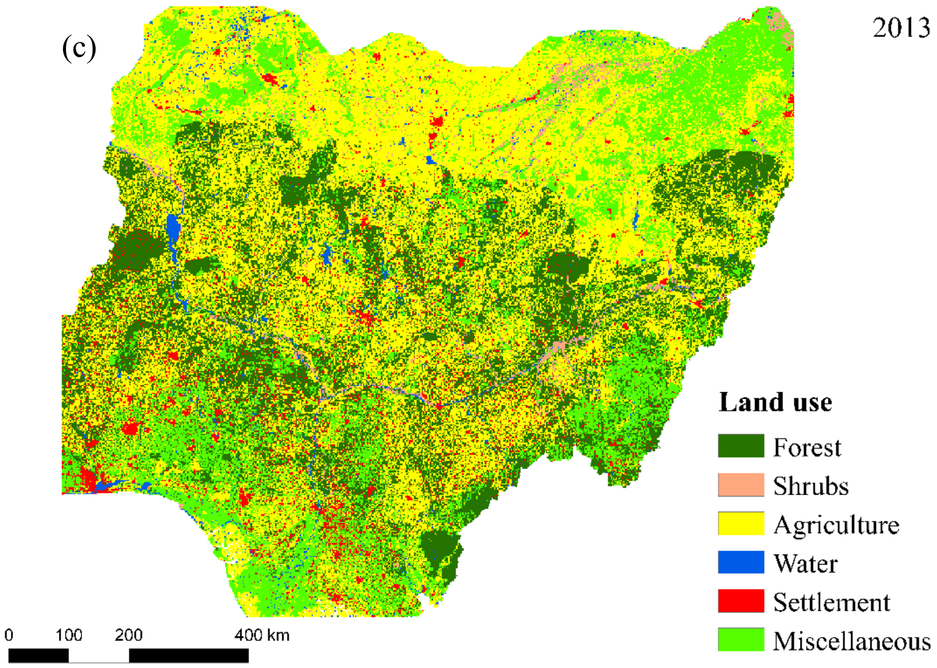


Figure 12 Land use maps of Nigeria (a) 1975; (b) 2000; (c) 2013.

Forest, agriculture, settlement, and miscellaneous land are among the dominant land cover types in Nigeria, accounting for 39.75 per cent, 24.94 per cent, 4.31 per cent, and 27.27 per cent of the total land area in 1975, according to statistics on the main types of land use change in the area ratio (Table 6). However, between 1975 and 2013, forest, agriculture, settlement, and miscellaneous land saw significant increases, rising to 25.56 per cent, 45.68 per cent, 4.88 per cent, and 20.28 per cent, respectively, from their previous levels (Table 6). Similarly, forest area has experienced the most significant reduction, with a decrease from 39.75 per cent to 25.56 per cent, implying a decrease of 14.20 per cent within 38 years (Tables 5 and 6). Likewise, the proportion of miscellaneous land in the grassland area decreased from 27.27 per cent to 20.26 per cent over 38 years, indicating a downward trend. On the other hand, agriculture and settlement areas both showed an increasing trend of 20.74 per cent and 0.57 per cent, respectively (Table 7).

Table 6 Land use dynamics in Nigeria between 1975 and 2013.

Land use type	**Year**					
	1975		2000		2013	
	Area (km2)	Area ratio %	Area (km2)	Area ratio %	Area (km2)	Area ratio %
Forest	418,557	39.75	345,061	32.77	269,094	25.56
Shrubs	24,306	2.31	23,532	2.24	23,018	2.19
Agriculture	262,606	24.94	385,002	36.57	480,925	45.68
Water Bodies	14,975	1.42	14,995	1.42	14,925	1.42
Settlement	45,352	4.31	46,622	4.43	51,364	4.88
Miscellaneous	287,097	27.27	237,681	22.57	213,567	20.28
Total	1,052,893	100	1,052,893	100	1,052,893	100

Table 7 Rate of change in land cover in Nigeria between 1975 and 2013.

Land use type	Land Use/Cover Change					
	1975 – 2000		2000 – 2013		1975 – 2013	
	Area (km2)	Area ratio %	Area (km2)	Area ratio %	Area (km2)	Area ratio %
Forest	–73,496	–6.98	–75,967	–7.22	–149,463	–14.20
Shrubs	–774	–0.07	–514	–0.05	–1,288	–0.12
Agriculture	122,396	11.62	95,923	9.11	218,319	20.74
Water Bodies	20	0.00	–70	0.00	-50	0.00
Settlement	1,270	0.12	4,742	0.45	6,012	0.57
Miscellaneous	–49,416	–4.69	–24,114	–2.29	–73,530	–6.98

4.6 The land use transition matrix from 1975 to 2013

The R software in this study estimated the transition matrix for land use change between 1975 and 2013 (Tables 8 and 9). Over the last thirty-eight years, there has been a dramatic increase in agricultural land use at the expense of forest, miscellaneous, and other land use types.

Between 1975 and 2000, agricultural land increased by 122,396 km2, with forest land accounting for 23.25 per cent of the total. Miscellaneous land accounted for 10.51 per cent, and shrubland accounted for 0.35 per cent. Similarly, between 2000 and 2013, agricultural land increased by 95,923 km2, with forest land accounting for 16.27 per cent of the total, miscellaneous land accounting for 5.01 per cent, and shrubland accounting for 0.26 per cent. According to the observed changes, agricultural land experienced the most significant growth between 1975 and 2013 due to the conversion of forest, miscellaneous, and shrubland to agricultural land.

A steady increase in settlement land was observed at the expense of other land uses and cover types. For example, between 1975 and 2000, settlement areas increased by 1,270 km2, with 4.48 per cent, 3.29 per cent, and 4.80 per cent of the total area being converted from forestry, agricultural, and miscellaneous land. Similarly, between 2000 and 2013, settlement increased by 4,742 km2, with forest, agriculture, and miscellaneous sectors accounting for 4.98 per cent, 6.12 per cent, and 4.34 per cent of the total increase in settlement, respectively.

Furthermore, forest, shrub, miscellaneous, and water areas have shown a downward trend over the last 38 years. It was estimated that forest cover decreased by 73,496 km2 between 1975 and 2000, with 2.10 per cent of that area being converted to agriculture, 0.59 per cent to settlement, and 5.01 per cent to miscellaneous. As a continuation of the previous years, the period between 2000 and 2013 showed similar trends in land use change, with forest land, in particular, declining by 75,967 km2, with 1.76 per cent allocated to agriculture, 0.36 per cent to settlement, and 3.23 per cent to miscellaneous land, respectively. It is evident from the findings (Tables 8 and 9) that there are significant alternations in land cover between forest and miscellaneous vegetation and agriculture and settlement land, with forest and miscellaneous vegetation being the primary land use categories changing quickly to agriculture land.

Finally, land use changes in Nigeria can be divided into four major categories: agricultural land expansion (from the forest, shrubs, and miscellaneous); deforestation (conversion of forest to agriculture, miscellaneous, and settlement land); settlement expansion (from the forest, agriculture, and miscellaneous land); and miscellaneous conversion (which involves the conversion of miscellaneous to other land use types such as agriculture, miscellaneous, and settlement land).

Table 8 Transition matrix of land use in Nigeria from 1975 to 2000 (km2).

Land use type	Forest	Shrubs	Agriculture	Water	Settlement	Others
Forest	317,645	606	89,495	668	2,087	8,056
Shrubs	443	20,603	1,357	940	165	798
Agriculture	7,553	302	252,180	533	1,532	506
Water	91	1,178	43	12,364	6	1,293
Settlement	2,032	269	1,454	118	40,592	887
Miscellaneous	17,297	574	40,473	372	2,240	226,141

Table 9 Transition matrix of land use in Nigeria from 2000 to 2013 (km2).

Land use type	Forest	Shrubs	Agriculture	Water	Settlement	Others
Forest	254,366	730	78,259	152	2,559	8,995
Shrubs	250	20,655	1,249	351	107	920
Agriculture	4,748	336	375,624	86	3,143	1,065
Water	68	403	52	14,165	9	298
Settlement	982	82	1,647	58	43,317	536
Miscellaneous	8,680	812	24,094	113	2,229	201,753

4.7 The Land Use Dynamics from 1975 to 2013

From 1975 to 2013, agricultural land increased significantly over 38 years. Moreover, between 2000 and 2013, forest land continued to decline rapidly, with an additional decrease of approximately 0.24 per cent. During the period 2000 to 2013, the rate of change in settlement land area increased consistently, with the highest rate of change occurring between 2000 and 2013 at 0.45 per cent. The change in miscellaneous land area was gradual, first increasing slightly and then decreasing dramatically. The shrub area has only slightly decreased within the two periods and remained relatively stable. However, miscellaneous land dramatically decreased between 1975 and 2000, but the rate of decline slowed between 2000 and 2013, and water areas decreased gradually between 2000 and 2013 (Table 10).

Table 10 Land use dynamics from 1975 to 2013 in Nigeria.

Land use type	Rate of Change from 1975 to 2000 (%)	Rate of Change from 2000 to 2013 (%)	Rate of Change from 1975 to 2013 (%)
Forest	-6.98	-7.22	-14.20
Shrubs	-0.07	-0.05	-0.12
Agriculture	11.63	9.11	20.74
Water	0.00	-0.01	-0.01
Settlement	0.12	0.45	0.57
Miscellaneous	-4.69	-2.29	-6.98

4.8 Land use correlation analysis

In this study, we conducted a correlation analysis to understand better the independent variables used during the modelling. Before beginning any modelling exercise, it is common practice to conduct a correlation study to gain insight into the presence of multicollinearity between the independent variables. For example, suppose there is a strong correlation between two factors; the ideal step to deal with such a phenomenon is to delete one of the items from the dataset and begin the investigation. The correlation result (Table 11) shows that the variable with the highest correlation is population and GDP (0.48). However, all other variables did not have a strong correlation and were suitable for analysing the drivers of land use change.

Table 11. Pearson's correlation coefficients result for the selected land use driving factors

	Temperature	Soil Type	Slope	Soil Quality	Distance to Railway	GDP	Elevation	Poverty Ratio
Temperature	1							
Soil Type	-0.05	1						
Slope	0.02	0.02	1					
Soil Quality	-0.01	-0.03	0.00	1				
Distance to Railway	0.08	-0.01	-0.05	-0.04	1			

GDP	0.01	-0.01	0.00	0.00	-0.05	1		
Elevation	0.11	-0.11	-0.04	0.01	-0.10	-0.02	1	
Poverty Ratio	0.61	0.01	0.02	-0.01	0.15	-0.21	0.22	1
Risk Level	0.01	-0.01	-0.01	0.01	-0.03	-0.02	-0.10	0.01
Precipitation	-0.64	-0.01	-0.02	0.01	-0.06	0.05	-0.49	-0.80
Distance to Water	0.20	0.03	0.01	0.02	-0.01	-0.01	-0.12	0.12
Distance to Road	-0.24	0.12	-0.04	0.01	0.16	-0.06	-0.06	-0.02
Land use	0.28	-0.07	0.00	0.00	-0.10	0.12	-0.01	0.07
Population	-0.01	-0.05	0.00	0.00	-0.13	0.48	-0.03	-0.32
Migration	-0.51	-0.01	0.01	0.00	-0.34	0.11	-0.17	-0.64

	Risk Level	Precipitation	Distance to Water	Distance to Road	Land use	Population	Migration
Temperature	0.01	-0.640	0.20	-0.240	0.28	-0.01	-0.51
Soil Type	-0.01	-0.01	0.03	0.12	-0.07	-0.05	-0.01
Slope	-0.01	-0.02	0.01	-0.04	0.00	0.00	0.01
Soil Quality	0.01	0.01	0.02	0.01	0.00	0.00	0.00
Distance to Railway	-0.03	-0.06	-0.01	0.16	-0.100	-0.13	-0.34
GDP	-0.02	0.05	-0.01	-0.06	0.12	0.48	0.11

Elevation	-0.10	-0.49	-0.12	-0.06	-0.01	-0.03	-0.17
Poverty Ratio	0.01	-0.80	0.12	-0.02	0.07	-0.32	-0.64
Risk Level	1	0.06	0.01	-0.08	0.01	-0.01	0.04
Precipitation		1	-0.02	0.19	-0.16	0.12	0.55
Distance to Water			1	0.00	0.06	-0.02	-0.24
Distance to Road				1	-0.25	-0.11	0.10
Land use					1	0.17	-0.02
Population						1	0.21
Migration							1

4.9 Drivers of land use change

4.9.1 Agricultural Land Use

Table 12 shows the results of the drivers of agricultural land use change. Again, the statistical significance for the model is set at 5% (p<0.05). From the analysis, the significant indicators of agriculture land use change are population density, elevation, GDP, distance to railway and water, temperature, internal migration, precipitation, poverty ratio, and soil type. However, the distance to water and soil quality did not impact agricultural land use change.

For agricultural land conversion, the most critical drivers are elevation, precipitation, and soil type (N1, N6 and N7), respectively. However, the variation in flood risk levels (low and medium), soil quality and the distance to water have no significance on the probability of agricultural land use conversion.

Table 12. The Multinomial probability of Agricultural land (n=10000)

Variables		Estimate	Standard Error	Z Value	Significant Probability (pr>[z])
Population density		0.00	0.00	4.41	0.00 ***
Elevation		0.00	0.00	−4.31	0.00 ***
Gross Regional Product		0.00	0.00	2.71	0.01 **
Railway		0.00	0.00	−2.81	0.00 **
Temperature		0.10	0.01	12.40	0.00 ***
Road		0.00	0.00	−10.30	0.00 ***
Migration		0.00	0.00	5.79	0.00 ***
Precipitation		0.00	0.00	4.61	0.00 ***
Poverty		6.67	0.92	7.24	0.00 ***
Water		0.00	0.00	−0.16	0.87
Soil quality		0.01	0.01	0.37	0.71
Soil type	N1(1 if yes, other	3.26	0.72	4.54	0.00 ***
	N2(1 if yes,	17.60	447	-	-
	N3(1 if yes,	−1.25	0.62	−2.00	0.05 *
	N4(1 if yes,	−0.31	0.10	−3.13	0.00 **
	N5(1 if yes,	0.26	0.08	3.13	0.00 **
	N6(1 if yes,	−0.36	0.10	−3.48	0.00 ***
	N7(1 if yes,	−0.63	0.11	−5.56	0.00 ***
Low risk		−0.20	0.42	−0.48	0.63
Medium risk		−0.17	0.42	−0.40	0.69

Significant. codes: *p*< '***' 0.001 '**' 0.01 '*' 0.05 '.'

The results (Table 12) show that agricultural land use change drivers originate from various sources, such as demographic, economic, biophysical, technological, and accessibility indicators.

4.9.2 Settlement land use

The findings (Table 13) indicate that 9 of the 13 selected indicators significantly impact settlement land conversion. The modelling results' significant drivers of settlement land use change are population density, Gross Domestic Product (GDP), temperature, internal migration, distance to water bodies, distances to road and water networks, soil type (N1) and medium-risk areas. On the other hand, elevation, distance to the railway, precipitation, soil quality, other soil types and low-risk areas have no significance in converting settlement land. From the results, the most significant drivers of settlement land area are population density, GDP, temperature, Road distance, migration, poverty ratio, and soil type (N1). It can be observed that demographic and economic variables are the main drivers of settlement land use change.

Table 13 The Multinomial probability of Settlement land (n=10000)

Variables		Estimate	Standard Error	Z Value	Significant Probability (pr>[z])
Population density		0.00	0.00	5.99	0.00 ***
Elevation		0.00	0.00	1.82	0.07 .
Gross Regional Product		0.00	0.00	4.45	0.00 ***
Railway		0.00	0.00	−0.91	0.36
Temperature		0.17	0.02	7.18	0.00 ***
Road		0.00	0.00	−3.72	0.00 ***
Migration		0.00	0.00	5.79	0.00 ***
Precipitation		0.00	0.00	−1.73	0.08 .
Poverty		−17.23	2.36	−7.29	0.00 ***
Water		0.00	0.00	0.18	0.86
Soil quality		0.03	0.34	-	-
Soil type	N1(1 if yes, other	3.27	0.97	3.38	0.00 ***
	N2(1 if yes,	17.50	447	0.04	0.97
	N3(1 if yes,	−1.37	1.15	−1.19	0.23
	N4(1 if yes,	−1.29	0.73	−1.76	0.08 .
	N5(1 if yes,	0.49	0.26	1.91	0.06 .
	N6(1 if yes,	−1.86	1.02	−1.82	0.07 .
	N7(1 if yes,	−0.26	0.40	−0.66	0.51
Low risk		−0.95	0.54	−1.76	0.08 .
Medium risk		−1.10	0.55	−1.99	0.05 *

Significant. codes: *p*< ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’

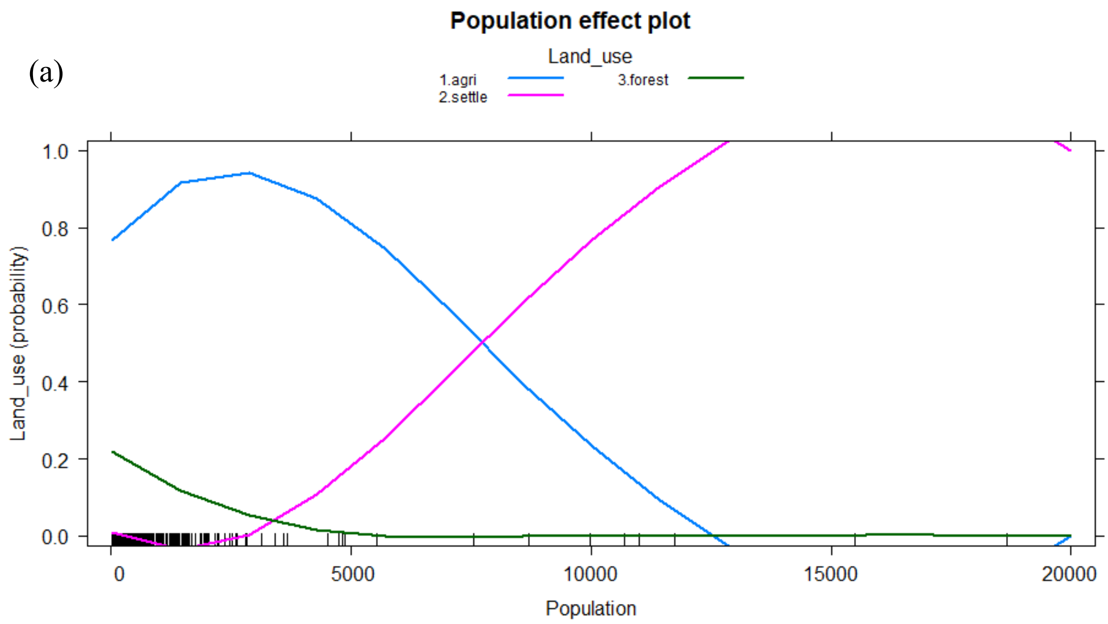
4.10 Effects of selected drivers and land use change

Figures 13 ~ 17 explain how the selected drivers affect land use change. It can be observed from the graphical representation of the relationship between each driver and its significance on the individual land use change. They highlight how a unit change in a variable, while others remain constant, affects the outcome of land use change. In order to fully comprehend the probabilistic impact of each variable on the land use model, we used the results of the multinomial logistic model (Tables 10 and 11), in which the derived probabilities of each variable in Figures 13 ~ 17 (axis x) combined against the probability of the dependent variable were compared to the probability of the dependent variable (axis y). More details are explained in the subsections that follow.

4.10.1 Demographic drivers

The demographic drivers' population density and migration rates have varied influences on each land use class. For example, population density (Figure 13a) highlights how the increase in population size around a particular location triggers the probability of expansion of settlement land, whereas forest land remains unchanged. However, the exciting observation from agriculture land probability pinpoints how population increases drastically diminishes agricultural land's likelihood. Moreover, migration changes (Figure 13b) also highlight that an increased flow of migrants within a location promotes agricultural land expansion at a steady pace, while forest land is likely to decrease and settlement land areas remain constant. Migration changes in the increased likelihood of agricultural land use may be closely related to the issues surrounding dependence on agricultural production to provide a livelihood for migrants in the Nigerian context.

(a)



(b)

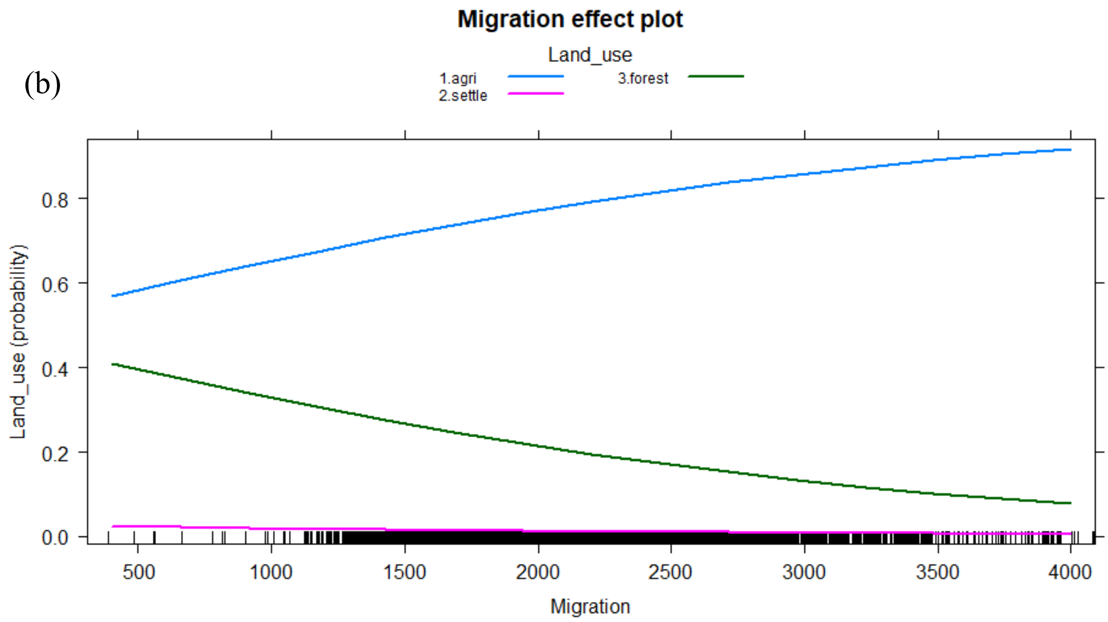


Figure 13 Demographic drivers' effects on land use change (a) population density; (b) migration.

4.10.2 Economic drivers

Observing the changes in the effects plot of GDP on land use probability indicates that if the gross domestic product (GDP) increases, the likelihood of settlement occurring would be higher. However, lower GDP rates indicate a higher likelihood of agricultural land (Figure 14a). For example, if the GDP falls below $4000, the probability of agricultural expansion increases while forest land will decline due to agriculture expansion. Therefore, rapid economic growth would influence gains in infrastructure development and vice versa.

In addition, poverty rates as an economic driver of land use change explain the relationship between increasing poverty levels and land use conversion. As the percentage of persons living below the poverty line increases, the higher the likelihood of agricultural land, while settlement land probability diminishes rapidly (Figure 14b). The result indicates that higher poverty denotes less investment in infrastructure but a higher emphasis on primary production to meet the daily necessities. As land is relatively accessible, landowners would increase investments into agriculture production as food is necessary for survival and provides a means of livelihood for the poor populace. From the current trends in land use in Nigeria previously highlighted in section 4, agricultural expansion over time has highlighted the growing poverty rate within the country.

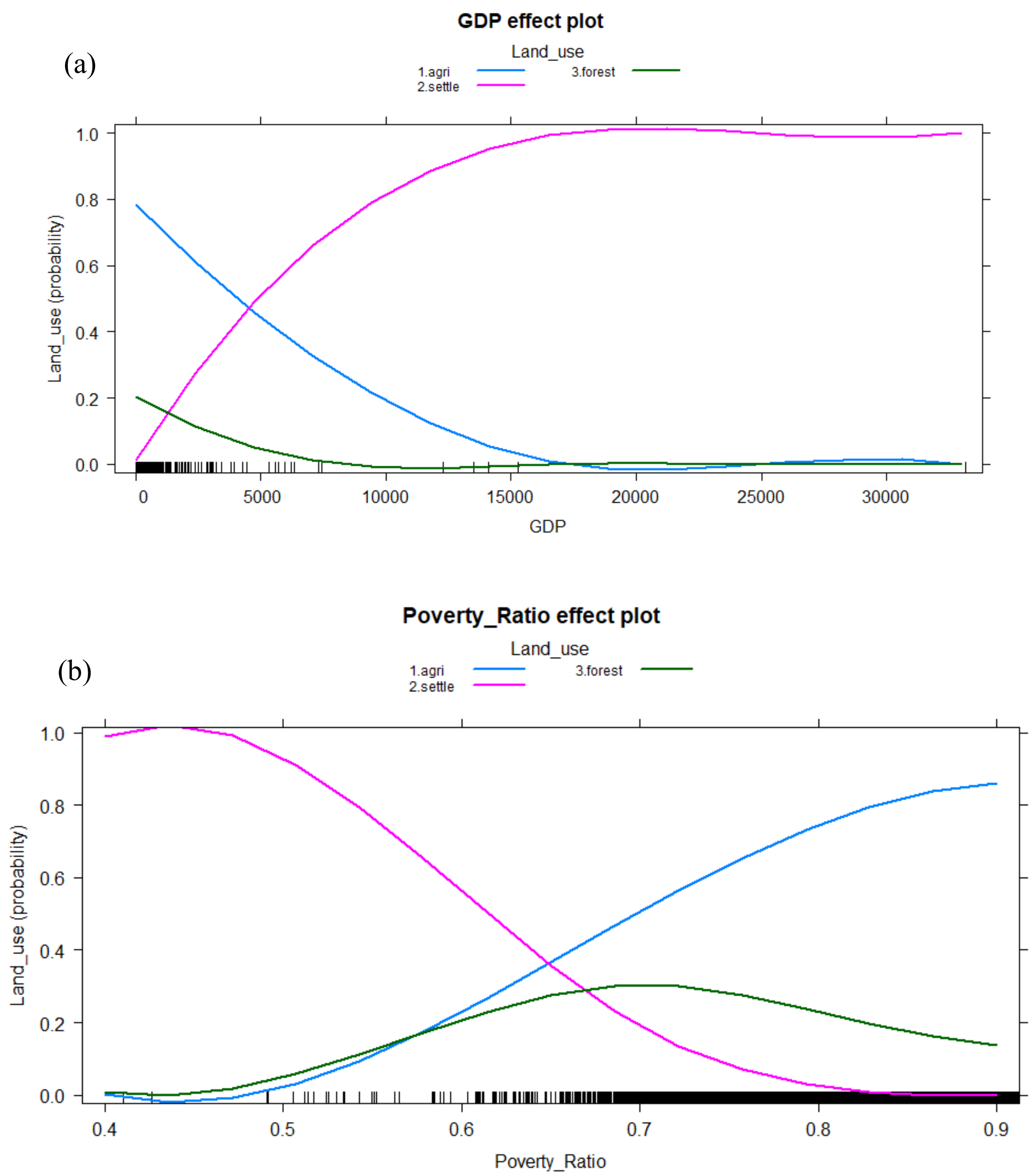


Figure 14 Economic drivers' effects on land use change (a) Gross Domestic Product (GDP); (b) Poverty ratio.

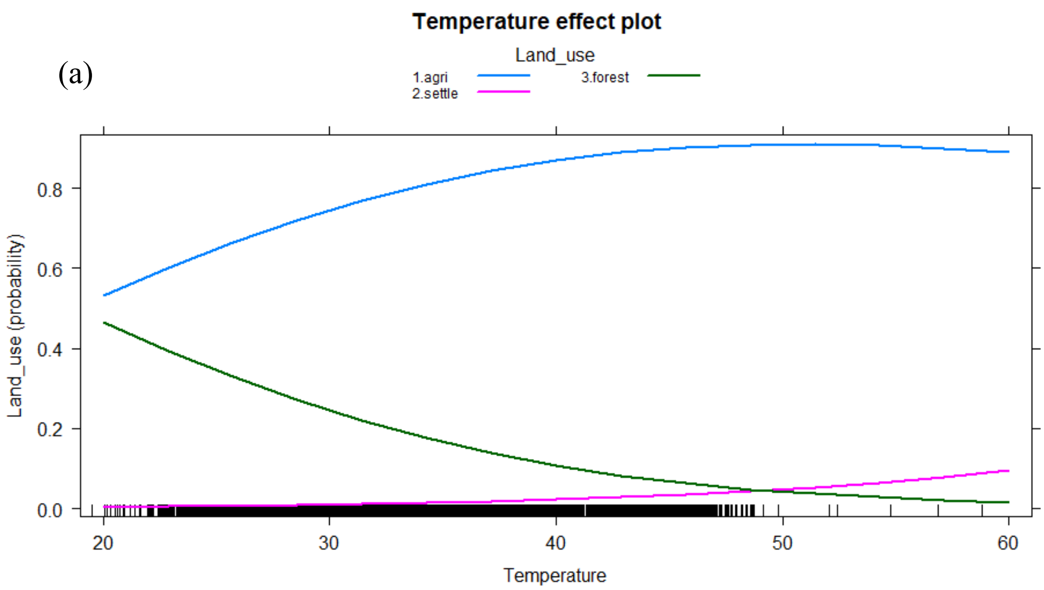
4.10.3 Biophysical drivers

There is a complex relationship between land use change and climate drivers, as illustrated below in Figure 15. Even though studies show that land use change is a significant driver of climate change, a change in climatic variables can lead to shifts in land use and vice versa. As a result of changing climatic conditions, some regions may experience an increase in temperature values and a reduction in rainfall annually, increasing desertification, droughts, and damage to existing crops due to rapid climatic changes. For example, farmers may switch from traditional crops to crops that will yield a higher economic return. Similarly, areas prone to droughts may experience more frequent incidents due to increased temperature values and reduced precipitation, negatively impacting the water required for irrigation.

Climatic changes such as rising temperatures (Figure 15a) would rapidly expand agricultural land areas while reducing the amount of forest cover. However, the likelihood of agricultural land increase may result from increased droughts and lower precipitation, forcing farmers to relocate to regions with lower temperature changes and higher precipitation conducive to their crops and livestock. By observing the changes in Figures 15a and b, increasing temperature and precipitation values increases agricultural land, reducing forest cover, while settlement land remains steady and unaffected by the climatic variations.

As the elevation increases, the likelihood of becoming agricultural land diminishes for elevation changes. For example, the development cost of agriculture on a higher plane may be significantly higher than on lower levels. As a result, agriculture production may not be dominant in higher elevations, requiring a higher workforce and increased services cost. However, the opposite trend is observed for settlement and forest land probability. The higher elevation, the more favourable it becomes to the likelihood of settlement and forest development (Figure 15c).

(a)



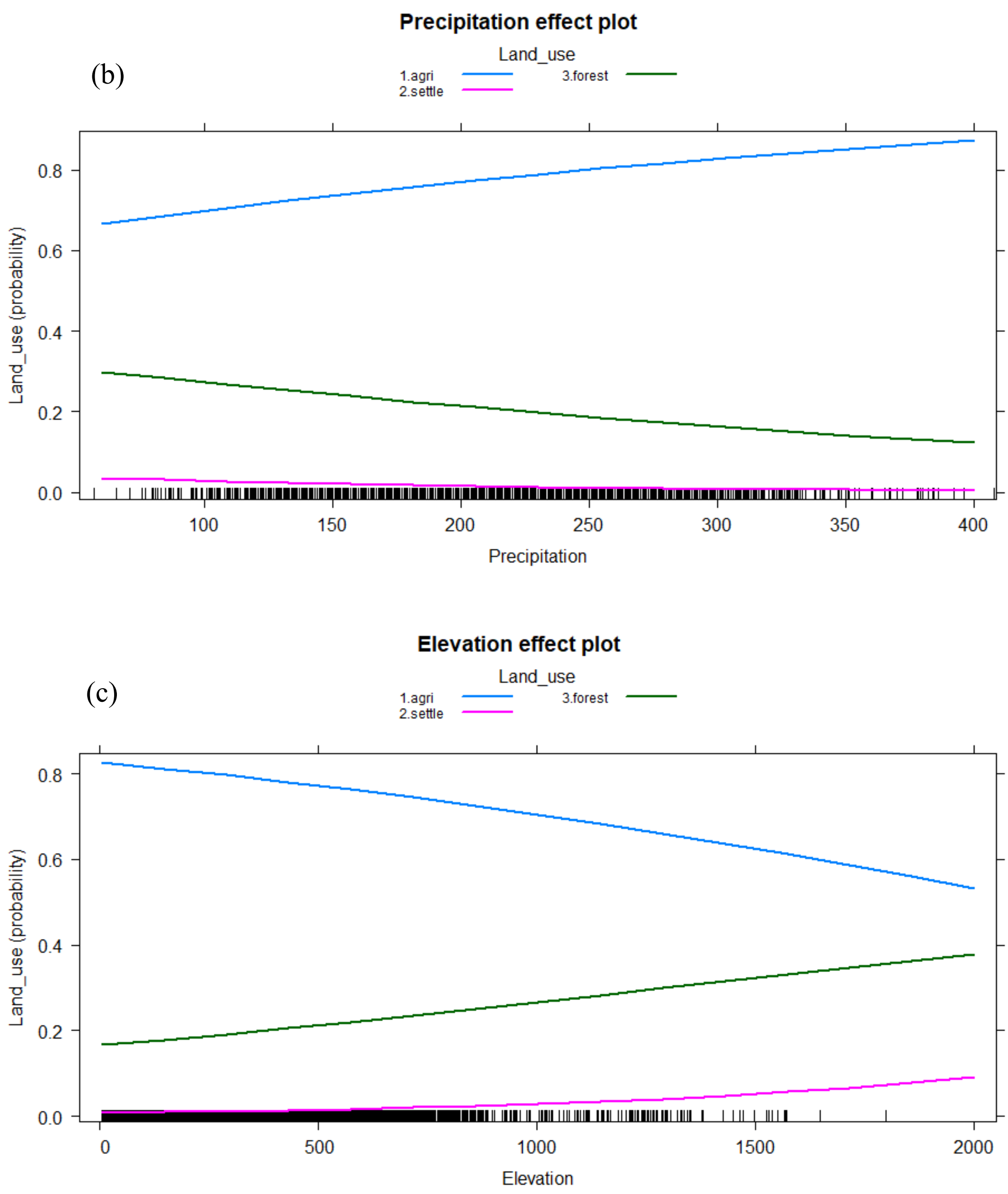


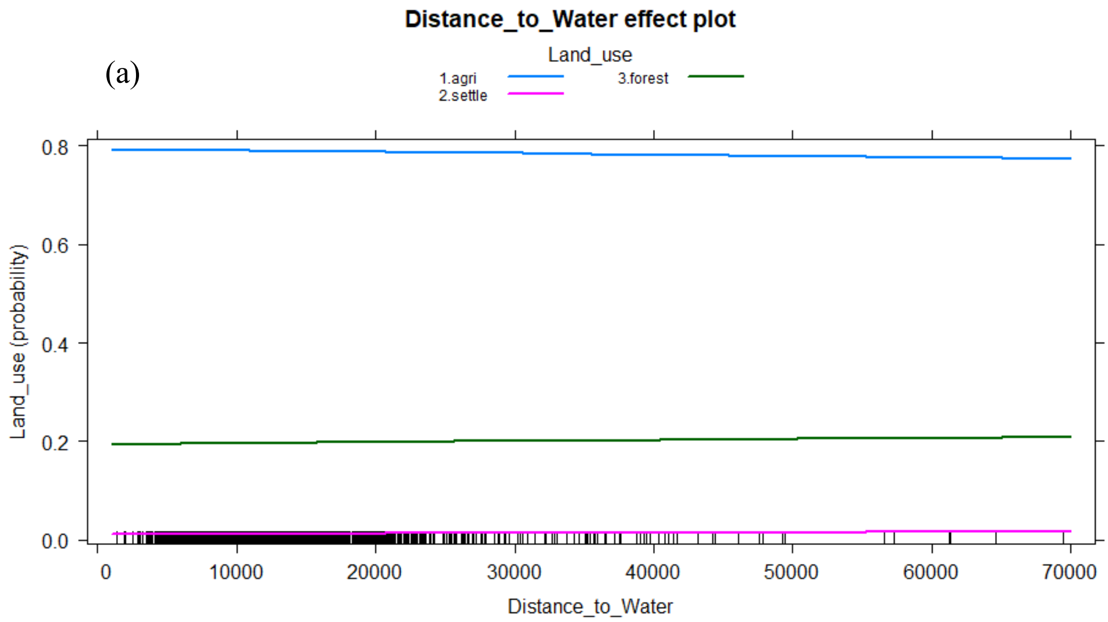
Figure 15 Biophysical drivers' effects on land use change (a) temperature; (b) Precipitation

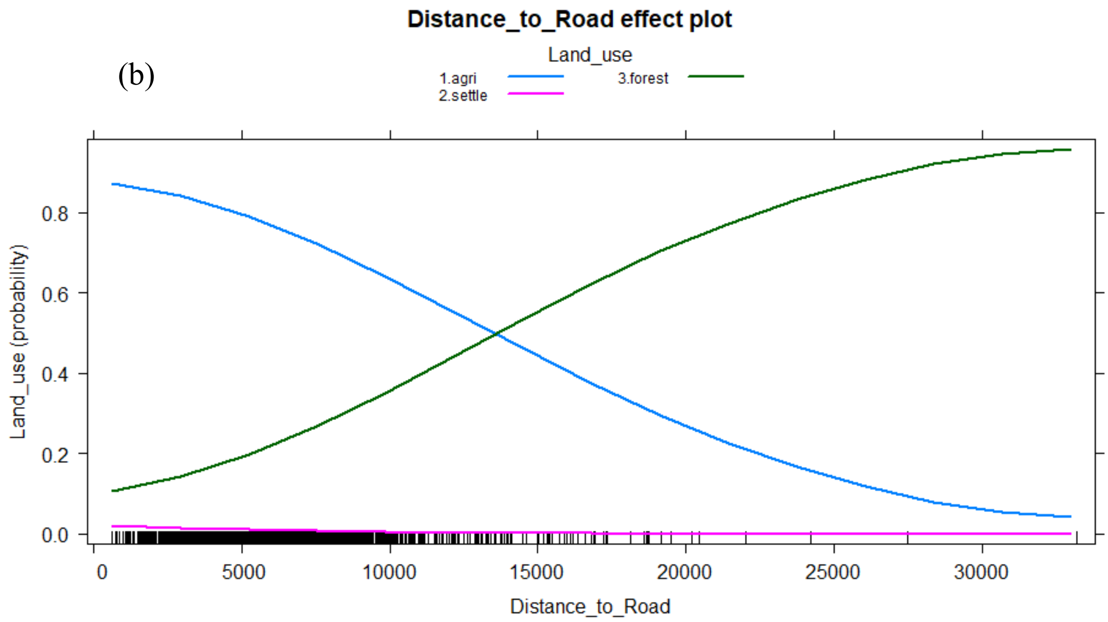
4.10.4 Accessibility drivers

The selected accessibility drivers' distances to water, road and railway produced varying results (Figure 16). However, the relationship between distance to water and land use change is minimal. For example, figure 8a shows that the probability of land use change is negligible as the distance to water areas increases. That is, irrespective of the distance from each land use class to a body of water, it does not impact land use change. A justification for this trend may result from Nigeria relying on groundwater as its water source, improved irrigation, and sufficient rainfall in many parts of the country. Alternatively, the distance to the road highlights how changing the distance from the road to a land use class influences land use change. For example, as the road distance increases, the land cover tends to be forest land increases, while agricultural land probability reduces the farther away from the road. However, for settlement land, the road distance had no impact.

Similarly, there is no significant effect on settlement land; however, for agricultural land, the farther the distance to the railway, the probability of conversion to agricultural land reduces and vice versa for forest land. The results (Figure 16) show that accessibility, especially road networks, significantly impacts land use change, highlighting that transportation networks are essential for industrial processes and transporting goods and services from one point to another.

(a)





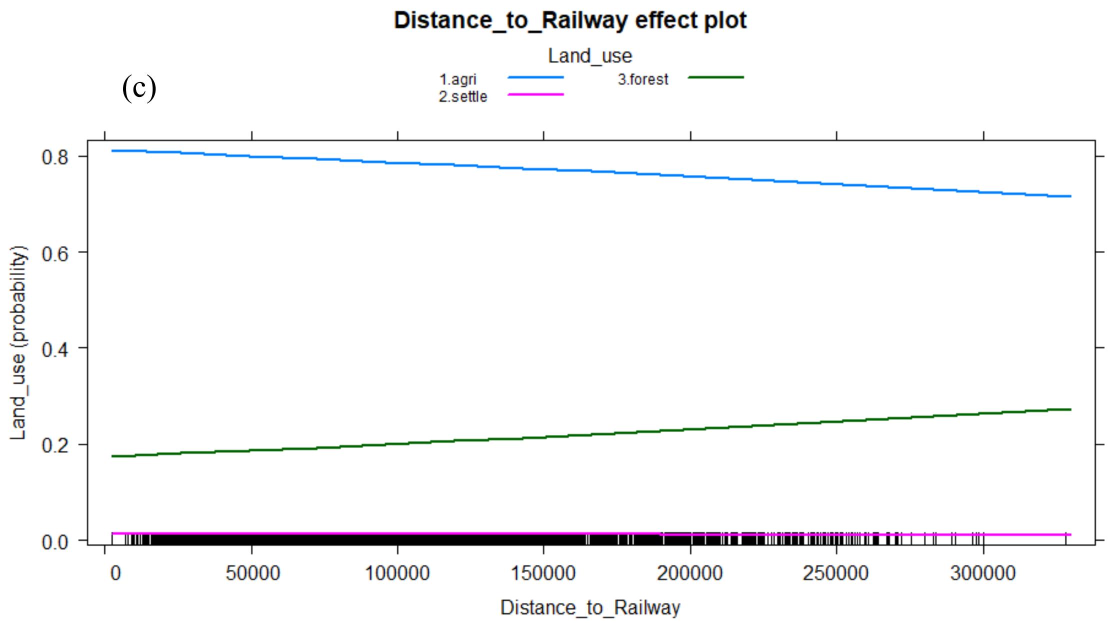
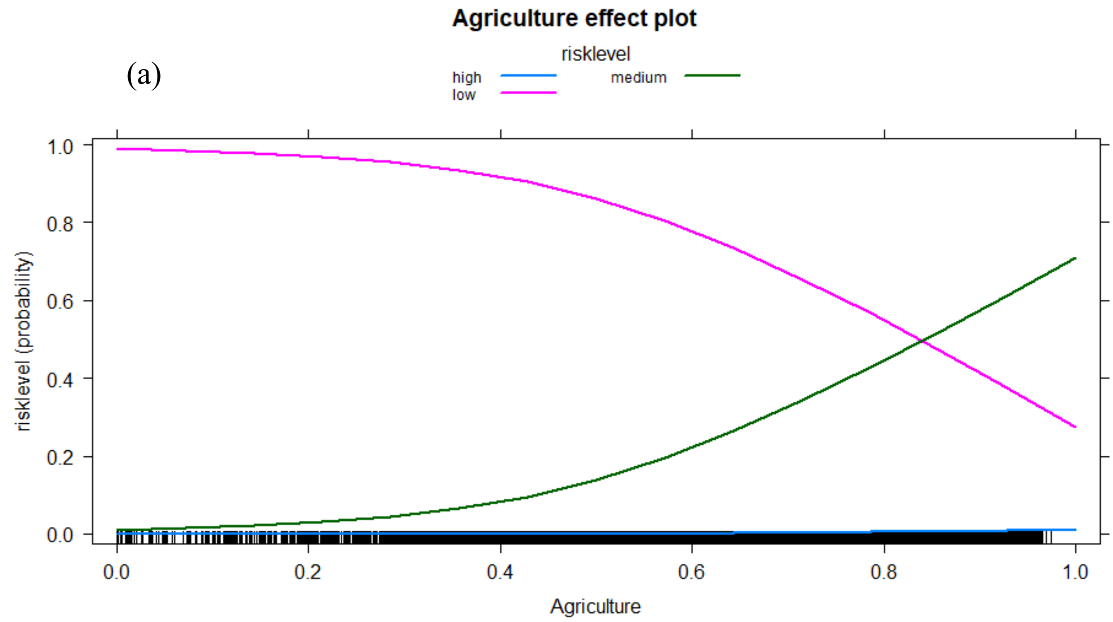
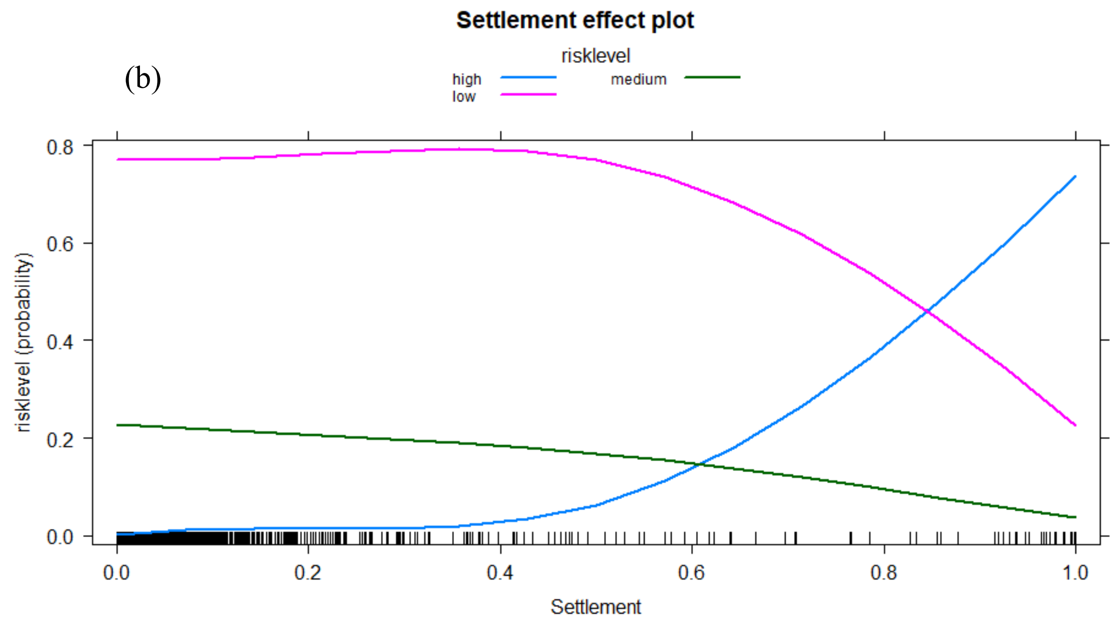


Figure 16 Accessibility drivers' effects on land use change (a) distance to road; (b) distance to water; (c) distance to the railway.

4.11 Land use change and flood risk

As depicted in Figure 17, the consequences of each land use type in Nigeria are explained by demonstrating how the likelihood of changes in each land use influences the degree of hazards in Nigeria. Regarding agricultural land usage, the increasing probability indicates that places with lower disaster risks would be reduced, whilst areas with moderate disaster risks would grow while those with high disaster risks remained unchanged. First, let us look at the probability of settlement land use in danger zones. Settlement land area expansion increases the probability of high-risk flooding while gradually decreasing low and medium-risk areas. However, when it comes to the possibility of forest land use, the changes in the level of risk are small. The outcome of the forecast can be compared to the existing distribution of land use types in the danger zones shown in Figure 17, which illustrates the prediction results for each land use type in the risk zones. Our predictive scenarios and the current information are well-matched, with settlement land use increasing risks in high-risk areas and agricultural land use significantly impacting medium-risk zones.





(c)

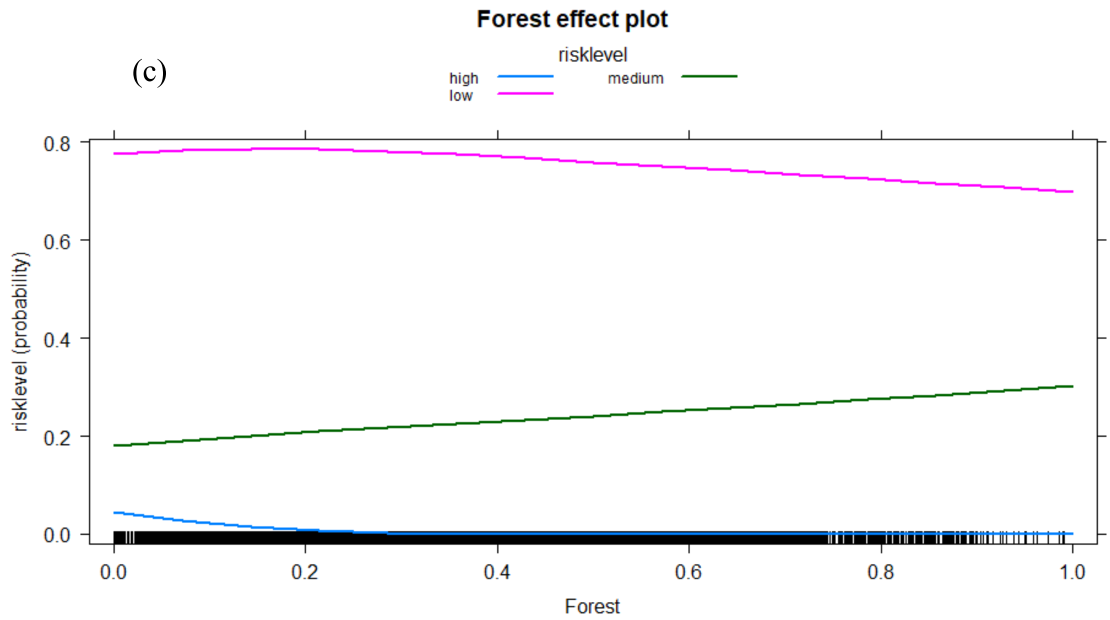


Figure 17 The effects of the probability of each land use type on risk levels (a) agriculture; (b) settlement; (c) forest.

The land use model and the risk analysis are used to develop a separate multiple regression model, which estimates the contributions of changes in the different land use types on the response variables in Nigeria. The response variables include those associated with the low, medium and high risks. As shown in Figure 17, the model's results clearly explain how the impacts of a change in individual land use affect the current hazards. The study found that the four land use classes (agricultural, settlement, and forest) impacted catastrophe risks.

4.12 Land use distribution within the flood risk zones

Figure 18 depicts the distribution of each land use class in the risk zones, as determined by the percentage distribution of each land use class. Agriculture land use accounts for the majority of the land in low-risk zones, at 59.3 per cent, with settlement land use at 0.8 per cent and forest land use accounting for 39.8 per cent, respectively. A similar trend in agricultural land use is found in the highest proportions in each risk zone (61.8 per cent in low/medium risk, 70.2 per cent in medium risk, and 59.8 per cent in high risk), with the lowest proportions in low/medium risk and the highest proportions in high risk. Compared to the land use allocation depicted in Figure 18, where agricultural land constitutes the most significant proportion of land use in Nigeria, the trend is positive. However, for settlement land use, settlement land use tends to have a more significant margin in the distributive scale for the high and extreme risk levels, with margins ranging between 14.6 and 66.7 per cent, respectively. Figure 18 reveals that settlement regions are primarily located in the high-risk zones, influencing the overall damage to Nigeria's social and economic dynamics in the case of a natural disaster.

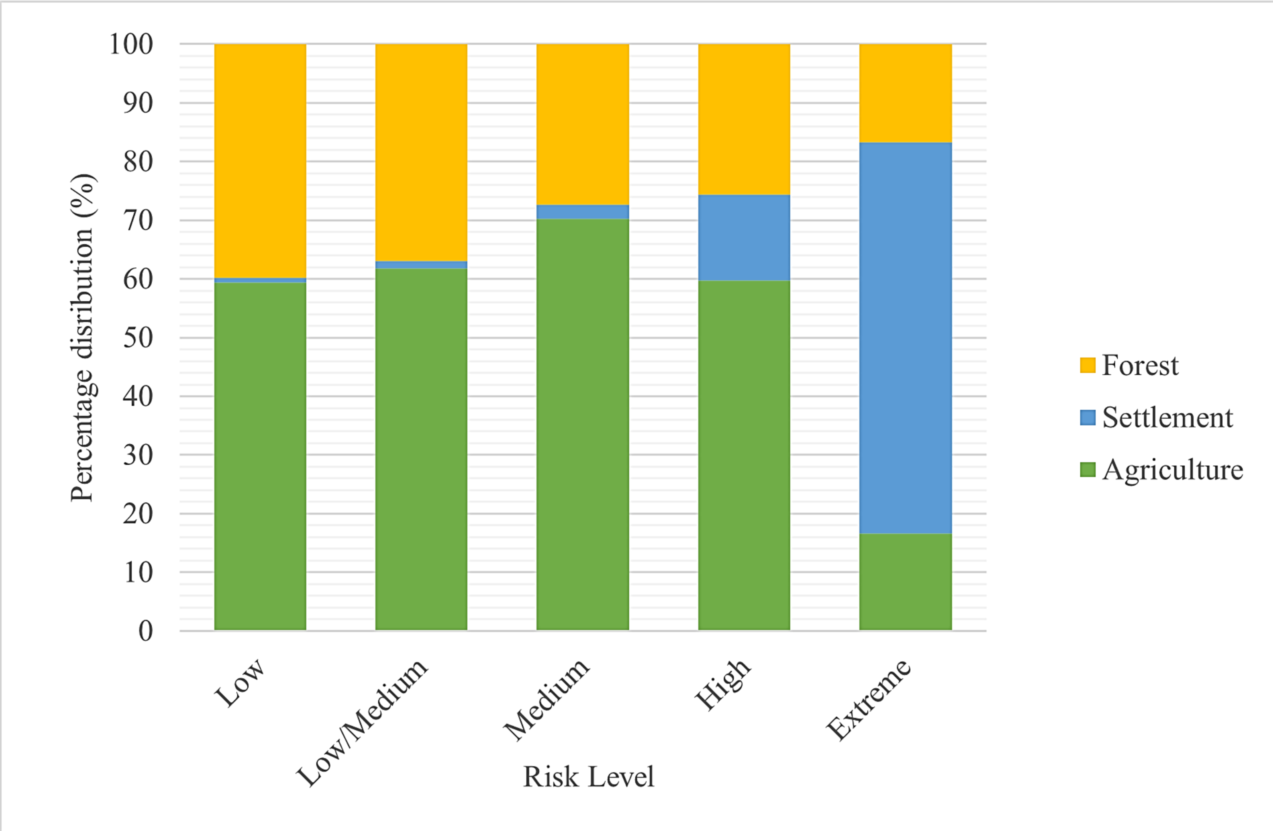


Figure 18. The distribution of land use in each flood hazard zone

Chapter 5 Future Land Use Pattern Analysis

5.1 Overview of the land use scenarios development

Nigeria's demographic, environmental, and economic land-related policies were used to develop future land use demands under three distinct scenarios by 2040: business as usual (BAU), market-oriented, and conservation. First, each proposed development scenario is produced based on Nigeria's historical, present, and formulated spatial policies, using the System Dynamics (SD) modelling approach. Then, using the model's derived results, we examined the spatial changes caused by the various land use scenarios using the Future Land Use Simulation (FLUS) model. Finally, the Kappa statistics and Figure of Merit validate the FLUS model's performance (FoM). The following sections provide a complete description of the technique.

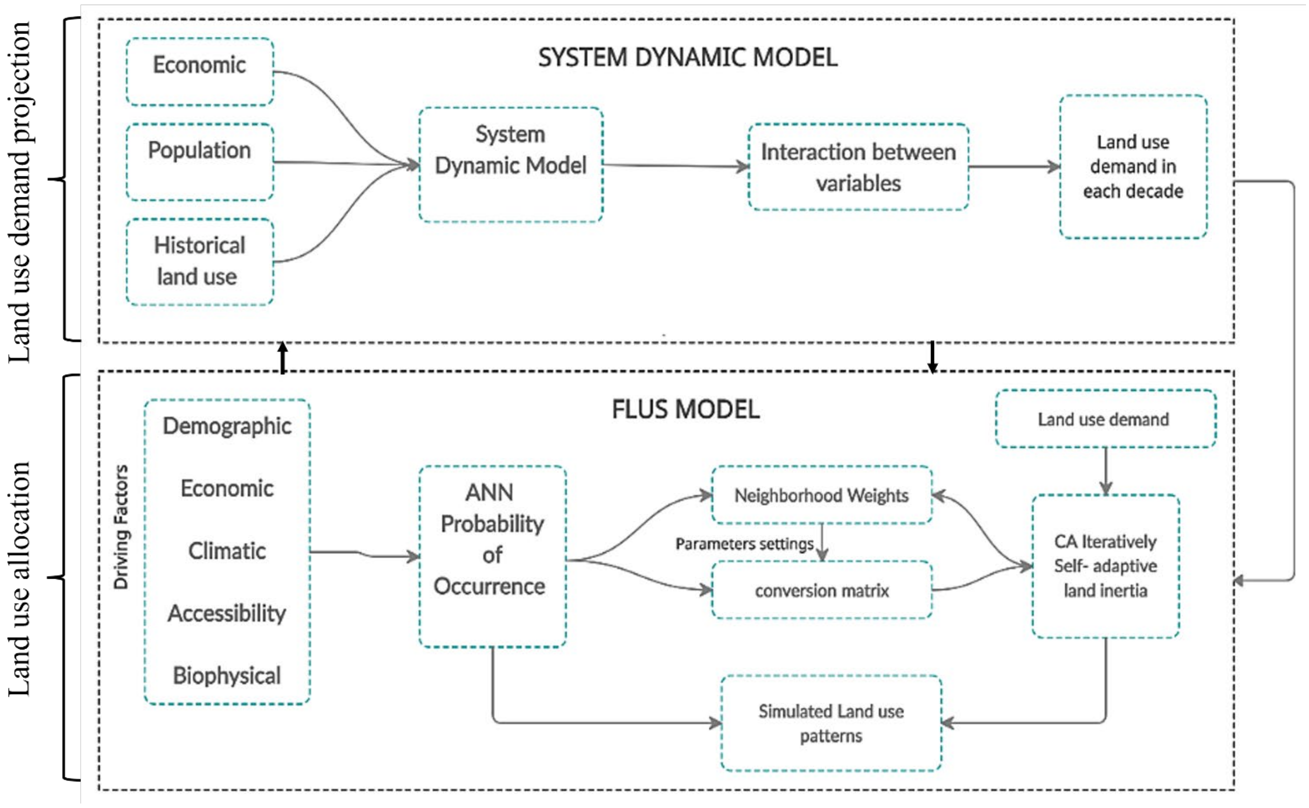


Figure 19 The flowchart for estimating future land use demand

Figure 19 shows the method used in this investigation, separated into two parts. First, using Vensim, the SD model estimates future land use demands under three alternative scenarios based on land use trends till 2040; the FLUS model investigates the spatial relationship of land use patterns. The data used in the study is in Table 14.

Table 14 Data and sources used in the system dynamic model

Data	Source	Type	Period
The household survey and social characteristics	National Bureau of Statistics, Nigeria	Statistics	1960 ~ 2017
Economic Information (Investments, budget allocation)	National Bureau of Statistics, Nigeria, Central Bank of Nigeria, Annual report	Statistics	1960 ~ 2017
Demographic changes	National Bureau of Statistics, Nigeria	Statistics	1960 ~ 2020
Production and commodities (imports and exports)of goods, services,	National Bureau of Statistics, Nigeria; Knoema Data portal	Statistics	1960 ~ 2020
consumption, revenue and expenditure on goods and services	National Bureau of Statistics, Nigeria; Knoema Data portal	Statistics	1981 ~ 2017

5.2 Developing the System Dynamic model

The SD model uses stocks and flows in many directions to simulate the behavioural patterns of complex systems (Coyle, 1997). It also aids in giving feedback and exchanges between multiple constituents within a system while assessing and forecasting their flows and stocks. Demographic, economics, and land use policy are the three primary subsystems of the SD model.

5.2.1 Demography sub-system

In the demography sub-system, assumptions were made that the number of births, deaths and the rate of immigration (Figure 20) in a given year are the factors that influence the total population changes. Because these indicators undergo significant changes annually, they directly impact the population. For example, migration may fluctuate if there is an increase or decrease in gainful employment, attracting more migrant workers (skilled and unskilled) and resulting in population changes. Similarly, a boom in population would result in increased demand for settlement, industrial or agricultural land to accommodate the growing population. We also assumed that increased job opportunities would encourage more people to migrate. As a result, the annual population growth is a significant indicator for the demography sub-system because population changes impact social landscape changes and indirectly affect economic changes.

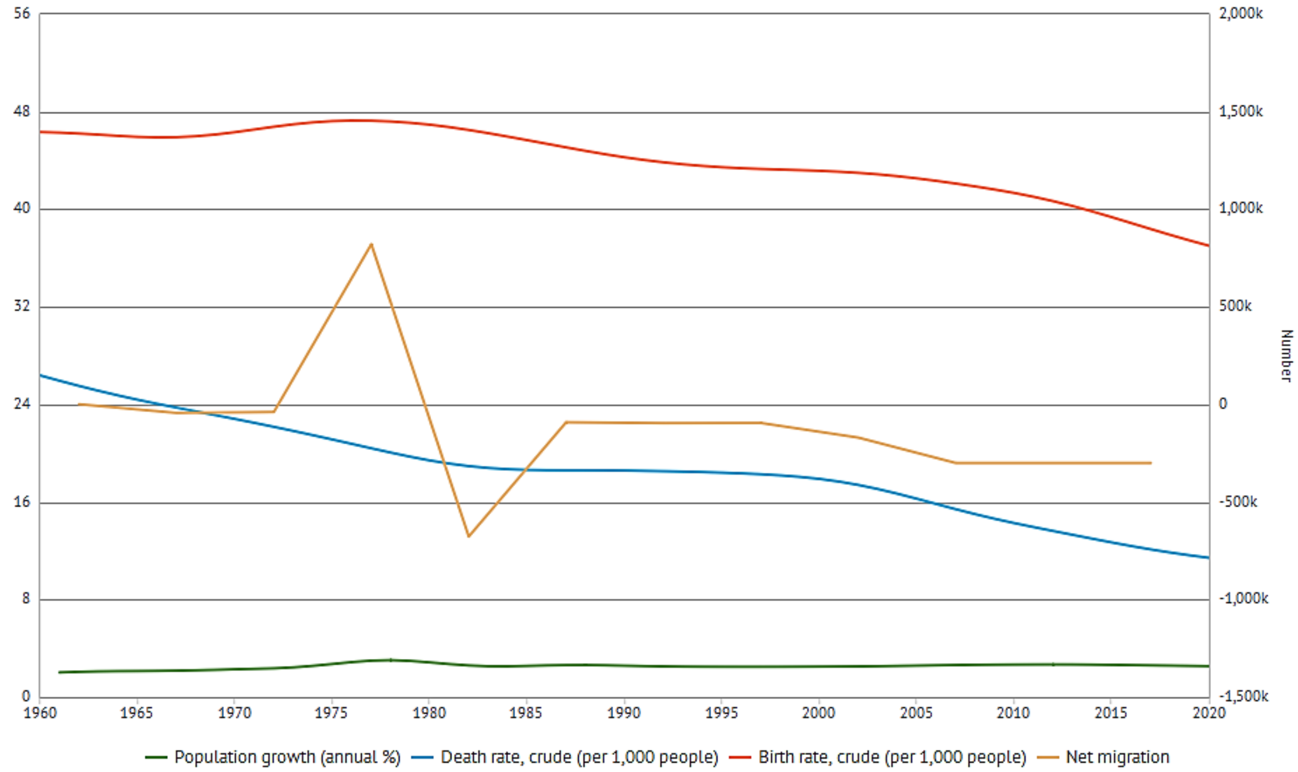


Figure 20 Annual population growth, births, deaths and net migration rates for Nigeria (source: National Bureau of Statistics, Nigeria via Knoema data portal. Modified by: Author)

5.2.2 Economic sub-system

Studies have demonstrated that economic indicators significantly impact land use change patterns (Ighile & Shirakawa, 2020). Therefore, the GDP and share of investment for Nigeria's three main sectors (agriculture, industry, and service) (Figure 21) were considered when selecting the economic sector parameters because they influence the investment rate in each land use type. As a result, the SD model helped capture how socio-economic changes affect land use demands in Nigeria. Furthermore, estimating how varying economic conditions will influence the rates of investments, thereby impacting the demand for land.

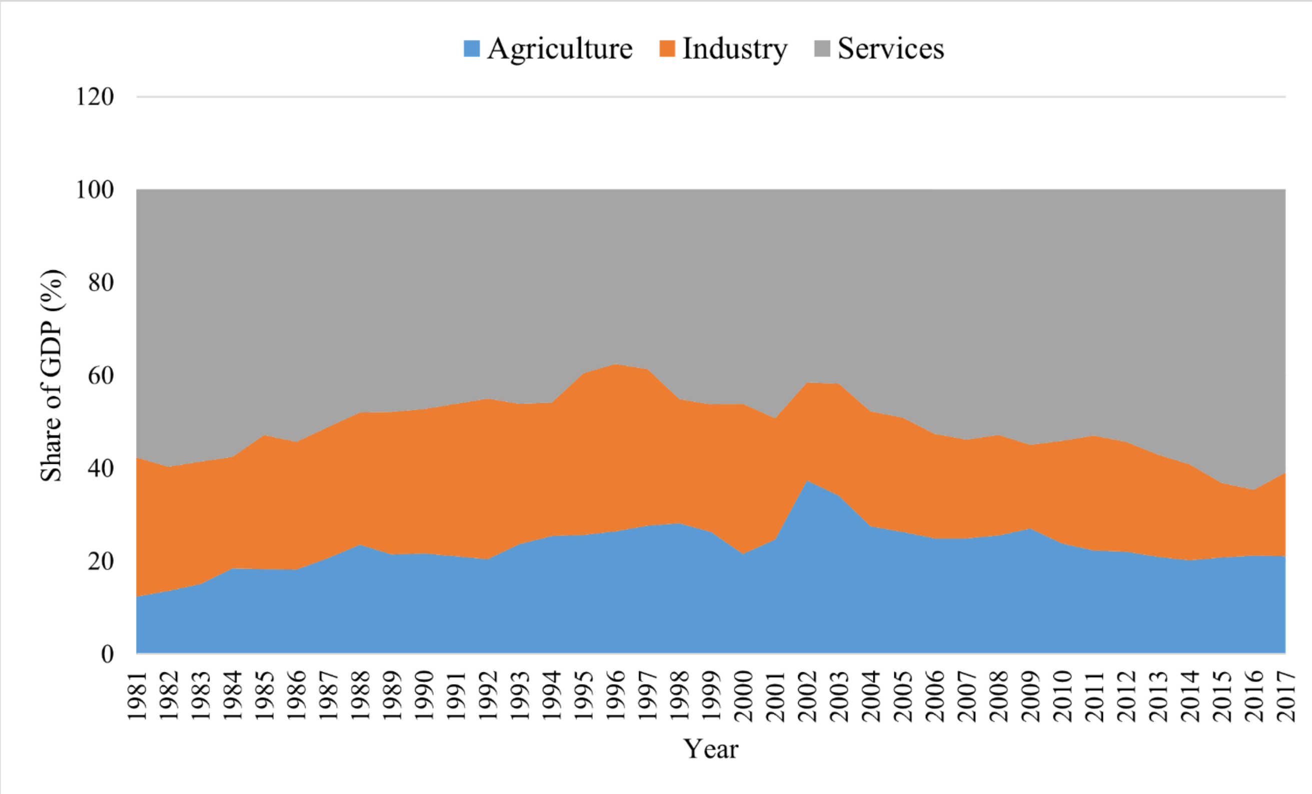


Figure 21 share of GDP contributions per sector (source: National Bureau of Statistics, Nigeria via Knoema data portal. Modified by: Author)

5.2.3 Land use policy sub-system

In the land use policy sub-system of the SD model, indicators on agricultural production, supply and distribution of agricultural commodities, land use and density and urbanisation were considered. Based on the historical trend of deforestation and agricultural land expanding at an alarming rate, and from the viewpoint of sustainability, the use of sustainable agricultural methods to increase agricultural production is essential for reducing the amount of land required for farming while also slowing environmental degradation and climate change caused by processes such as deforestation (Hawken, 2017).

As a rule of thumb, data on agriculture imports and exports, domestic food consumption, total production, and the investment ratio in agriculture were used in the modelling. It is believed that agriculture development will require less land if sufficient funds are allocated to technological advancements, machinery development, research, and crop improvement to promote high-yield crops and diminish harvest loss. Hence, estimating how increased agricultural productivity lowers the demand for cultivated land. Agricultural productivity is estimated as,

$$Agricultural\ productivity = \frac{Agricultural\ output\ per\ unit\ area}{Agricultural\ input\ per\ unit\ area} \quad (5)$$

Agricultural outputs to agricultural inputs measure agricultural productivity (Dharmasiri, 2012). Agriculture inputs are an aggregate of the cost of labour, machinery, and other required elements during the planting and harvesting of agricultural land. In contrast, outputs consider the total production and overall yield from agricultural land in monetary terms. Similarly, data on annual food production, domestic consumption, imports and exports of all agricultural products were collated (Figure 22). Finally, the annual consumption per capita and land demand estimates were derived using the collected data.

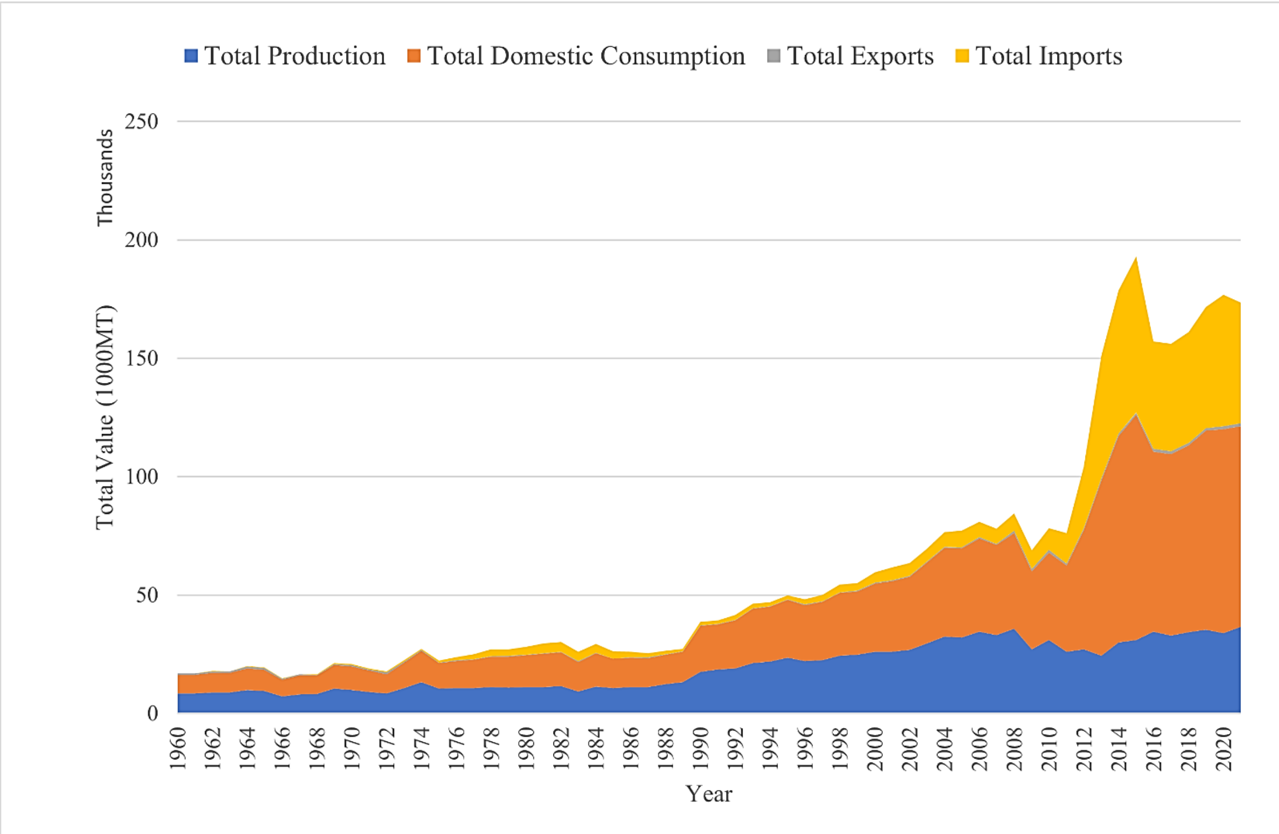


Figure 22 Production, supply and distribution of agricultural commodities by market (per 1000 metric tonnes) (Source: National Bureau of Statistics, Nigeria via Knoema data portal. Modified by: Author)

The development of the SD model to simulate future land use scenarios has allowed a better understanding of how different social, economic and land use policies affect land use changes. Figure 23 illustrates the interactions between the dynamic variables and land use.

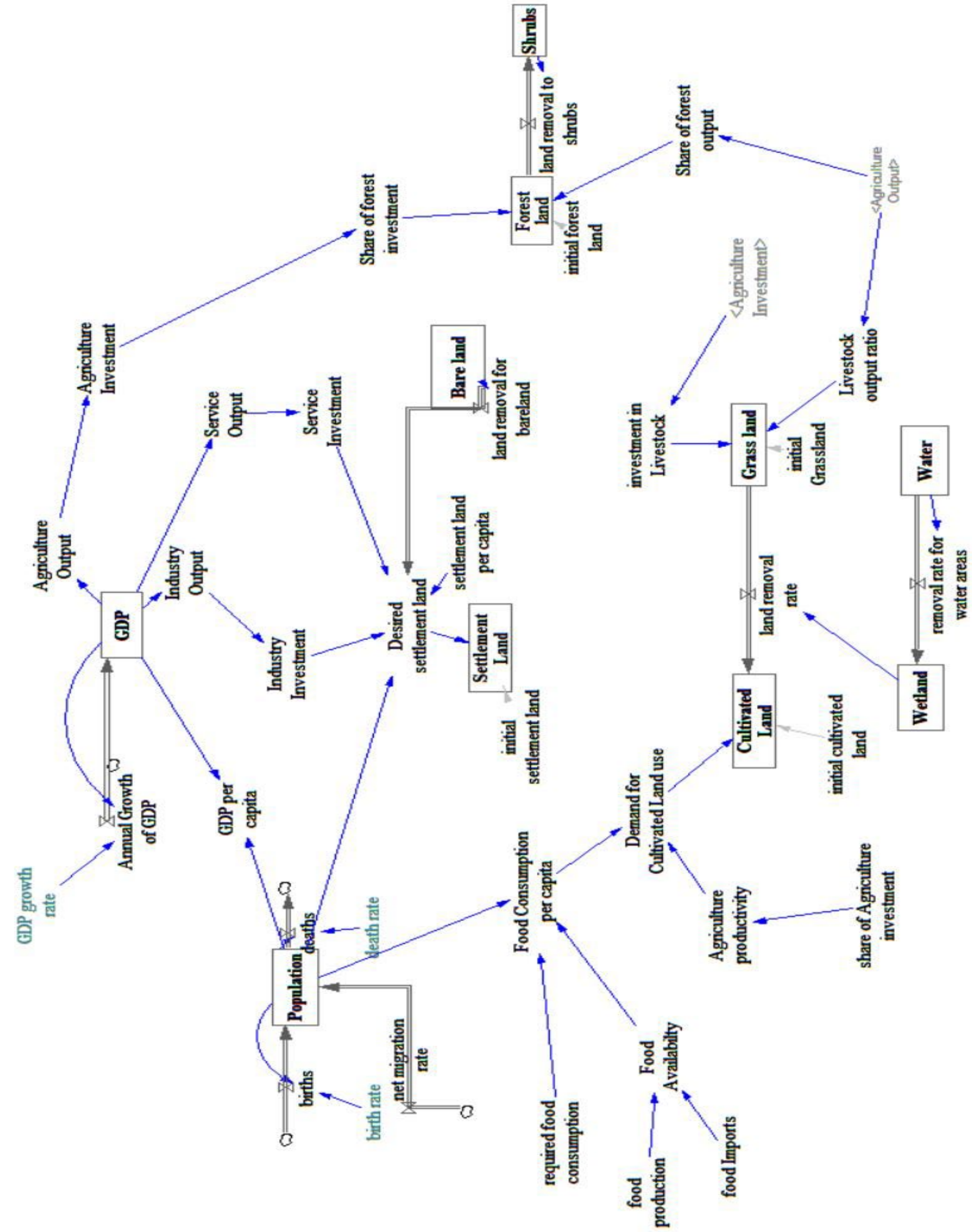


Figure 23 Interactions between the dynamic variables and land use

5.3 Scenario development

Several elements (economic, demographic, and land use policy) were explored and examined in the SD model to predict and examine the influence on land use demand by 2040. Land use demand is simulated using demographic, economic, and land use policy trends in three scenarios: business as usual (BAU), market-oriented, and conservation. Every scenario is allocated a separate set of socio-economic trends and land rules. The trend extrapolation approach helped calculate land use dynamics based on existing historical data because quantifying the impacts of economic and demographic changes on shrubs, miscellaneous land, and water areas is difficult.

The BAU scenario depicts the factors that drive land use change over the baseline year while being constant. The current demographic, economic, and land use policy parameters are consistent with previous trends. The BAU scenario is based on the current growth paths, assuming that the existing economic and demographic trends will continue. The market-oriented scenario is intended as a path to advancement that encourages socio-economic prosperity. Compared to the BAU scenario, whereby the growing population is relatively large, the scenario believes that population growth will gradually decrease as the economy improves. As a result, fixed investments in all sectors rise (agriculture, service, and industry). Finally, the conservation scenario keeps the steady population while encouraging modest economic development and investments. Land use restrictions for biodiversity and ecosystem conservation are severely enforced in this scenario. In addition, forest regions and existing protected areas are crucial for biodiversity conservation.

5.3.1 Parameterisation of the SD model

Over the preceding decades, Nigeria's economy has been characterised by inconsistency in its socio-economic policies, riddled with uncertainties from multiple factors. However, notwithstanding the continued slowing in economic progress, Nigeria aims to maintain the annual GDP growth of about 2.5 per cent for its future development. Based on historical statistical data, this study produced three alternative demographic, economic, and land policy futures (Table 14). Finally, it looked at how these possibilities would impact land use. Changes in investment levels are considered a critical aspect in each scenario development since economic changes affect investment rates. Therefore, we generated three investment growth modes for each scenario that are roughly connected with the economic trend in the study. Improved investment levels, for example, would lead to better land practices, higher technology, and possibly improved productivity in each sector, resulting in a decrease in the demand for land resources.

a. Business as usual

The BAU scenario is expected to have modest economic and population growth patterns, with an annual population growth of 2.67 per cent and GDP growth of 2.21 per cent, respectively, while maintaining existing growth rates. Similarly, overall investment has remained steady at 13.96%, with the fraction of total investment committed to agricultural production maintaining constant at 14.86% per year. Population and economic growth rates in developing countries, including Nigeria, are likely to accelerate due to fast urbanisation and population expansion, according to the World Bank's 2017 Global Development Outlook (GDP) for emerging economies. However, to stay up to date with past patterns and anticipate future land use requirements, all existing characteristics were assumed to remain constant, resulting in significant deforestation and rapid development of cultivated land.

b. Market-oriented

The market-oriented scenario is meant to replicate land use demand under a little conservative and ecologically friendly development environment; population growth is considerably slower (2.40 per cent) while economic growth is better (5 per cent). As a result, the total investment grows dramatically across all industries, reaching around 25%. The idea is that better economic policies will result in higher living standards, longer life expectancy, and increasing investment rates. In addition, these reforms would minimise agricultural production's reliance on unsustainable land use practices. Furthermore, more robust economic policies and investment in higher-tech manufacturing processes will reduce the land necessary for agricultural development.

c. Conservation

A more idealistic and long-term development approach, the conservation scenario maintains stable and modest economic growth (3.5%) while enacting reasonable environmental controls. The population is predicted to grow significantly slower (2%) than the baseline and market-oriented scenarios, which are meant to have a lesser environmental impact. When all possibilities are combined, the yearly investment rate is expected to average 19.48 per cent, assuming strict adherence to land use conversion laws. Agriculture investments would increase by 18.50 per cent with a modest increase in total investment, helping to prevent additional encroachment into other land regions, primary forests and protected areas.

As a result, the expansion of cultivated land would be significantly reduced, while settlement areas would continue to increase at their current rates. Table 15 shows the final estimates utilised in the model.

Table 15 The different parameters under the three scenarios

Parameters	Business as Usual	Conservation	Market-Oriented
GDP growth rate (%), at the current price, 2019	2.21	3.50	5
Annual population growth	2.67	2	2.40
Total investment (% of GDP)	13.96	19.48	25
The proportion of the industry sector (% of GDP)	25	22.50	20
The proportion of the agriculture sector (% of GDP)	18	24	30
The proportion of the service sector (% of GDP)	57	53	50
The ratio of agricultural investment (% of GDP)	14.86	18.50	22

5.4 FLUS model computation

The Future Land Use Simulation (FLUS) model is a multi-land use simulation model that combines various natural and human factors to produce changes to existing land patterns based on multiple defined scenarios, developed by Sun Yat-sen University, China. It combines the theory of Cellular Automata (CA), machine learning algorithms, and the self-adaptive inertia mechanism to simulate land use change dynamics, enabling its application in various applications. One advantage of the model is the integration of machine learning algorithms to produce land use change probabilities based on the selected driving factors within the model functioning. For example, the ANN considers human activities and natural ecological effects by identifying complex relationships between land use patterns and various human and natural driving factors. Furthermore, given this mechanism's stochastic properties, the model can capture the uncertainty inherent in real-world land use dynamics.

5.4.1 Conversion cost and neighbourhood weights parameterisation

The probability of occurrence was determined by neighbourhood density, conversion weight, spatial resolution, land type competition, and an adaptive inertia coefficient. After estimating the probability of occurrence, the next phase utilises the self-adaptive inertia computation. The conversion cost matrix indicates the ease at which a land cover type in its current state could be transformed into another (Huo et al., 2022; Liu et al., 2017). Finally, the adaptive inertia coefficient is calculated based on the difference between the actual land use quantity and the target demand quantity, adjusted during each iteration.

$$inertia_y^t = \begin{cases} inertia_y^{t-1} & \text{if } \mid D_y^{t-1} \mid \le \mid D_y^{t-2} \mid \\ inertia_y^{t-1} \times \dfrac{D_y^{t-2}}{D_y^{t-1}} & \text{if } 0 > D_y^{t-2} > D_y^{t-1} \\ inertia_y^{t-1} \times \dfrac{D_y^{t-1}}{D_y^{t-2}} & if\ 0 < D_y^{t-1} > D_y^{t-2} \end{cases} \tag{6}$$

where $inertia_y^t$: is the inertia coefficient of y land at the $t-th$ iteration timeD_y^{t-2}, D_y^{t-1}: are the differences between the functional grids and the target grids at the time $t-1$ and $t-2$.
In a grid cell x, the neighbourhood development density for each land use is defined as,

$$\Omega_{x,y}^t = \frac{\sum_{\mathrm{N}\times\mathrm{N}} con(c_x^{t-1} = y)}{\mathrm{N}\times\mathrm{N}-1} \times w_y \tag{7}$$

Where $\Omega_{x,y}^t$: is the neighbourhood effect of land use type y on grid cell x at time t; $\sum_{\mathrm{N}\times\mathrm{N}} con(c_x^{t-1} = y)$ is the quantity of grids of y land at the end of time t−1 on the N×N Moore laws; w_y: is the weight of each land type y.

Next, calculating the combined probability of occurrence $LP_{x,y}^t$; that grid x could be converted into land y at a time t. The CA iteration assigns each land type to the grid, and the expression is,

$$P_{x,y}^t = P_{x,y} \times \Omega_{x,y}^t \times inertia_y^t \times \left(1 - SC_{c\to y}\right) \tag{8}$$

where $SC_{c\to y}$: is the conversion cost of the initial land use type c into type y; $1 - SC_{c\to y}$: is the conversion difficulty; $P_{x,y}$: is the individual probability of occurrence of each land use type.

The range of conversion values consists of either 0 or 1. Where 1 denotes that transition to another land use is permissible, and 0 no transition permitted. Each scenario is based on how various land policies impact land use demand. The conversion cost matrix used in each scenario is highlighted in Table 16 below.

Table 16 conversion matrix used in the FLUS model under the three scenarios

Business as Usual						
Land Use	Cultivated	Forest	Shrubs	Water	Settlement	Miscellaneous
Cultivated	1	1	1	0	1	0
Forest	1	1	1	0	1	1
Shrubs	1	0	1	0	1	1
Water	1	0	0	1	1	0
Settlement	0	0	0	0	1	0
Miscellaneous	1	1	1	0	1	1
Market- Oriented						
Land Use	Cultivated	Forest	Shrubs	Water	Settlement	Miscellaneous
Cultivated	1	1	1	0	1	1
Forest	0	1	0	0	1	1
Shrubs	1	1	1	0	1	0
Water	1	0	0	1	0	0
Settlement	0	0	0	0	1	0
Miscellaneous	1	1	0	0	1	1
Conservation						
Land Use	Cultivated	Forest	Shrubs	Water	Settlement	Miscellaneous
Cultivated	1	1	0	0	0	0
Forest	0	1	0	0	0	0
Shrubs	1	1	1	0	1	0
Water	0	0	0	1	0	0
Settlement	0	0	0	0	1	0
Miscellaneous	1	1	1	0	1	1

The module also requires the SD models already simulated land use requirements for the final year. Finally, the model accuracy is calibrated after verifying the land use parameters.

5.4.2 The FLUS model validation

The Kappa coefficient, Figure of Merit (FoM), and the overall accuracy validated the FLUS model computation. The Kappa coefficient measures how much agreement exists between two individual data samples. Kappa is usually between -1 and 1, in most cases, greater than 0. 1 indicates complete agreement, while values less than 1 indicate partial agreement. As a result, the kappa accuracy can better express the predicted results' quantitative accuracy and spatial distribution accuracy. The Kappa coefficient is expressed as,

$$K = \frac{\left(P_x - P_y\right)}{\left(1 - P_y\right)} \tag{9}$$

where P_x is the proportion of simulation results and P_y Is the correct proportion of simulation results of targets all chosen at random. Similarly, the ratio between the model's correct prediction on all test sets and the overall number is the overall accuracy. For example, the model has high accuracy with a Kappa value between 0.75 and 1. However, there is a moderate accuracy with Kappa 0.5 and less than 0.75 and poor accuracy when Kappa is less than 0.5.

5.5 Results of the future land use pattern analysis

5.5.1 Land use classification results

Understanding the land cover characteristics is essential to predicting future land use demand. Therefore, the historical land classification was observed using improved land use cover maps at the 30-m resolution. The rate of change in land cover throughout the 20-year study suggests that agricultural, miscellaneous, and forest land areas have undergone a significant transformation (Table 17, Figure 24). For example, the proportion of cultivated land increased from approximately 26.10 per cent to 42.52 per cent between 2000 and 2020, showing that the rate of change in cultivated land use is accelerating rapidly. Similarly, the miscellaneous area had decreased from 38.56 per cent to 27.73 per cent, while the amount of forest land had decreased from 24.53 per cent to 20.44 per cent, which indicates that land use change conversion has accelerated within the last 20 years. However, for settlement land areas, the overall coverage was 0.81 per cent in 2000 and increased to 1.38 per cent in 2020 (Table 16).

Table 17 land use/ land cover change classification in 2000, 2010 and 2020

Land Use	2000		2010		2020	
	Hectares	% cover	Hectares	% cover	Hectares	% cover
Cultivated	2,045,786	26.10	2,440,158	31.13	3,332,667	42.52
Forest	1,922,407	24.53	1,741,764	22.22	1,601,934	20.44
Shrubs	701,284	8.95	704,075	8.98	550,884	7.03
Water	82,321	1.05	70,162	0.90	70,845	0.90
Settlement	63,789	0.81	72,602	0.93	107,878	1.38
Miscellaneous	3,022,061	38.56	2,808,887	35.84	2,173,440	27.73
Total	7,837,648	100	7,837,648	100	7,837,648	100

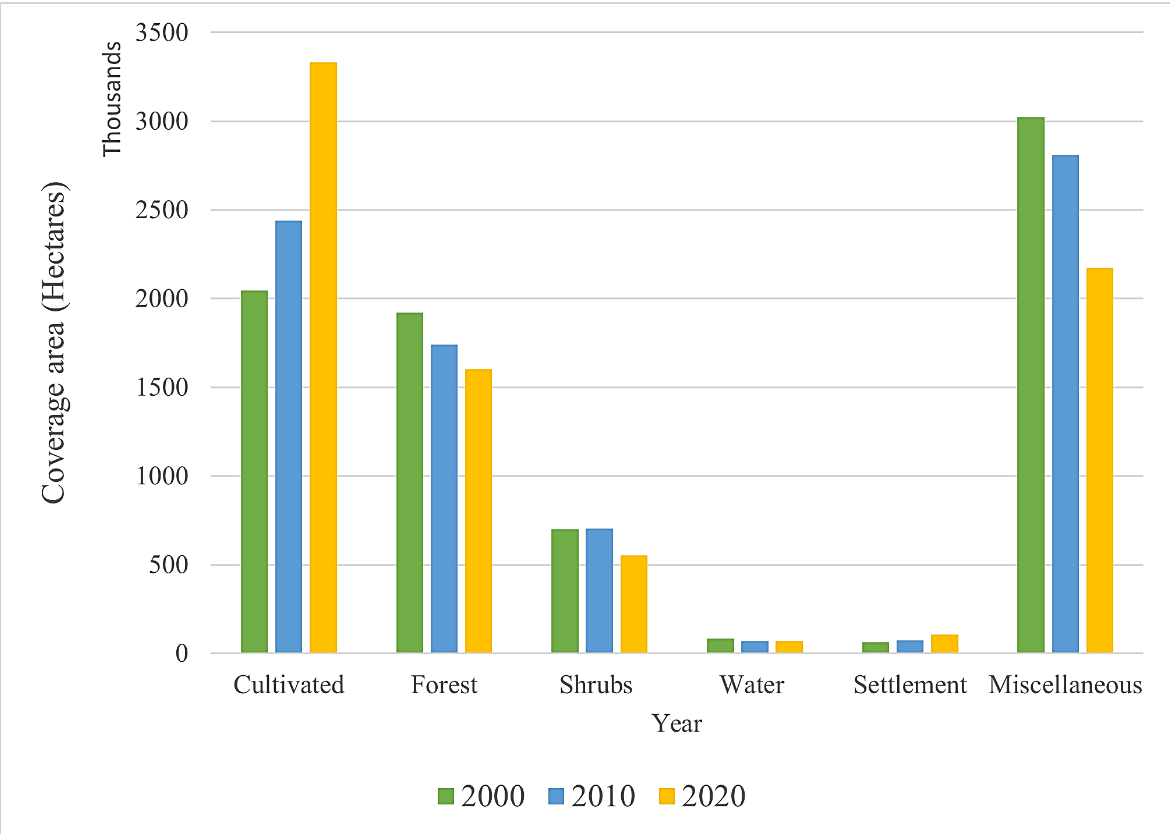


Figure 24 land use classification between 2000 and 2020

5.5.2 Future land use demand

Figure 25 depicts the changes in land use needs that emerge over time due to various socio-economic growth paths. The BAU implies that the current trend in socioeconomic development and land use will continue, whereas socioeconomic improvement prioritises all other factors in a market-oriented economy. Finally, biodiversity and sustainable resource use are the most crucial factors in the conservation scenario.

In the BAU scenario, cultivated land area increases while miscellaneous and forest land decrease compared to the baseline scenario. To preserve the sector's long-term viability, it emphasises the significance of setting constraints on agricultural land development into other land use zones. Comparing the BAU scenario's land use demand outcomes to market-oriented and conservation scenarios. In 2040, cultivated land will have increased from 3,332,670 hectares to 4,526,411 hectares (Table 18).

Table 18 land use change classification under the scenarios in 2040.

Land Use	Business-as-Usual		Market-Oriented		Conservation	
	Hectares	% cover	Hectares	% cover	Hectares	% cover
Cultivated	4,526,411	57.75	4,102,022	52.34	3,472,857	44.31
Forest	1,591,020	20.30	1,702,280	21.72	1,785,040	22.78
Shrubs	539,970	6.89	450,572	5.75	367,775	4.69
Water	57,945	0.74	66,713	0.85	69,442	0.89
Settlement	142,069	1.81	157,591	2.01	135,832	1.73
Miscellaneous	980,233	12.51	1,358,470	17.33	2,006,703	25.60

It is also worth noting that the BAU scenario's rapid development of cultivated land mirrors Nigeria's socioeconomic structure. Based on the determinants of land use change, Ighile and Shirakawa (2020) concluded that a high poverty ratio indicated a cultivated land use shift. Compared to the baseline scenario, our assumptions for scenario generation demonstrate that as the socio-economic condition improves (i.e., the poverty ratio reduces), cultivated land gradually decreases to 4,102,022 and 3,472,857 (hectares) in market-oriented and conservation scenarios, respectively.

A comparison of the three scenarios reveals that in 2020, the overall area occupied by agricultural land use (3,332,670 hectares) is similar to the conservation scenario (3,472,857). The demand for cultivated land may have peaked because of improving socioeconomic conditions, land use constraints, and increasing technological investment to enhance agricultural output (Figure). Similarly, we may describe the future spatial trends of the six land use categories by comparing the other land use types under the three scenarios. Due to weak socio-economic conditions and excessive reliance on agricultural output to meet nutritional needs, miscellaneous land (980,233 hectares) and shrubland 539,970 hectares) are more likely than other categories of land to be converted to cultivated land in the BAU scenario.

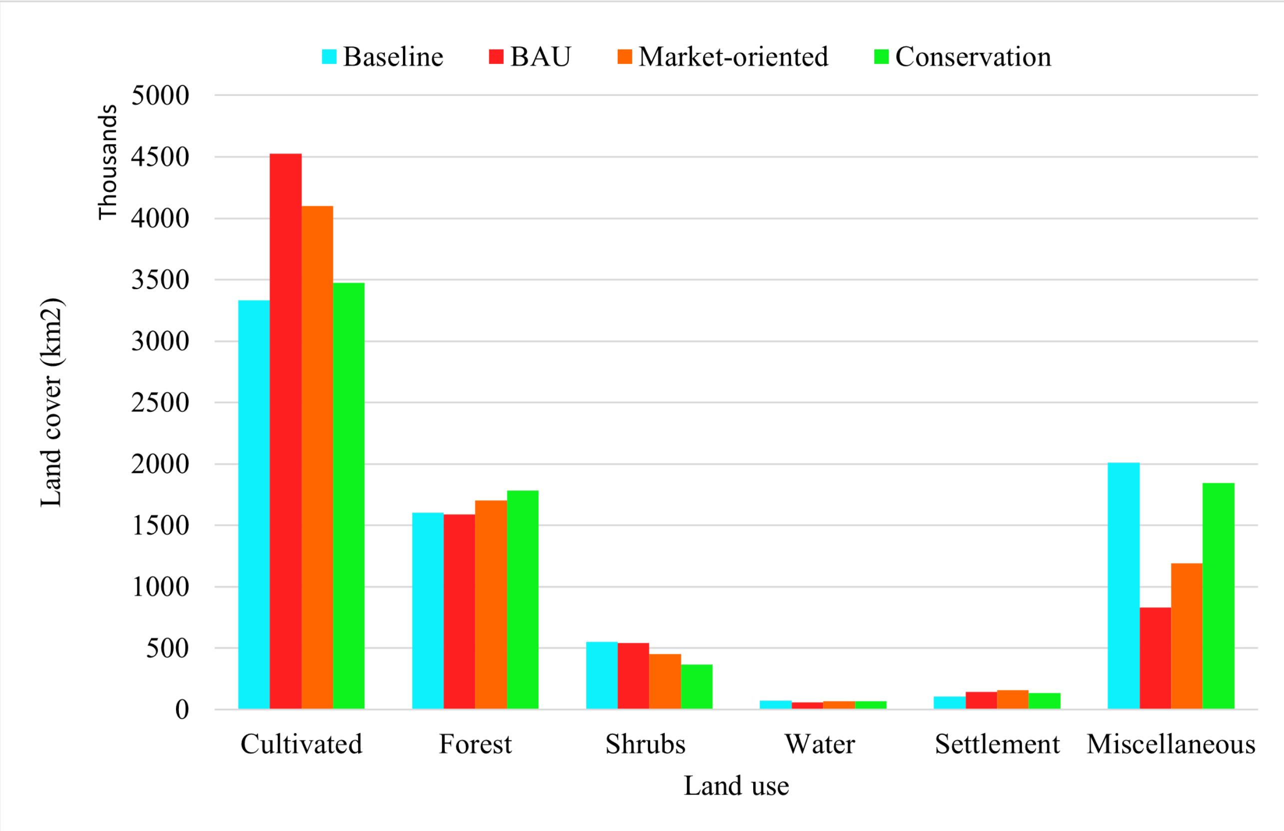


Figure 25 Comparison between the simulated land use demands in 2040

However, due to population increase, forest land (1,591,020 hectares) is more likely than other types of land to be transformed into settlement areas (142,069 hectares). Second, under the market-oriented scenario, the expansion of cultivated land is slightly slower than in the BAU scenario, which is consistent with the BAU scenario. The settlement, grassland, and forest areas, on the other hand, are expanding because of improved socio-economic conditions and a faster rate of investment in each sector, settlement land areas expanded by almost 46 per cent (from 107,878 to 152,591 hectares) in comparison to the baseline year, which is due mainly to rapid infrastructure development.

The result confirms the findings from the land use change drivers, which indicated that GDP had a favourable impact on settlement land use change. Although miscellaneous land continues to decrease from the baseline (2,173,441 hectares), in the BAU scenario (980,223 hectares) however, with improved land policies, miscellaneous land areas increased in the Market-oriented scenario (1,358,470 hectares) due to a decrease in demand for cultivated land.

The conservation scenario increases forest land areas by approximately 11 per cent (from 1,601,930 to 1,785,040 hectares) over the baseline year, whilst the miscellaneous and cultivated land trend remains unchanged from the baseline year but slower than the BAU (Figure 25). The robust implementation of land rules, improved socio-economic circumstances, increase in investment, and devotion to supporting biodiversity protection may result in the trend in land transformation assumed in the conservation scenario.

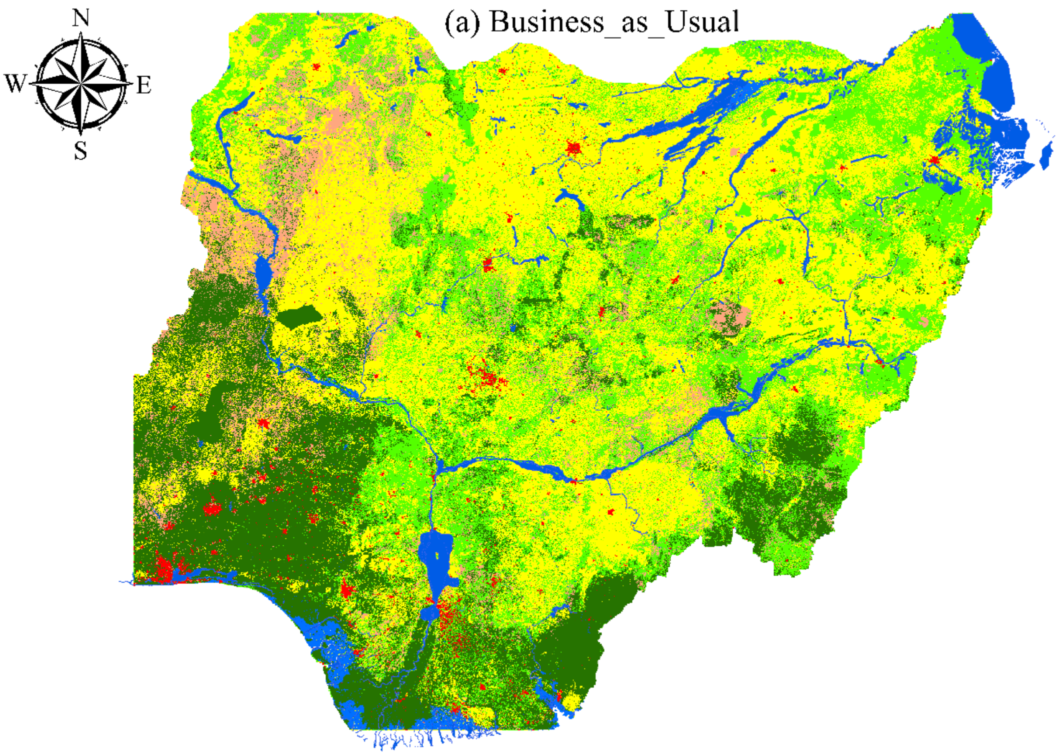
5.5.3 FLUS model land use estimation

Based on various land use needs, the FLUS model was used to simulate the spatial dynamics of land demand under three different scenarios from 2020 to 2040. Figure 26 depicts the results of the simulations in 2040. Most miscellaneous (grassland and bare areas) are situated in the central belt and northeast regions, around Niger, Kogi, Bauchi and Lake Chad. While, cultivated land is dominant in the northern areas, famous for large agricultural farms, food production and distribution to other regions of Nigeria. Additionally, in all scenarios, settlement land development happens mainly in existing metropolitan areas (Lagos, Rivers, Abuja and Kano), famous for their high population density, a mirage of industries and gainful employment opportunities. On the other hand, the forests and protected areas dominate the southern regions- Osun, Oyo, Cross River, and Bayelsa states, respectively.

Using the outcomes of the three scenarios, one can observe how regional heterogeneity differs even more clearly. For example, Nigeria's land area is primarily cultivated land, while a greater concentration of forest is in the country's western, southern and eastern regions. A result of low agricultural yields, depressed economic conditions, and unsustainable land use policies are expected to trigger a widespread conversion of miscellaneous (grassland) and shrubs to cultivated land, highlighted in the BAU scenario. On the other hand, cultivated land expansion is less severe in the market-oriented scenario due to greater agricultural output and decreased demand for land. The most notable difference between the two scenarios results from the improved socio-economic character, with less dependence on agriculture.

To meet the critical food production demand in the BAU Scenario, fast reclamation of available arable land (forest, grassland, and shrubs) was necessary. However, as the economy improved, demand for farms and other arable lands fell, but settlement land expanded substantially, particularly around major urban centres. In addition, due to socio-economic prosperity and population increase, the need for infrastructure investment promotes the rapid expansion of settlement areas in both the BAU and Market-oriented scenarios. As a result, settlement land expands considerably in the market-oriented scenario while cultivated land declines slightly around large urban and mostly farmed zones.

In contrast to the BAU and market-oriented scenarios, the conservation scenario is associated with long sustainability. It illustrates a future in which forestry restoration occurs, with a significant reduction in the demand for farmed land to maintain bio-diversity and restore the ecosystem. Grassland and forest lands are not as degraded in the conservation scenario as in the BAU. The pace of urbanization for settlement land is suitable because there is less urgency to achieve economic growth. Additionally, the scenario envisions a sustainable and inclusive development approach due to reduced adverse effects of human activities on the natural habitat.



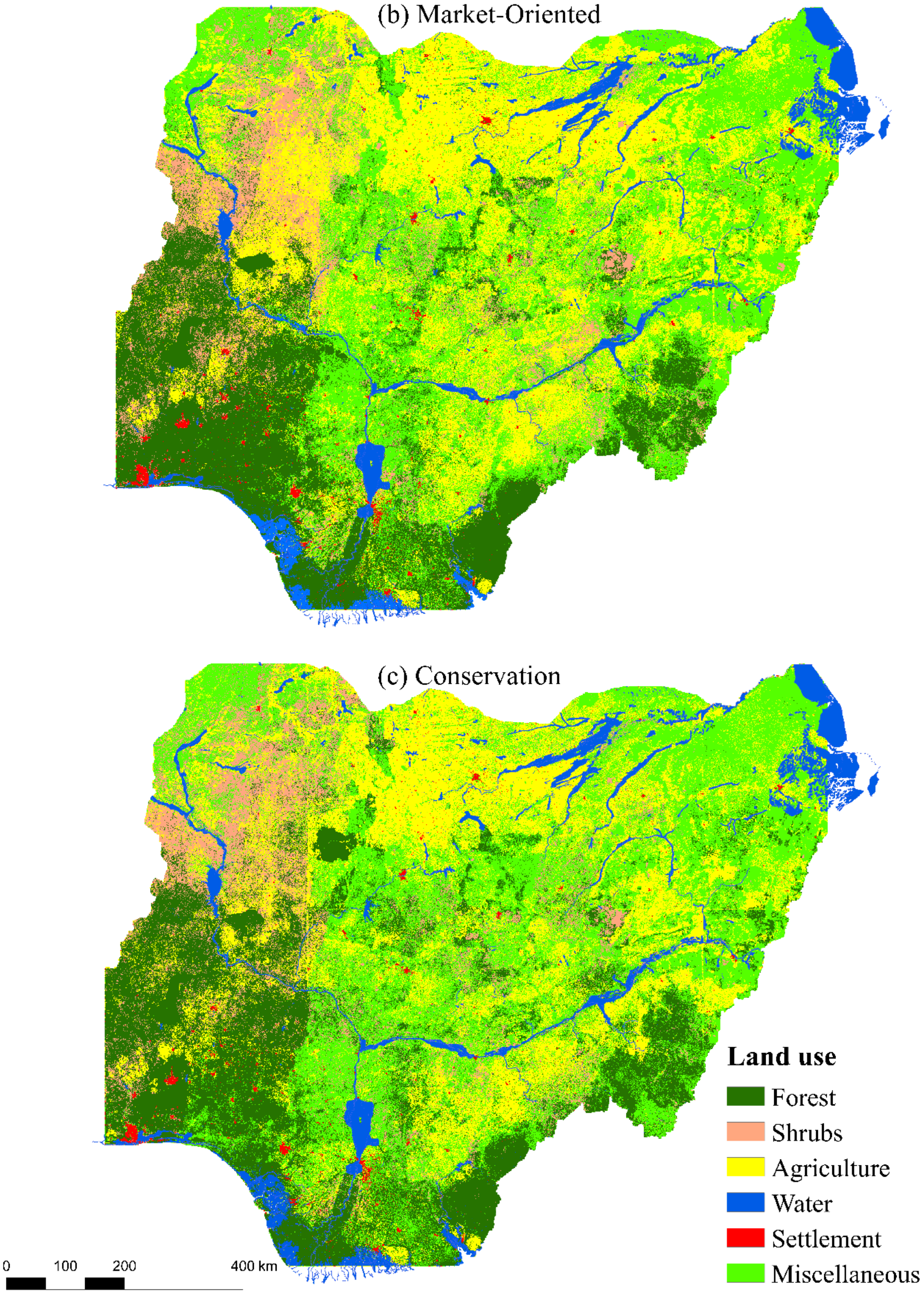


Figure 26 land use demand in 2040 (a) Business_as_Usual; (b) Market-Oriented; (c) Conservation.

5.6 Land use demand validation

The actual 2010 land use data, the probability of occurrence map derived from the ANN model evaluation, and the 2020 land use simulation map were used to compare the accuracy of the model simulations. The results were validated using the Kappa coefficient, Figure of Merit (FoM), and overall model accuracy. One can verify whether or not the simulation results are distributed equally using the confusion matrix and kappa coefficients. Furthermore, the FoM is a separate validator for the simulated results (Oishi-Tomiyau, 2013). As a result, the simulated land use map's Kappa coefficient is 0.866, the overall accuracy is 0.898, and the FoM is 0.002, showing that the model results are reliable and capable of replicating land use change under varied scenarios. Table 19 shows the validation results.

Table 19 Validation of the simulated land use types based on the FLUS model

Random sampling				
Land use	Commission Error	Omission Error	Producer's Accuracy	User's Accuracy
Cultivated	0.03	0.22	0.78	0.97
Forest	0.26	0.06	0.95	0.74
Shrubs	0.16	0.11	0.89	0.84
Water	0.09	0.07	0.93	0.91
Settlement	0.09	0.18	0.82	0.91
Miscellaneous	0.15	0.07	0.93	0.85
Kappa	0.87		Overall Accuracy (%)	89.80
FoM	0.00			

Chapter 6 Flood Risk Assessment

6.1 Developing the Flood Geospatial database

Mapping flood susceptibility in Nigeria consisted of four significant steps (Figure 27). (i) developing the geospatial database; (ii) machine learning model development; (iii) validation; and (iv) susceptibility map production. A detailed description of each stage is contained in the subsections below.

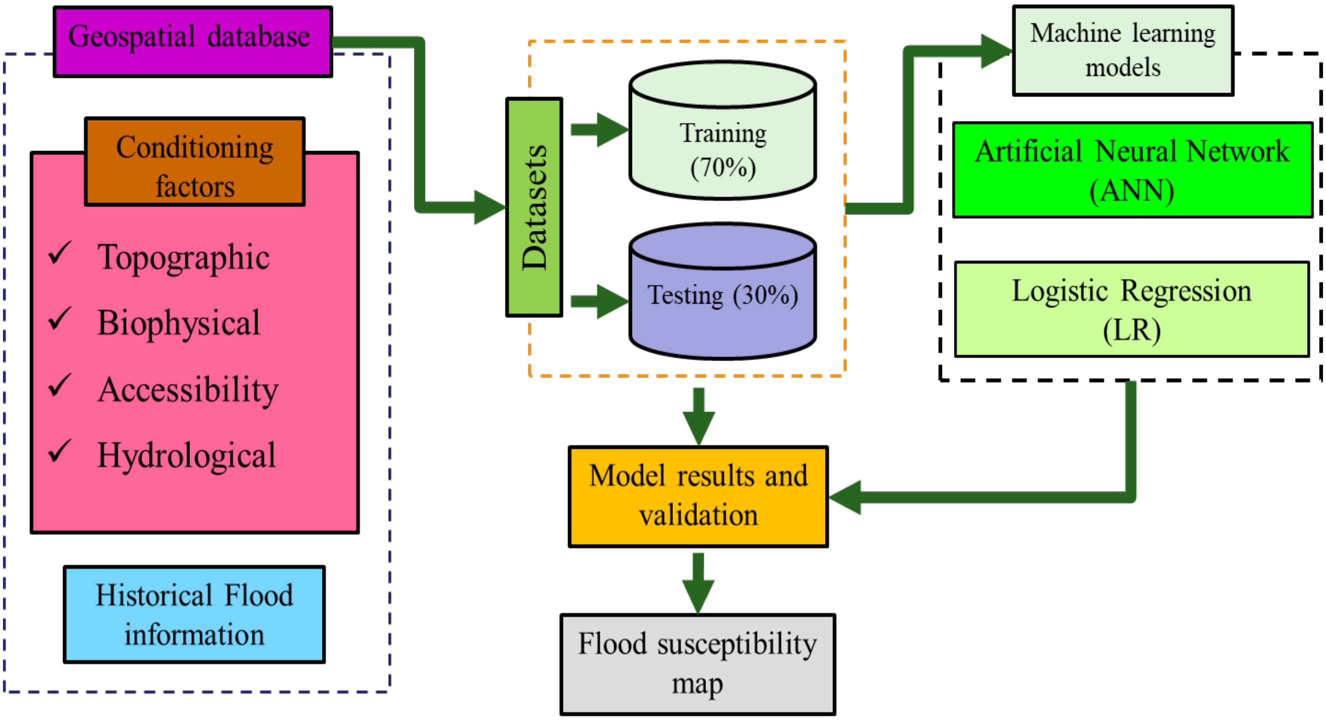


Figure 27 Flowchart of the study methodology.

6.1.1 Creation of the Flood Inventory map from historical events

Historical flood locations must be identified and mapped to investigate the spatial connection between the probability of flooding and the factors that impact it (Tehrany et al., 2018). Historical archives, field surveys, and geospatial techniques can all be used to create a flood inventory map. The flood inventory map in this study was created using historical flood archives maintained by the Dartmouth Flood Observatory (DFO) and the Emergency Events Database (EM-DAT) (Table 20). In addition, historical news archives and reports from the Nigerian National Emergency Management Agency (NEMA) and other news agencies were used to validate the datasets' authenticity.

Table 20 Flood inventory information and its source

Period	Contents of the Data	Data Type	Source
1985–2020	Location, date, validation, displaced, deaths, severity	Polygon (points)	EM-DAT, CRED
1985–2020	Location, date, affected	Polygon (points)	Dartmouth Flood Observatory (DFO)

According to the compiled research database, about 765 flood events occurred between 1985 and 2020 (Figure 28). Therefore, an additional set of seven hundred sixty-five 765 non-flood incident points was sampled from areas without a history of non-flooding incidents and were added to the existing known flood incidents data to complete the flood inventory map development. The combined inventory data of flood and non-flooding points contained 0 and 1. Where the value 0 represents non-flooded and 1 flooded. The entirety of the datasets was combined and split into two groups, with training datasets comprising 70 per cent and testing datasets comprising 30 per cent of the total (Chung et al., 2008). In total, 1071 data points served as training sets, while the remaining validation sets had 459 data points.

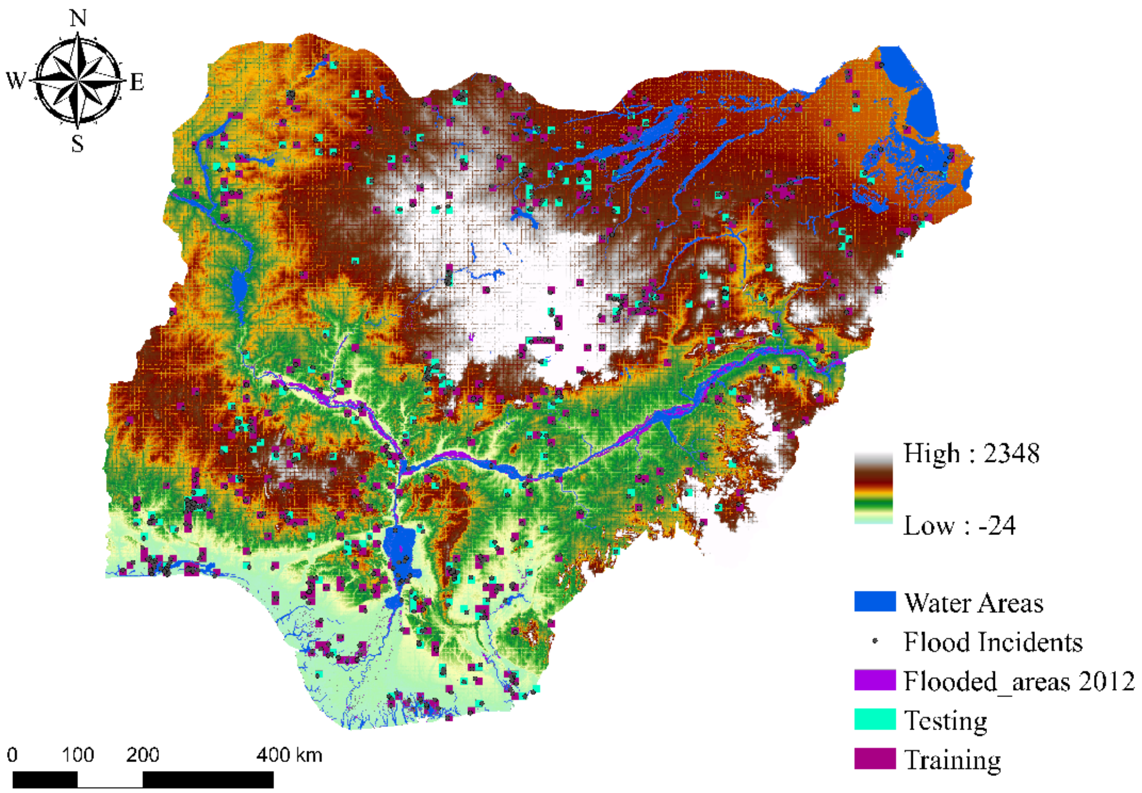


Figure 28 historical flood occurrence map (1985~2020).

6.1.2 Flood Conditioning Factors

Flood conditioning factors are those elements that contribute to the probability, magnitude and frequency of flooding incidents. They could be topographic, hydrologic, climatic or technological. Each factor contributes to forming a flood incident, both independently or combined. In order to determine the most appropriate flood conditioning factors for the investigation, existing studies were considered, as well as localised studies on the geographical characteristics of Nigeria (Paul et al., 2019; Ullah et al., 2020; Rahman et al., 2019; Campolo et al., 2003; Tehrany et al., 2015).

In most flood susceptibility studies, previous research and expert opinions determine the selection of flood conditioning factors. However, it is crucial to understand the geographical context of the study area and its surroundings when conducting flood modelling because each region contains a unique combination of natural and anthropogenic components (Fantin-Cruz et al., 2011). As a result, the following section discusses the criteria for choosing each conditioning factor. First, the conditioning factors are split into two broad categories; physical and anthropogenic. The physical factors include the topographic, hydrographic, and climatic components.

On the other hand, anthropogenic factors are those aspects of the study region attributed to human activity. The USGS Earthexplorer's digital elevation model (DEM) with a spatial resolution of 30 metres assisted in creating some of the required topographic elements, such as the aspect ratio, slope, curvature, SPI, and TWI, among the natural conditioning factors. The selected flood conditioning factors and their source is highlighted in Table 21.

Table 21 selected conditioning factors information used in the analysis and their data source

Data	Sources	Format	Period
Rainfall	Nimet, Nigeria	vector	1975–2015
Temperature	Global Climate data: Worldclim	1 km	1975–2017
Land cover	Globeland30	30 m	2020
Soil	The Harmonised World Soil Database v1.2	vector	-
	Global Hydrological Soil Group- ORNL DAAC	250 m	2020
Elevation	USGS, Earthexplorer	30 m	2015

Road network	NASA, Socioeconomic Data and Applications Center; Global Roads Open Access Dataset v1	vector	2010
Rail network	OCHA, Nigeria	vector	2009
Water areas	OCHA, Nigeria	vector	2010

6.2 Criteria for conditioning factor selection

6.2.1 Topographic factors

The topography of a site is crucial in detecting flood-prone areas and evaluating their severity (Wang et al., 2020; Dodangeh et al., 2020).

- Elevation: Among the frequently used topographical factors, elevation is the most important, as it plays a significant role in the occurrence of floods. Areas with higher elevations increase runoff, while areas with low elevations are more prone to flooding due to increased water discharge (Kia et al., 2012).
- Slope: Additionally, with water flowing from higher to lower elevations, the degree of the slope impacts the amount of surface runoff and the amount of water infiltration (Razavi-Termeh et al., 2018). As a result, low-degree slope areas are more susceptible to flooding (Hong et al., 2018).
- Curvature: Curvature is a morphometric feature that determines the divergent and convergent runoff zones, an influential factor in flood occurrence. The curvature can be flat, convex or concave. Flooding may occur in flat and concave areas (Tehrany et al., 2019), as these cause water retainment for a lengthier period than convex-shaped areas (Abubakar et al., 2012).
- Aspect ratio: The aspect is the slope's direction on a topographic surface. It considers the weathering effects due to precipitation necessary for flood analysis (Mojaddadi et al., 2017).

6.2.2 Hydrological factors

- Stream Power Index: The Stream Power Index (SPI) is one of flood modelling's most commonly used parameters. It measures the erosive power of runoffs, which is essential for estimating terrain stability (Khosravi et al., 2018). In addition, the SPI makes it possible to assess where soil conservation measures may be beneficial in preventing erosion from surface runoff.

- Topographical Wetness Index: The TWI describes the movement and buildup of water at a particular location due to gravitational force. In addition, it identifies flood-susceptible areas (Mahmoud et al., 2018).
- Roughness: The roughness is concerned with surface changes and the imperfections of a land surface. They vary in intensity. Among other things, trees, plants, and logs can be found on the topographical surface (Casas et al., 2010).

6.2.3 Biophysical factors

- Soil properties: Due to changes in particle composition, soil qualities differ from one location to another. Therefore, Soil type is chosen as a conditioning element to illuminate the nature and causes of floods throughout the country and its surrounding region.
- Curve Number: The curve number (CN) is a metric that estimates direct runoff from excessive precipitation. For example, impermeable surfaces like roads and buildings or other artificial surfaces are more prone to flooding, while natural surfaces are less likely to be affected.
- Land use: Land use is chosen as a flood conditioning factor because it explains the relationship between the natural environment, human activities, and flooding probability.
- Precipitation (rainfall): Rainfall has been highlighted as a critical component in the occurrence of floods in most flood studies (Seo et al., 2016). An increase in rainfall leads to a significant increase in runoffs, thereby increasing the likelihood of flooding (Zhao et al., 2018; Arabameri et al., 2020; Cao et al., 2016).
- Temperature: Changes in hydrologic extremes are informed by temperature correlation data collected over time, which can be used to influence everything from simple proportional change techniques to conditioning stochastic rainfall. As temperature variations can vary the amount of precipitation/rainfall received in a given area, they have the potential to influence the likelihood of flooding situations (Wasko, 2021), demonstrated by the sensitivity of temperature variations to precipitation variations and increased flow volume during the peak of flooding episodes (Wasko, 2021).

6.2.4 Accessibility factors

- Distance to Water: The distance between the floodplain and the river has been shown to impact flooding, affecting the extent and size of the flood (Uddin et al., 2019). When the volume of water in rivers exceeds the capacity of the river network, a riverine flood occurs (Felzer et al., 2020). As a result, the distance between the river is considered an influencing factor.

- Distance to Road and railway: According to Zhao et al. (2019), roads and other artificial surfaces exacerbate water inundation and serve as a channel for water to flow through the environment because of their imperviousness. As a result, the infiltration rate is reduced, which results in a higher runoff rate (Zhao et al., 2019). A similar pattern may be observed in human settlements, which are more likely to be located near highways, putting them at greater risk of flooding (Woodrow et al., 2016).

Finally, 15 conditioning factors roughness, slope, curve number, rainfall, topographic wetness index (TWI), aspect ratio, elevation, stream power index (SPI), soil type, land cover, curvature, distances to the nearest road, water, and railway, and temperature were used in modelling flood susceptible areas (Figure 29).

6.3 Description of the Flood conditioning factors

6.3.1 The topographic factors

The topographic wetness index (TWI) evaluates the water accumulation at a specific location. The larger the TWI value, the higher the likelihood of flooding. TWI is expressed as:

$$\mathrm{TWI} = \mathrm{Ln}\frac{\mathrm{A_s}}{\tan\beta} \tag{10}$$

where: $\mathrm{A_s}$ is the local upslope area draining through a certain point per unit contour length; and $\tan\beta$ is the local slope measured in radians.

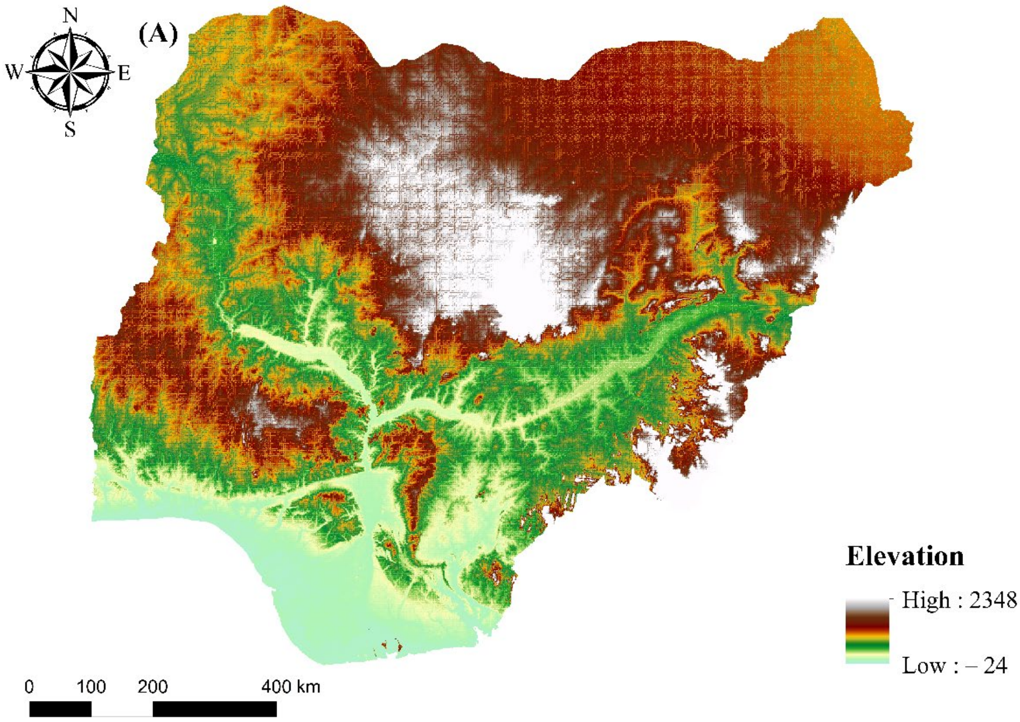
The Stream Power Index (SPI) measures the erosive power of flowing water on a topographic surface. SPI is expressed as:

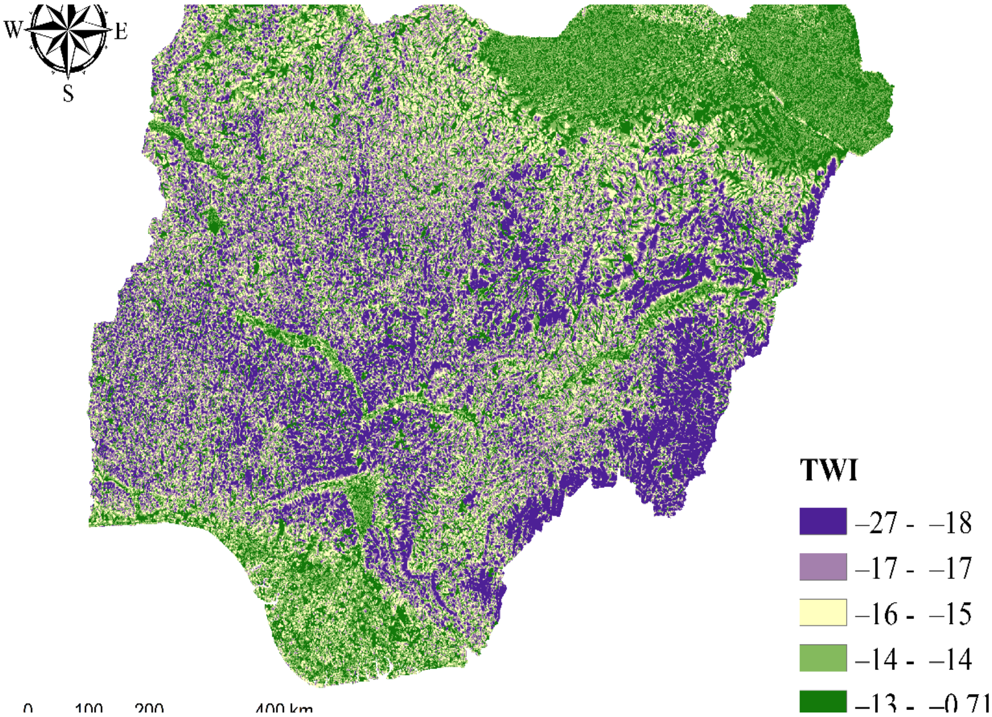
$$\mathrm{SPI} = \mathrm{A_s} \times \tan\beta \tag{11}$$

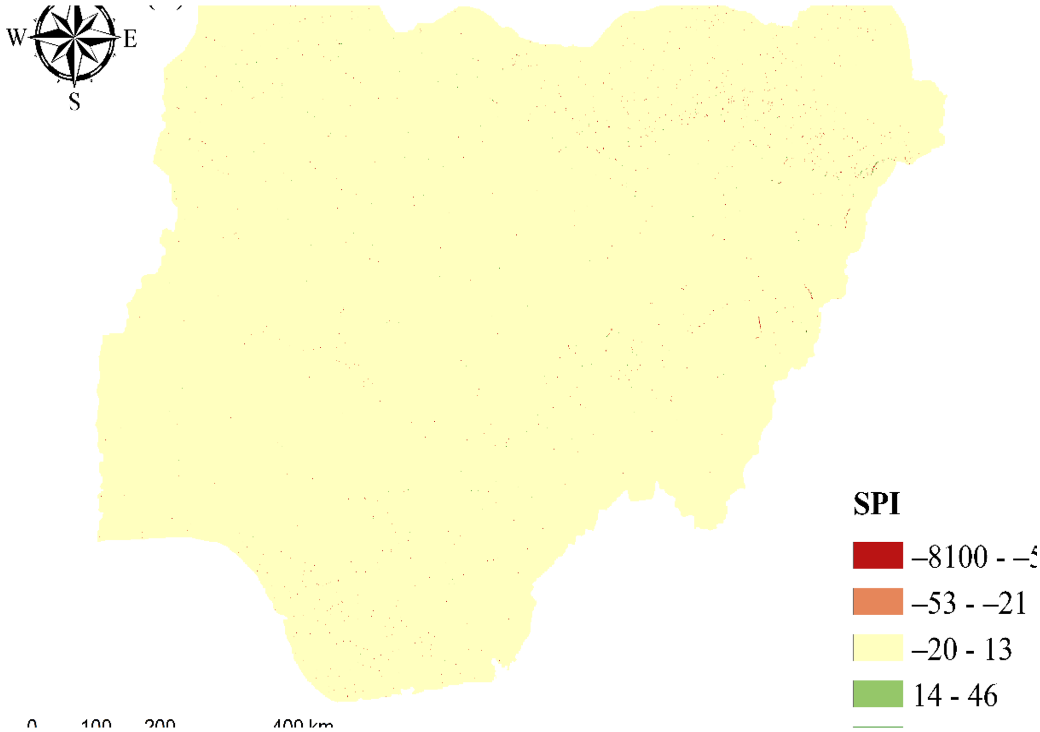
where: $\mathrm{A_S}$ is the local upslope area draining through a certain point per unit contour length and $\tan\beta$ is the local slope measured in radians.

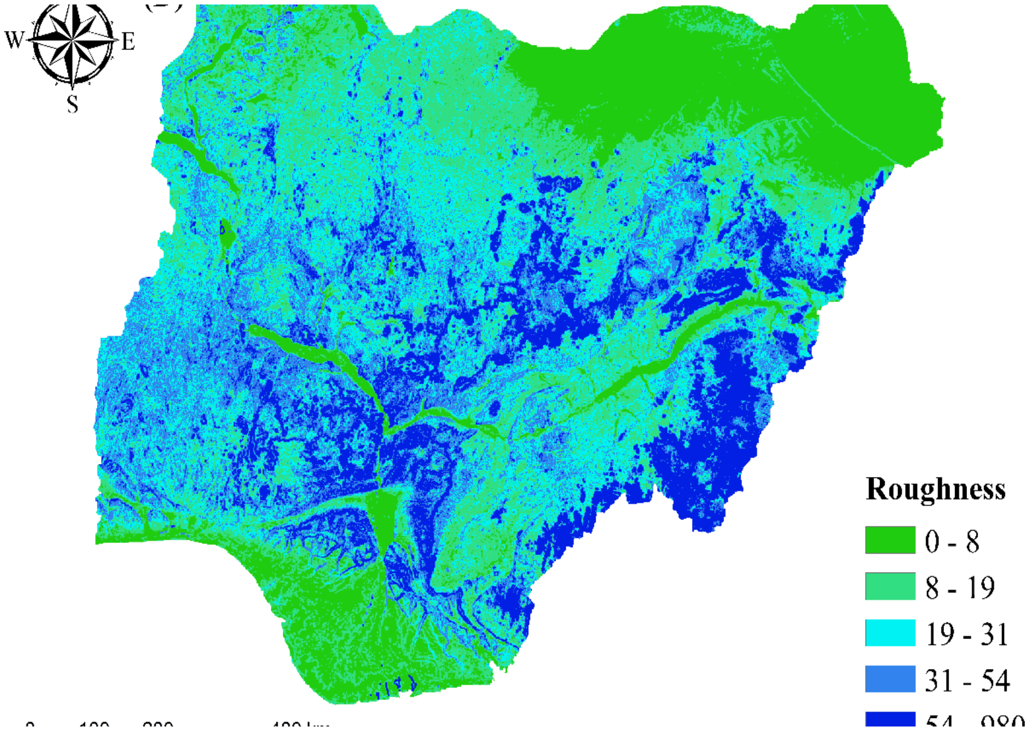
Roughness measures how much a topography surface has changed over time. The slope is one of the most commonly used conditioning factors in flood studies due to the connection between the direction of the slope and the rainfall infiltration rate on the topographical surface during a rain event. The slope values ranged from 0 to 90 degrees.

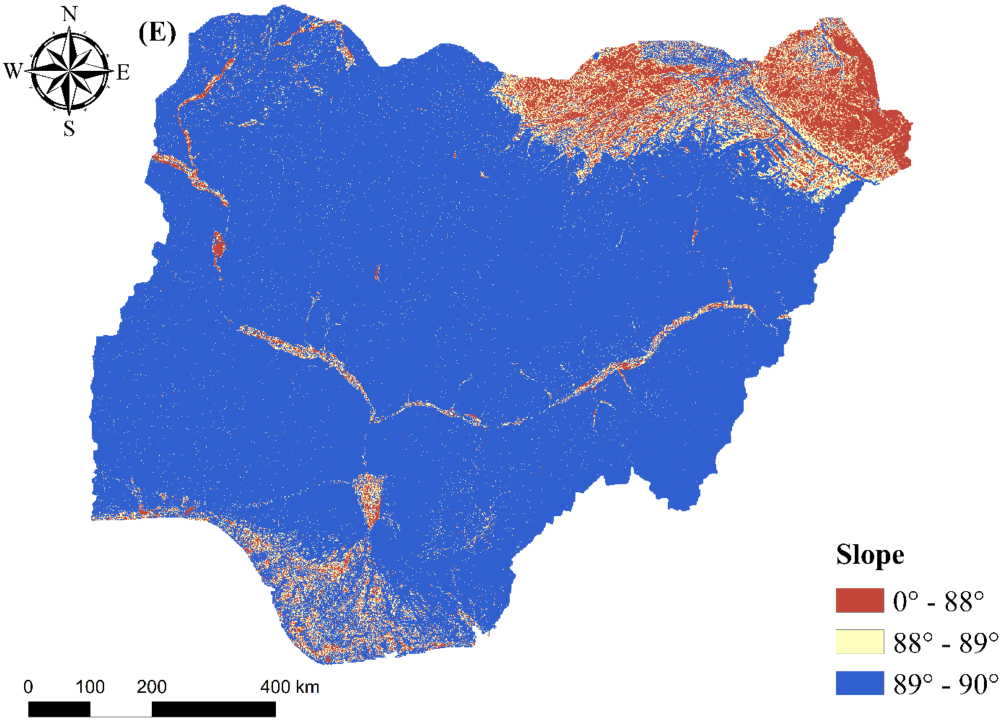
The aspect highlights the direction of the slope. As a result, it can be used to determine the steepness of a topographical surface. The aspect is divided into nine (9) groups spaced at 45-degree intervals. One more element to consider while conducting flood studies is curvature. It refers to the morphology of the topography. It can be classified as flat, convex, or concave.

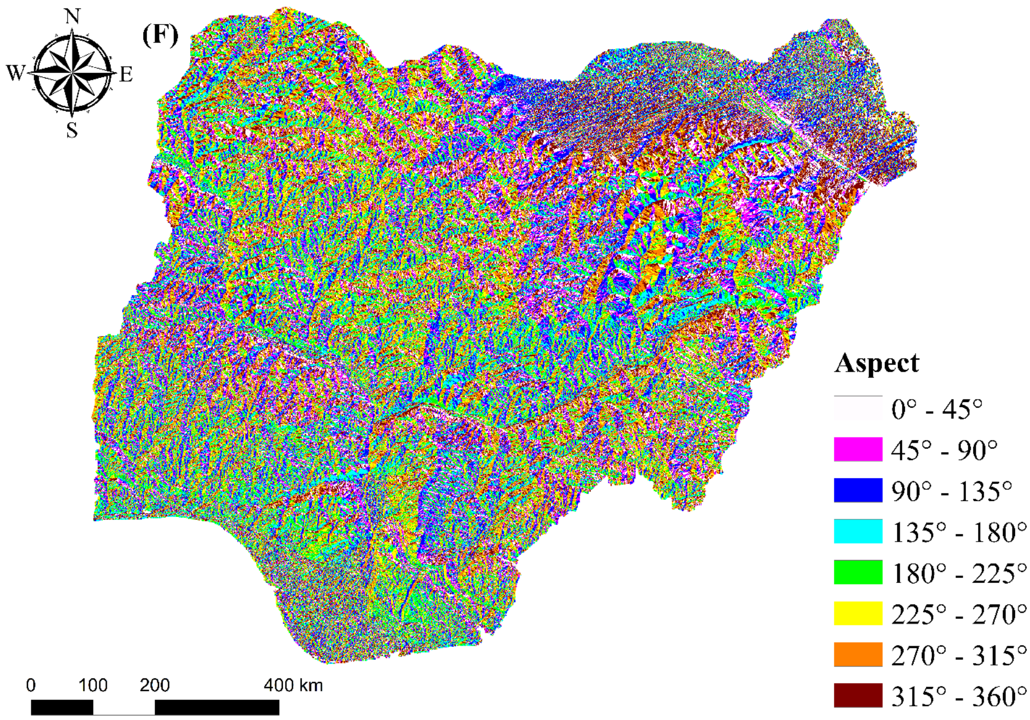


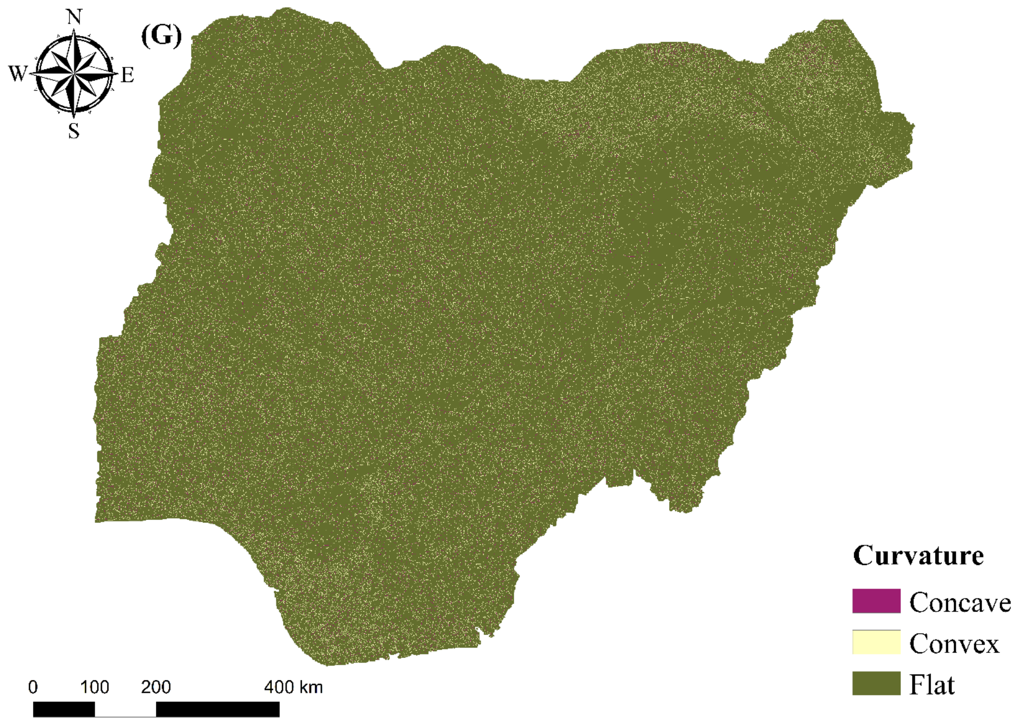

W
E
S
TWI
–27 - –18
–17 - –17
–16 - –15
–14 - –14
–13 - –0.71
0
100
200
400 km

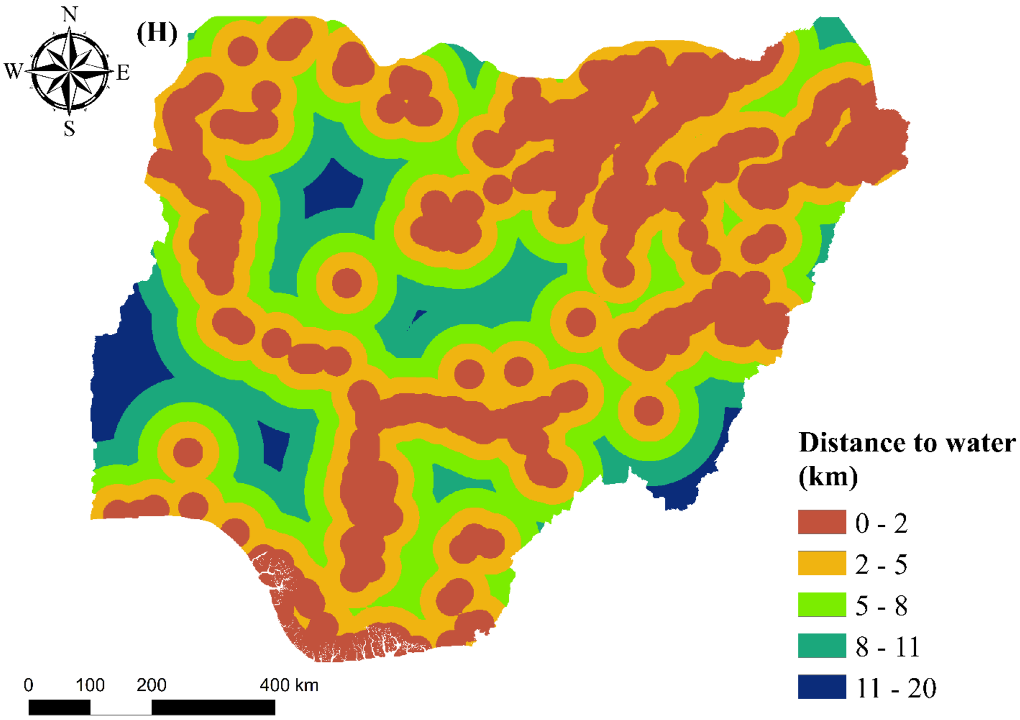

W
E
S
SPI
–53 - –21
–20 - 13
14 - 46
0
100
200
400 km

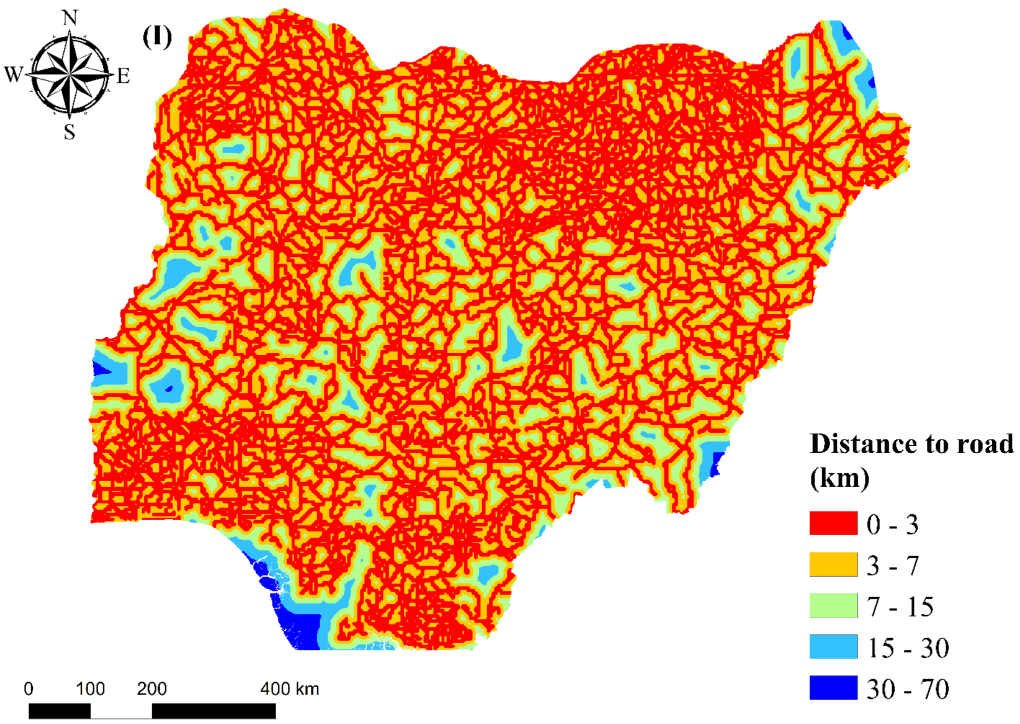

W
E
S
Roughness
0 - 8
8 - 19
19 - 31
31 - 54

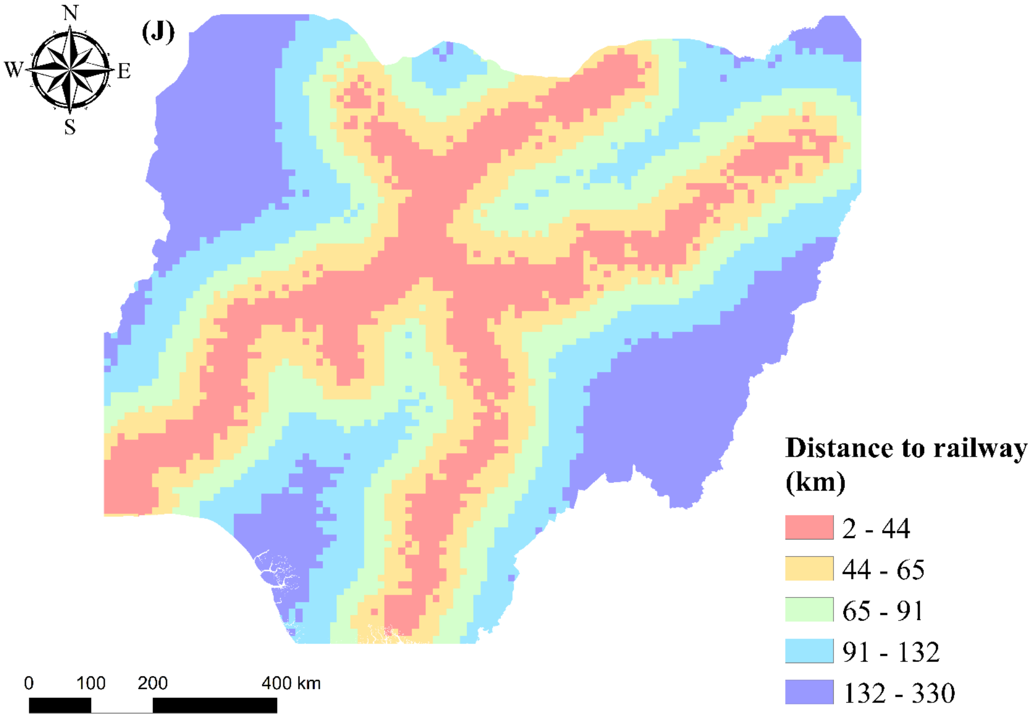

N
W
E
S
(E)
Slope
0° - 88°
88° - 89°
89° - 90°
0
100
200
400 km

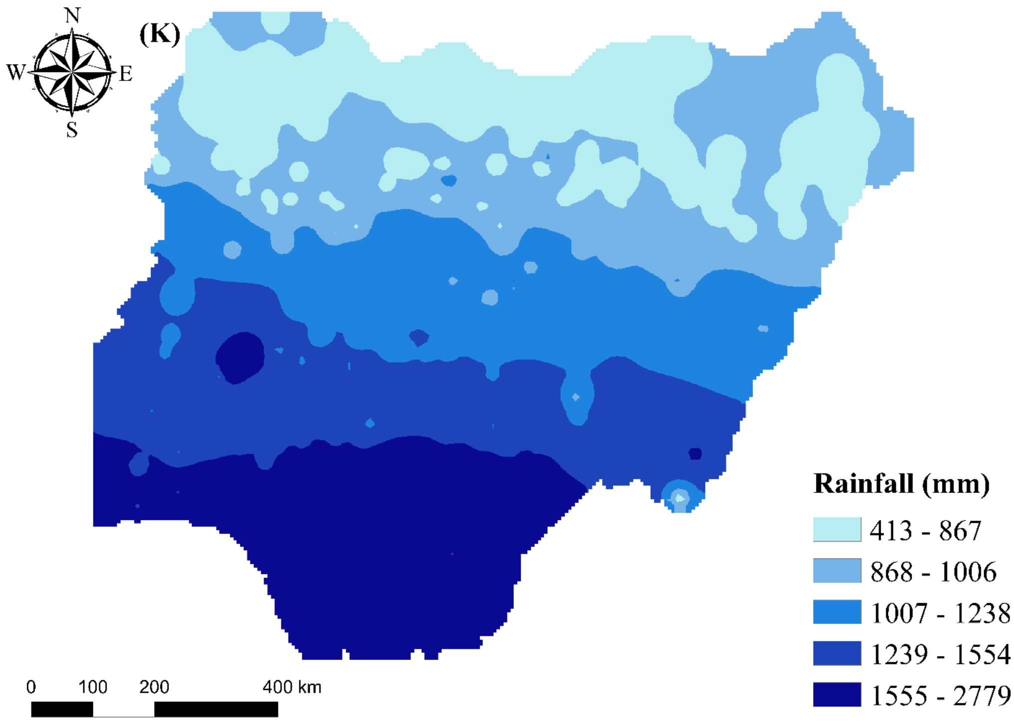

(F)
N
W
E
S
Aspect
0° - 45°
45° - 90°
90° - 135°
135° - 180°
180° - 225°
225° - 270°
270° - 315°
315° - 360°
0
100
200
400 km

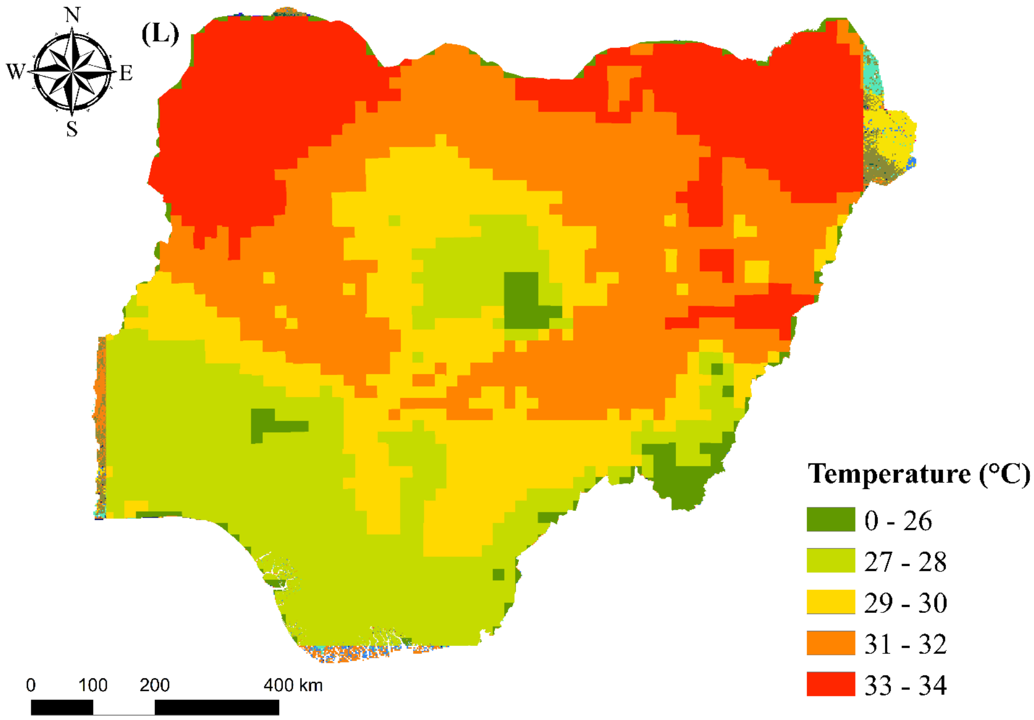

(G)
N
W
E
S
Curvature
Concave
Convex
Flat
0
100
200
400 km

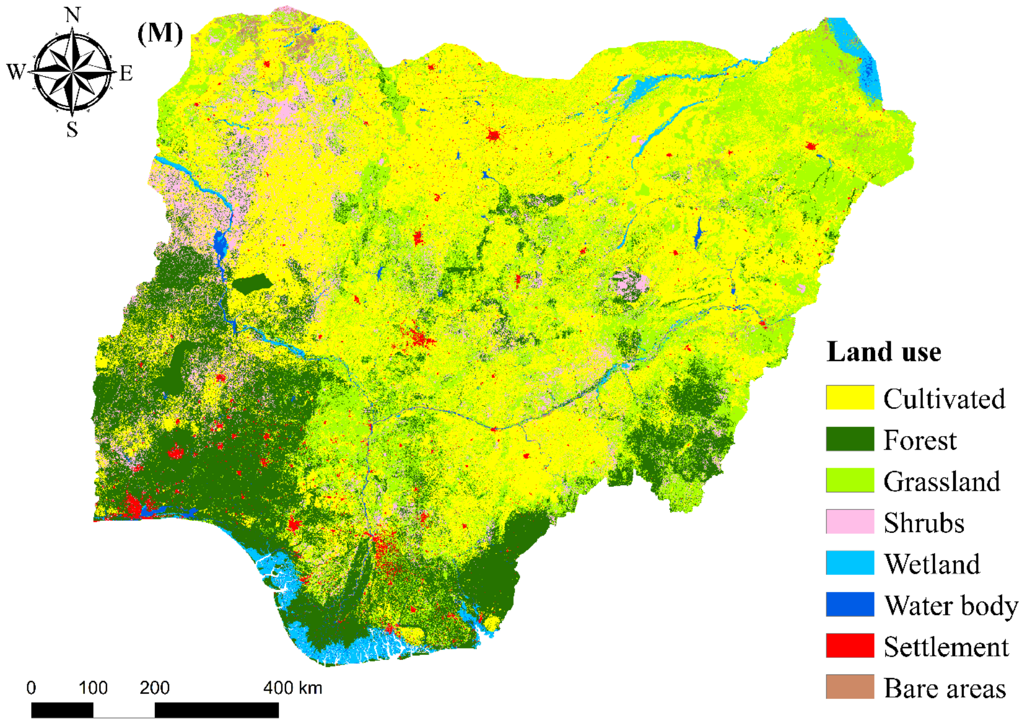

N
W
E
S
(H)
Distance to water (km)
0 - 2
2 - 5
5 - 8
8 - 11
11 - 20
0
100
200
400 km


N
W
E
S
(I)
Distance to road (km)
0 - 3
3 - 7
7 - 15
15 - 30
30 - 70
0
100
200
400 km


N
W
E
S
(J)
Distance to railway (km)
2 - 44
44 - 65
65 - 91
91 - 132
132 - 330
0
100
200
400 km


N
W
E
S
(K)
Rainfall (mm)
413 - 867
868 - 1006
1007 - 1238
1239 - 1554
1555 - 2779
0
100
200
400 km


N
W
E
S
(L)
Temperature (°C)
0 - 26
27 - 28
29 - 30
31 - 32
33 - 34
0
100
200
400 km


N
W
E
S
(M)
Land use
Cultivated
Forest
Grassland
Shrubs
Wetland
Water body
Settlement
Bare areas
0
100
200
400 km

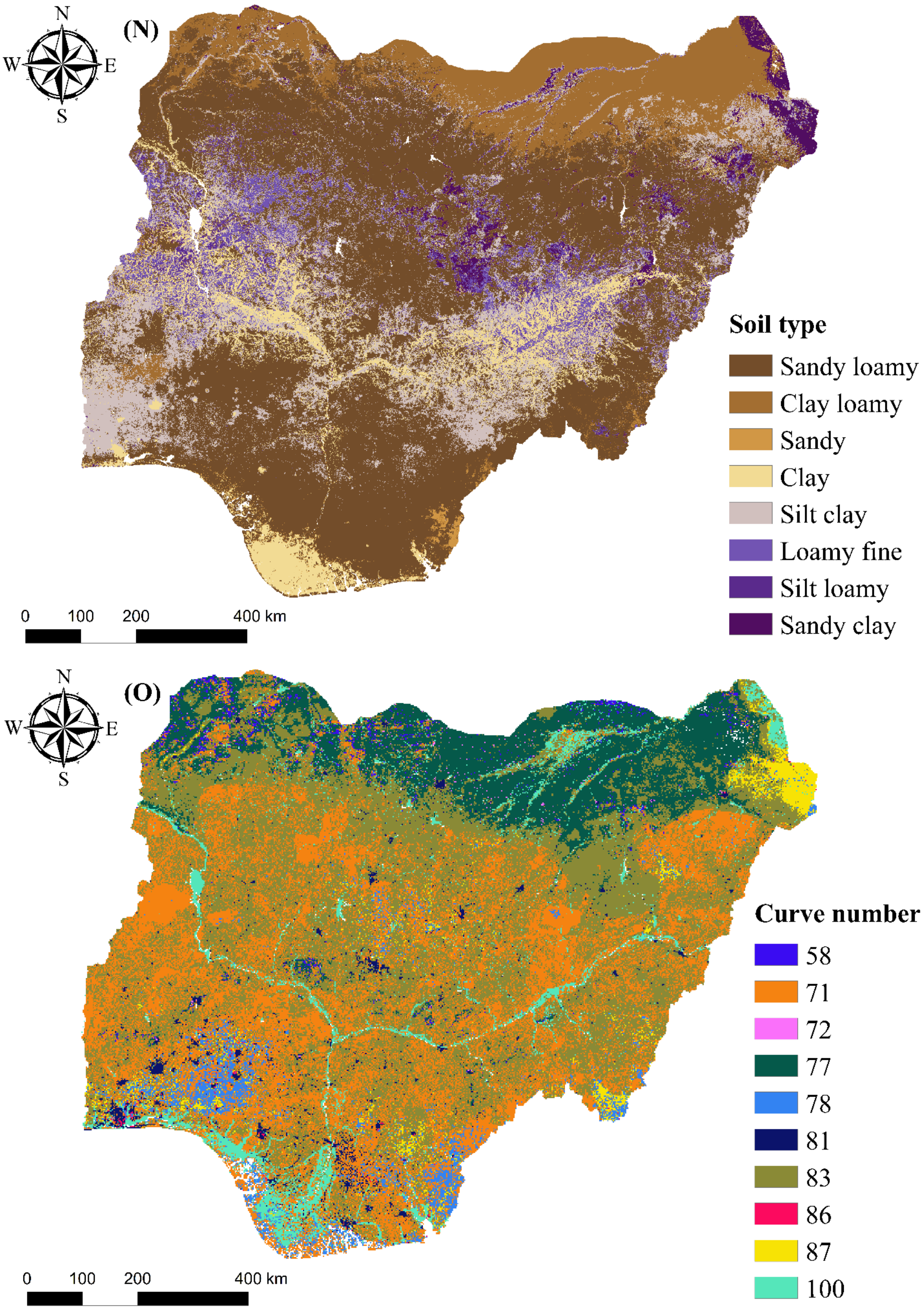


Figure 29 The selected conditioning factors (a) elevation (b) TWI (c) SPI (d) roughness (e)slope (f) aspect (g) curvature (h) distance to water (i) distance to road (j) distance to railway (k) Rainfall (l) temperature (m) land user (n) soil type (o) curve number

6.3.2 Accessibility factors

In addition, proximity criteria such as distances to water, roads, and railways were considered. For example, the distance to the water is required when assessing the components that influence flood likelihood due to flooding, which is often caused by an overflow of adjoining water surfaces (Luu et al., 2021). Similarly, the distance between other infrastructure services such as roads and railways was calculated. Similarly, the distance between a road and a railway station is an essential factor because artificial surfaces next to bodies of water significantly impact the hydraulic conductivity of soils (Ross et al., 2018). Therefore, due to urban expansion, places with reduced hydraulic conductivity resulting from infrastructure development are more likely to flood.

6.3.3 Biophysical factors

Rainfall and temperature are critical elements to consider, especially in Nigeria, where the vast differences in climate between regions significantly affect the likelihood of flooding. Past rainfall data from 28 stations are interpolated to develop the precipitation map using the inverse distance weighted (IDW) approach. Enabling the estimation of rainfall values within a certain distance, based on the numerical assumption that the values nearer to each other have a higher degree of relationship than the values farther apart. Aside from that, data on mean annual temperature from the Worldclim database were acquired and analysed for this investigation.

6.4 Machine learning algorithms

The machine learning (ANN and LR) algorithms estimate which areas are most likely to flood. Machine learning approaches evaluate each conditioning element and its correlations without first classifying the independent datasets (conditioning factors). The methodology used in this work can also be replicated and applied to other computational modelling applications because it does not require considerable data on the hydrology and topography of the research area.

6.4.1 The Artificial Neural Network (ANN)

An artificial neural network, or ANN, is a machine learning method that uses data to learn. They demonstrate a complex relationship between the inputs and outputs variables, which allows them to uncover novel pattern identification opportunities. Image identification, audio recognition, prediction mapping, and medical diagnosis are just a few tasks that artificial neural networks can perform. They are made up of a neural network with many layers linked together. There is an input layer, one or more hidden layers, and an output layer (Zhang et al., 2020).

The input information is what is fed into the network to function correctly. While the hidden identifies and stores the operations between the initial data and the resulting weights in each connection. Lastly, the model's output shows how the parameters (covariates and response) interact (Zhang et al., 2020). The neural net training is:

$$\mathrm{O(b)} = f\left(\omega_0 + \sum_{r=1}^{k} \omega_r x_r\right) = f(\omega_0 + W^T v) \tag{12}$$

where: $\mathrm{O(b)}$ is the neural network output, ω_0: the intercept, k: number of conditioning factors, ω_r the conditioning factors' weights and f: the activation function ranged between 0 and 1. The activation function is calculated by:

$$W^T v = (\omega_1 v_1 + \omega_2 v_2 + \cdots \ldots\ldots + \omega_k v_k) \tag{13}$$

where: W: a vector that contains all of the weights but not the intercept; ν: the covariates; $W^T v$ is the weights and input vectors scaled together.

Since the ANN produces the output O(b) using the provided inputs and their weights, the error function, which describes the differences between anticipated and actual outcomes, must be defined. A significant divergence in a model indicates a poor fit and requires changes. As a result, our research selected the cross-entropy function over the traditional back-propagation method.

The cross-entropy classification method is an information theory measure that calculates the difference between two probability distributions using the entropy backbone. Cross-entropy is a way to measure how different two probability distributions are for a random vector or set of events. It also figures out how many bits are needed to define or move an event between one distribution to another, extending the concept of entropy from information technology. The error function for cross-entropy is written as:

$$E_{ce} = \frac{1}{2}\sum_{l=1}^{L}\sum_{h=1}^{H}(y_{lh}\log(O_{lh}) + (1 + y_{lh})\log 1 - O_{lh})) \tag{14}$$

where: l=1: the indices of the inputs and outputs, and $h = 1$: the number of output connections.

Although the neural network can produce accurate predictions compared to other models, interpreting the results can be challenging (Intrator and Intrator, 2001). The generalised weights help define each covariate's effect and contribution to the response variable (flood). The following are the generalised weights expressions:

$$\widetilde{\omega}_{\mathrm{i}} = \frac{\partial \log\left[\frac{\mathrm{o(x)}}{1 - \mathrm{o(x)}}\right]}{\partial \mathrm{x_i}} \tag{15}$$

where: i: the covariate index, o(x): the predicted values as a function of the covariates (Atkinson et al.,1998).

The weight distribution of the output variables represents the relationship and interaction between the input and output variables. The parameter variable does not affect the result status if the distributed weights accumulate around zero. On the other hand, the input parameters have a non-linear effect on the outcome variables whenever the distribution is broad. As a result, it is easier to analyse individual predictors depending on their contributions to the model outcome. Furthermore, they facilitate the comprehension, evaluation, and omission of input variables that have no significance to the model outcome.

6.4.2 The Logistic Regression (LR) model

Using the logistic regression model makes it possible to establish a multivariate relationship between the independent and dependent variables. The explanatory variables could be either atomic or categorical, contrasting with the dependent variable's binary nature. Like the multiple linear regression model, the logistic model better interprets the interaction between flooding occurrence and the stated independent factors. The dependent variable is binary (0,1), which indicates whether or not a flood has occurred in the past, and the independent variables can take multiple forms. The logistic regression model is expressed as:

$$TP = \frac{\exp(x)}{1 + \exp(x)} \tag{16}$$

where: TP is the probability of flooding and x is the linear combination of the flood conditioning parameters, expressed as:

$$x = \beta_0 + \beta_1 A_1 + \beta_2 A_2 + \ldots\ldots\ldots\ldots + \beta_n A_n \quad (17)$$

where: x: is the combination of all the conditioning factors; $A_1, A_2, A_3 \ldots. A_n$, β_0: the intercept and $\beta_1, \beta_2 \ldots.. \beta_n$: the logistic regression parameters.

6.5 Correlation Analysis

Examining the relationships among the independent variables is crucial to verify that the model generates accurate results in predictive modelling. Correlation assessment is the technique of determining the link between the independent variables chosen for investigation. Multicollinearity develops when the correlation between two or more selected variables is exceptionally high (Pourghasemi et al., 2013). Additionally, whenever a group of independent variables exhibits a high degree of correlation, they are called multicollinear and can increase the likelihood of diagnostic errors in modelling (Bui et al., 2016). Numerous methods, such as Pearson's correlation, variance inflation factor (VIF) and the conditional index, have been developed to assess multicollinearity (Schuerman, 1983; Belsley, 1991; Booth et al., 1994; Bai et al., 2010; Dormann et al., 2013).

The VIF measures the degree of interconnectedness between a variable and other explanatory variables in a regression model. In the model context, a higher variance causes a rise in the standard error of the variable. When VIF is expressed as a square root, it indicates how collinearity increases the confidence interval for that variable. When the VIF is 5, 10, or greater, it indicates the emergence of multicollinearity (O'Brien, 2007).

6.5.1 The Pearson's correlation

In statistics, the Pearson correlation coefficient describes the relationship between two variables. Values are assigned between -1 to 1, where a value of -1 denotes an absolute negative linear relationship, 0 signifies no connection, and a value of + 1 denotes a positive linear relationship. The correction coefficient is calculated as follows:

$$X = \frac{\sum(A_i - \bar{A})(B_i - \bar{B})}{\sqrt{(A_i - \bar{A})^2 \sum(B_i - \bar{B})^2}} \quad (18)$$

where: X is the correlation coefficient, A_i and B_i: the values of variables A and B and $\bar{A}$ and $\bar{B}$: the mean of each variable.

6.6 Variable importance estimation

For forecasting the dependent variable, the relative significance measures how well the input variable contributes to predicting the dependent variable. There are many methods for estimating the relative relevance of input variables in a machine learning model. Variable importance approaches commonly employed include the sensitivity analysis, partial derivatives, connection weights algorithm, Lek's profile approach, and Garson's algorithm. The connection weights algorithm was used in this investigation. Compared to other approaches, the connection weight method has the best performance in evaluating and rating the importance of all variables in the model based on the degree of accuracy and precision.

Additionally, when accurately analysing the true significance of each variable in the neural network, the connection weight technique outperformed the competition. When input and output neurons are connected, it is the product of the hidden-input and hidden-output connection weights that have been created between them and the sum of these products across all hidden neurons. The relative importance is expressed as follows:

$$\mathrm{RI}_{a} = \sum_{\mathrm{b}=1}^{\mathrm{m}} Z_{\mathrm{ab}} Z_{\mathrm{bc}} \tag{19}$$

where: $\mathrm{RI_a}$ is variable a relative importance. $\sum_{\mathrm{b}=1}^{\mathrm{m}} \mathrm{Z_{ab}} \mathrm{Z_{bc}}$: an aggregate of the final connection weights between the neurons (inputs and hidden), b represents the number of hidden, and c denotes the number of outputs.

6.7 Assessment of Modeling Accuracy

The accuracy of the models was assessed using the area under the curve (AUC) and the receiver operator curve (ROC). When it comes to quantitatively evaluating the accuracy of a diagnostic model's success and predictive power, the area under the curve (AUC) is one of the most widely used metrics. Researchers have employed the AUC technique in several studies on flood susceptibility mapping and demonstrated its effectiveness in validating diagnostic models. For the models' training and validation, 1486 flood and non-flood locations were randomly divided into two ratios (70:30).

6.7.1 Model performance evaluation

High-performing machine learning (ML) models are identified and used based on the model's accuracy to predict possible outcomes. One of the essential factors in developing high-performance machine learning models is the selection of different factors that affect the models' outcomes. This method is referred to as hyperparameter tuning in machine learning. Developing a first-rate collection of parameters to attain the model's optimal result is known as hyperparameter tuning. They usually include decisions on the required amount of layers or neurons for the model, learning rate, loss function and other metrics that can help improve the model's overall ability to predict the desired outcome based on trial and error. The performance evaluation of both models included numerous statistical indicators such as the mean square error (MSE) and root mean square error (RMSE). In addition, every evaluation criteria used depends on the confusion matrix of the models. Following a series of model runs, the model consists of 8 hidden layers and 64 neurons (Table 22). The MSE is expressed as follows;

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (20)$$

The RMSE is expressed as follows;

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (21)$$

where n = number of observations; y_i = observed values; $\hat{y}_i$= predicted values

Table 22 Parameterisation of the machine learning models

Model Parameters	Models and values	
	Artificial Neural Network	Logistic Regression
Training	70	70
Validation	30	30
hidden layers	8	0
neurons	64	0
The Activation function	logistic	logistic
The Learning rate	0.001	0.001
Architecture	Trial-and-error	Trial-and-error

6.8 Results of the machine learning models

6.8.1 Artificial neural network model (ANN)

It is possible to identify flood conditioning elements and their impact on flood susceptibility using an artificial neural network model (ANN). The analysis findings reveal a graphical representation of the ANN model training outcomes, illustrating each covariate (condition factor) relative contribution to flood susceptibility. As a bonus, the generalised weights of the ANN are shown in Figure 30, representing the first result group (continuous data), and it is an excellent way to identify the relative relevance of each covariate.

Following the generalised weights distribution, curvature and slope have significant positive non-linear effects on the occurrence of floods. TWI, distance to water, road, roughness, elevation, rainfall, distance to the railway, and temperature all significantly non-linear effects on flood occurrence. Figure 30a~k demonstrates that most factors have both negative and positive effects on the occurrence of floods. When analysing the findings of the ANN generalised weights, keep in mind that if all of the weights are around zero (0), the covariate does not affect the outcome (flood status). However, having most of the weights above zero (0) indicates that the response variable has had a positive effect and vice versa. Conversely, if most of the weights are below zero (0), the response variable has no effect (Agwu et al., 2019).

For this investigation, curvature, distance to water, the roughness of the road, elevation SPI and TWI, rainfall, distance to rail, and temperature all have positive and negative non-linear effects on the experiment's outcome. In the same vein, lower TWI levels have negative consequences in the event of a flood. Furthermore, greater temperature values positively impact flood results, whereas slope negatively impacts flood outcomes.

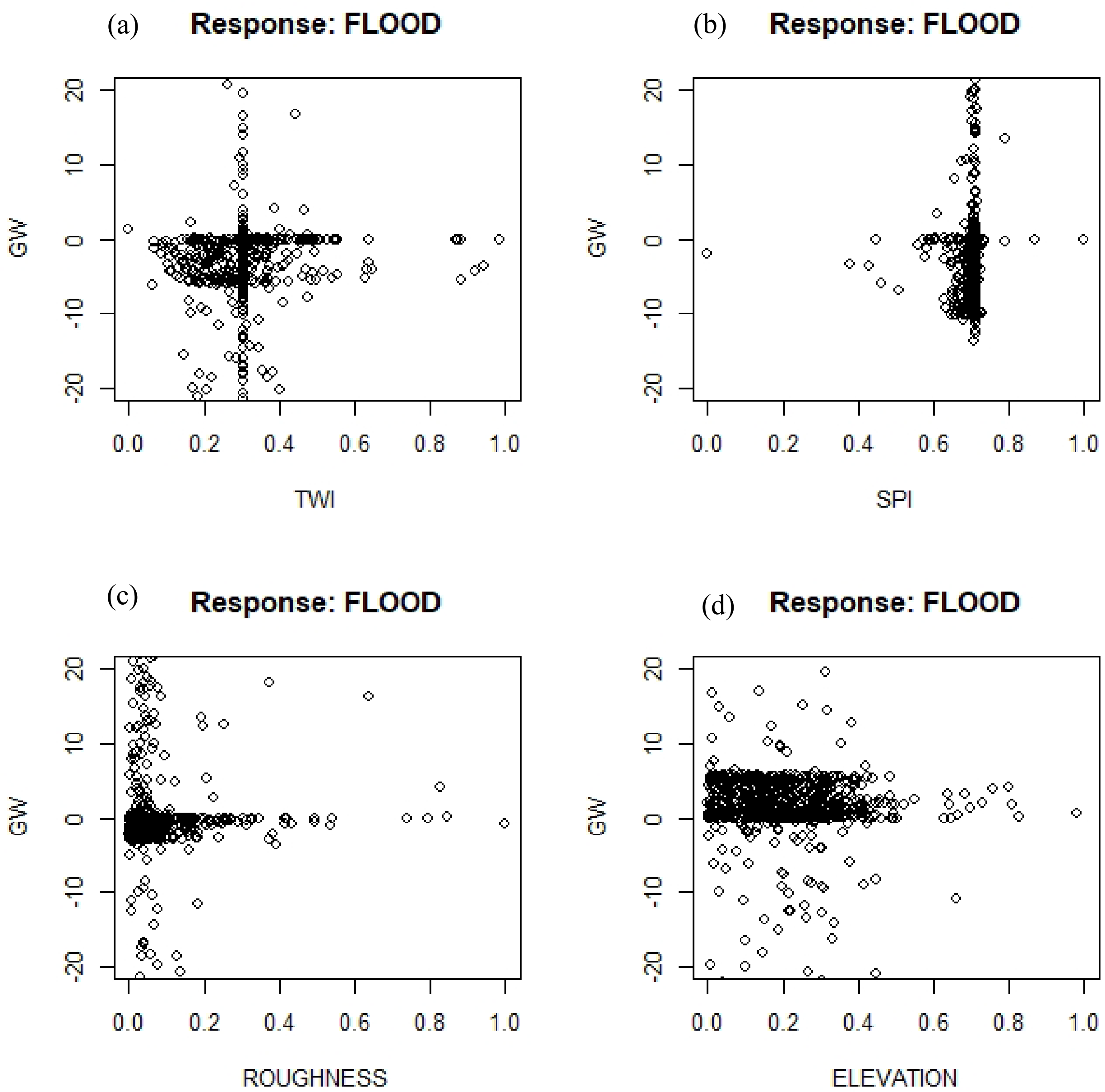


Figure 30 Generalised weights plot of the ANN model (a)TWI (b)SPI (c) roughness (d) elevation) (e) curvature (f) slope (g) distance to water (water) (h) distance to road (road) (i) rainfall (j) distance to railway (rail) (k) temperature.

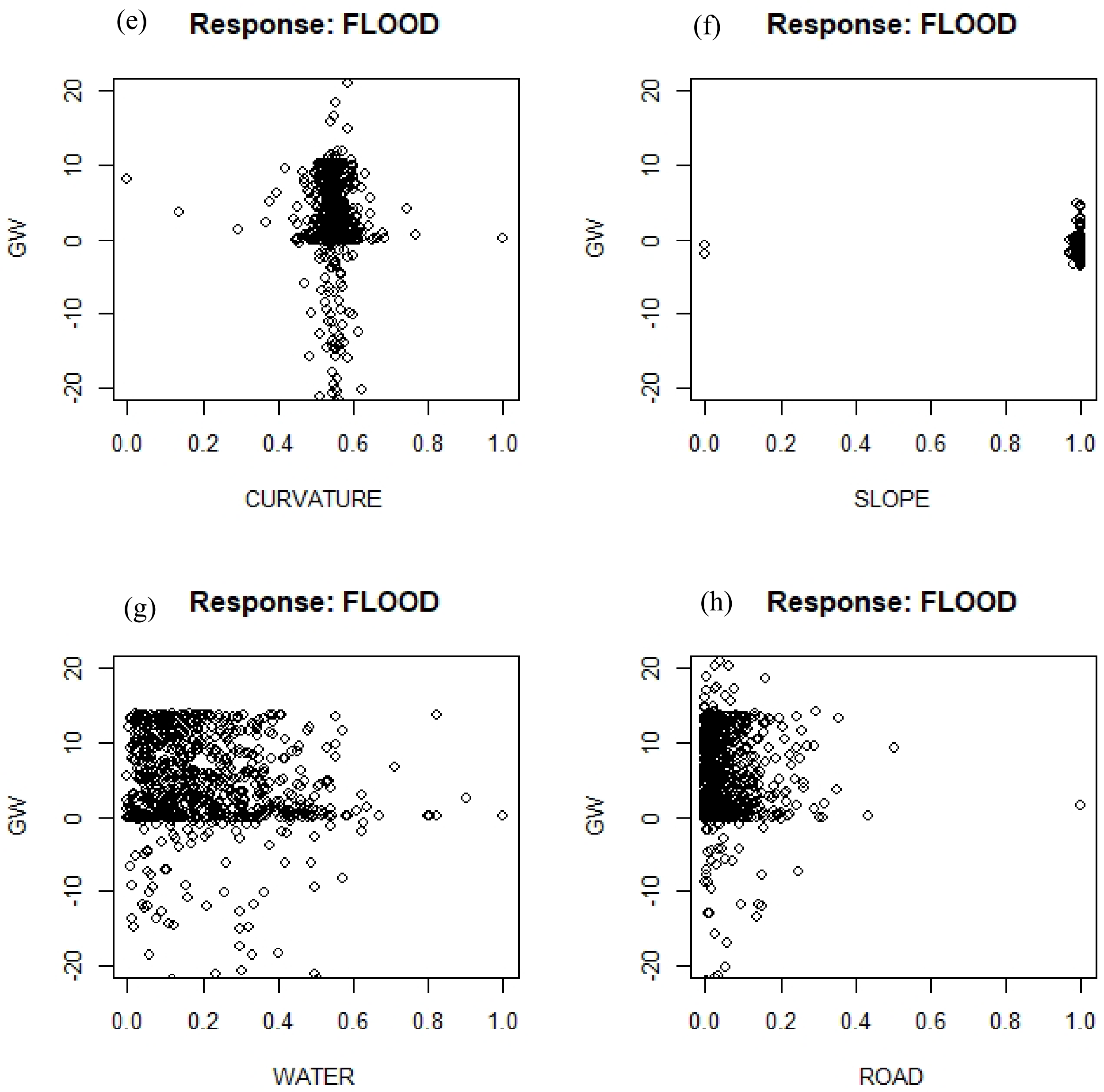


Figure 30. continued.

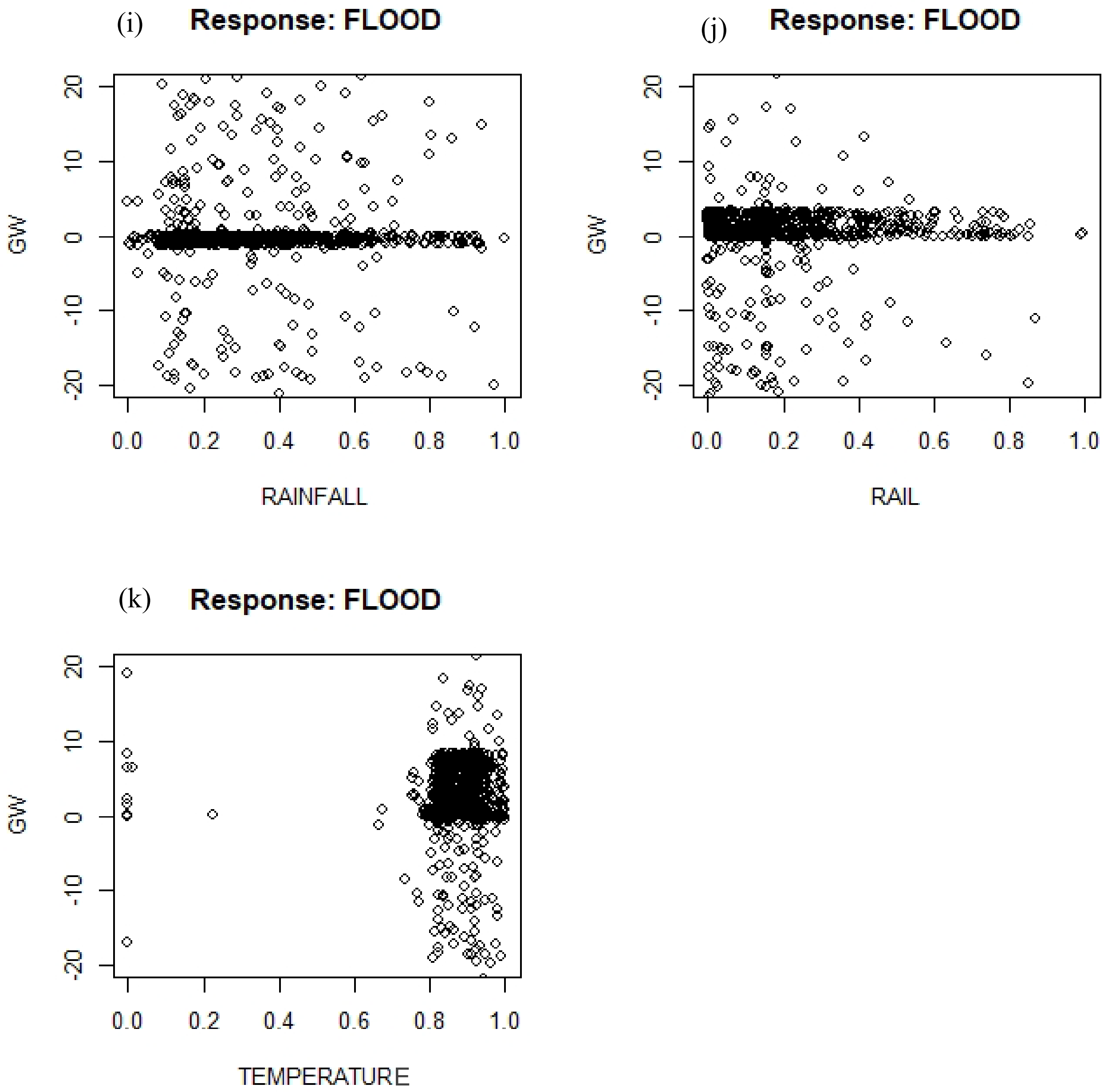


Figure 30. continued.

6.8.2 The Logistic model

The logistic model results show how each variable affects flood risk levels. Table 23 shows the results for each independent variable used in the model. We set the significance level at 5% (p = 0.05) to determine how significant the factors were in mapping flood risk. The model result shows that the road curvature and distance significantly impacted flood occurrence probability. The significant variables in the model are aspect ratio, land use, rainfall, roughness, and distance to water. However, other conditioning factors: elevation, temperature, and distance to the railway, were all deemed insignificant variables in the model.

From the results, the distance to a road, curvature, land use, distance to water, rainfall, the roughness of the terrain, and soil type are statistically significant and can help predict flood susceptibility, having p-values less than 0.05 (5%). Similarly, the slope, SPI, TWI, curve number, and aspect were also significant in the model, consistent with previous findings. However, the model's estimation was unaffected by elevation, distance to railway, or temperature.

Table 23 The logistic regression model coefficients.

Conditioning Factor	β coefficient	Significance (*P*-value)
Curvature	0.00	0.00 ***
Distance to Road	−0.20	0.00***
Aspect ratio	−0.00	0.00 **
Land use	−0.01	0.00 **
Distance to Water	0.07	0.01 **
Rainfall	0.00	0.01 **
Roughness	0.00	0.00 **
Curve Number	0.02	0.02 *
Soil type	−0.00	0.04 *
Slope	0.00	0.05 *
SPI	−0.29	0.03 *
TWI	0.00	0.04 *
Elevation	−0.00	0.37
Temperature	−0.02	0.30
Distance to Railway	0.04	0.73

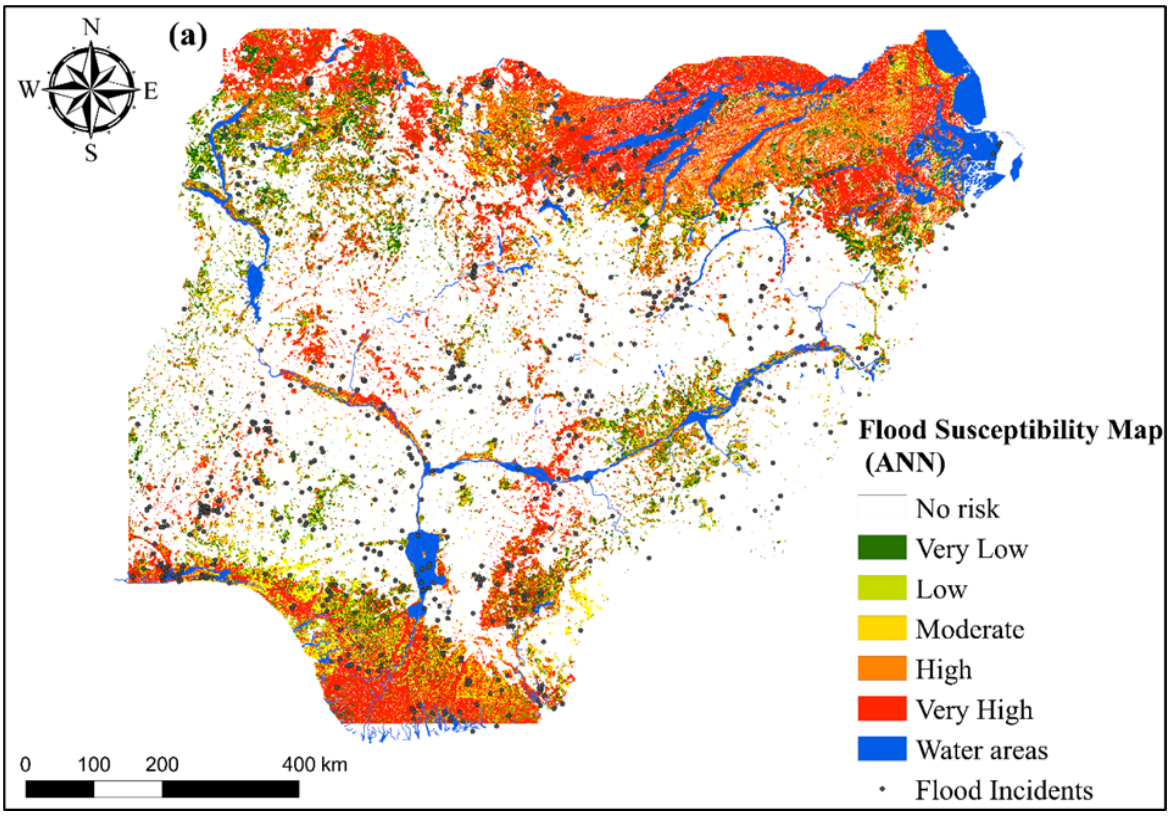
Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘’

6.9 The Flood susceptibility map

The flood susceptibility map is produced as the ultimate result of the machine modelling process. In addition to assisting with emergency preparedness, the flood susceptibility map can also be used as the first step in flood control. The visually represented map immediately identifies the most susceptible areas and prompts suitable responses. After training and testing the machine learning models, the final maps are built (Ghasemian et al., 2022).

The ANN and LR models determine the flood-prone zones in a given area. Depending on the pixel's location, it will be assigned a number between zero (0) and one (1), reflecting the likelihood of flooding at that site. A value (0) indicates a low likelihood of flooding, whereas 1 indicates a more significant likelihood of flooding (Islam et al., 2021). As part of the probability of occurrence map development, the flood susceptibility index values are divided into five classes using the quantile-based method (Mahmoud et al., 2018), which is a regularly used strategy in hazard research using ArcGIS ranging from extremely low to extremely high in importance (Rahman et al., 2019). Figure 31 depicts the flood susceptibility maps the ANN and LR models created. Dark green denotes places with modest flood sensitivity; that is there, a very low likelihood of a flood occurring, whereas dark red indicates areas with extremely high flood susceptibility and the probability of a flood occurring is almost inevitable in the future, according to the classification methods on the map (Figures 31a and 31b).

Even though we are using the same data samples, when we compare the maps created by both models, one can observe the difference in the susceptibility indices produced due to varying categorisation even though using the same data samples. The ANN-produced map (Figure 31a), for example, appears to show greater flood susceptibility in regions surrounding the northern region, along the coast, and near water bodies, compared to the LR-produced image (Figure 31b). On the other hand, the LR model map shows that areas near water bodies were not classed as high susceptibility zones except for coastal areas and the southern extremes.



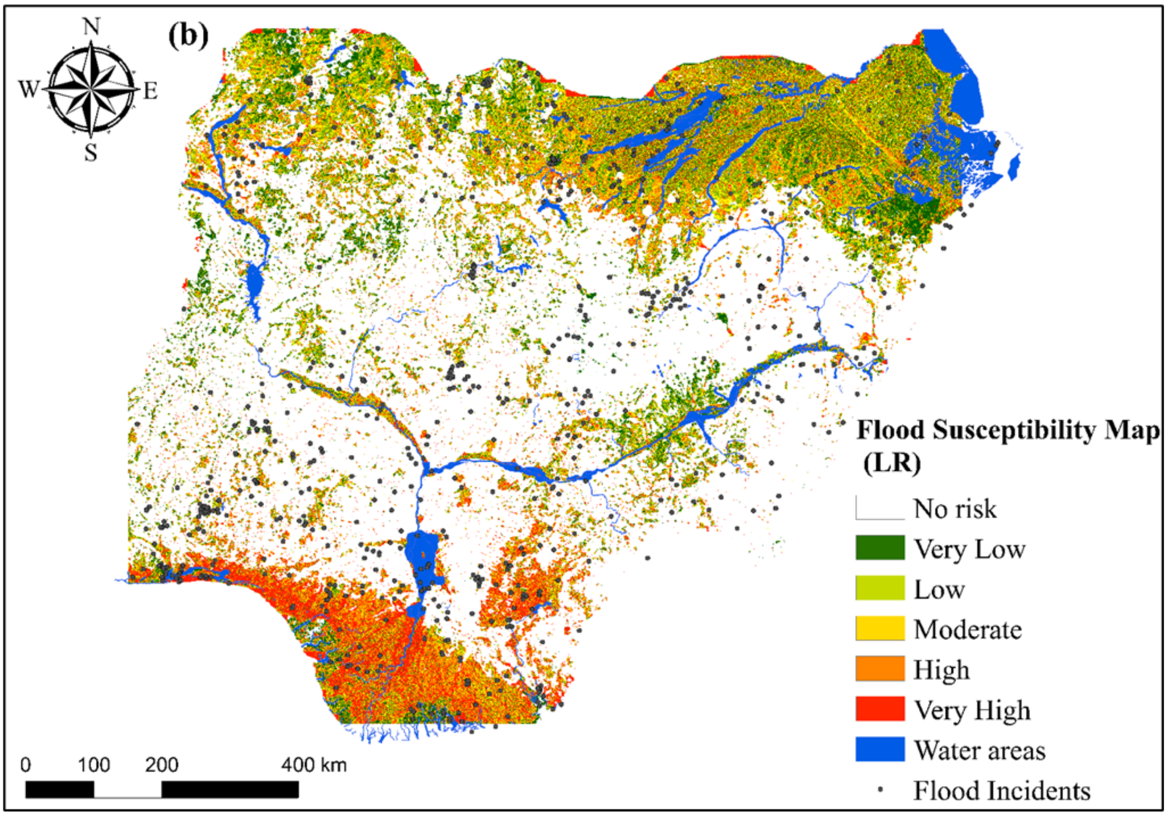
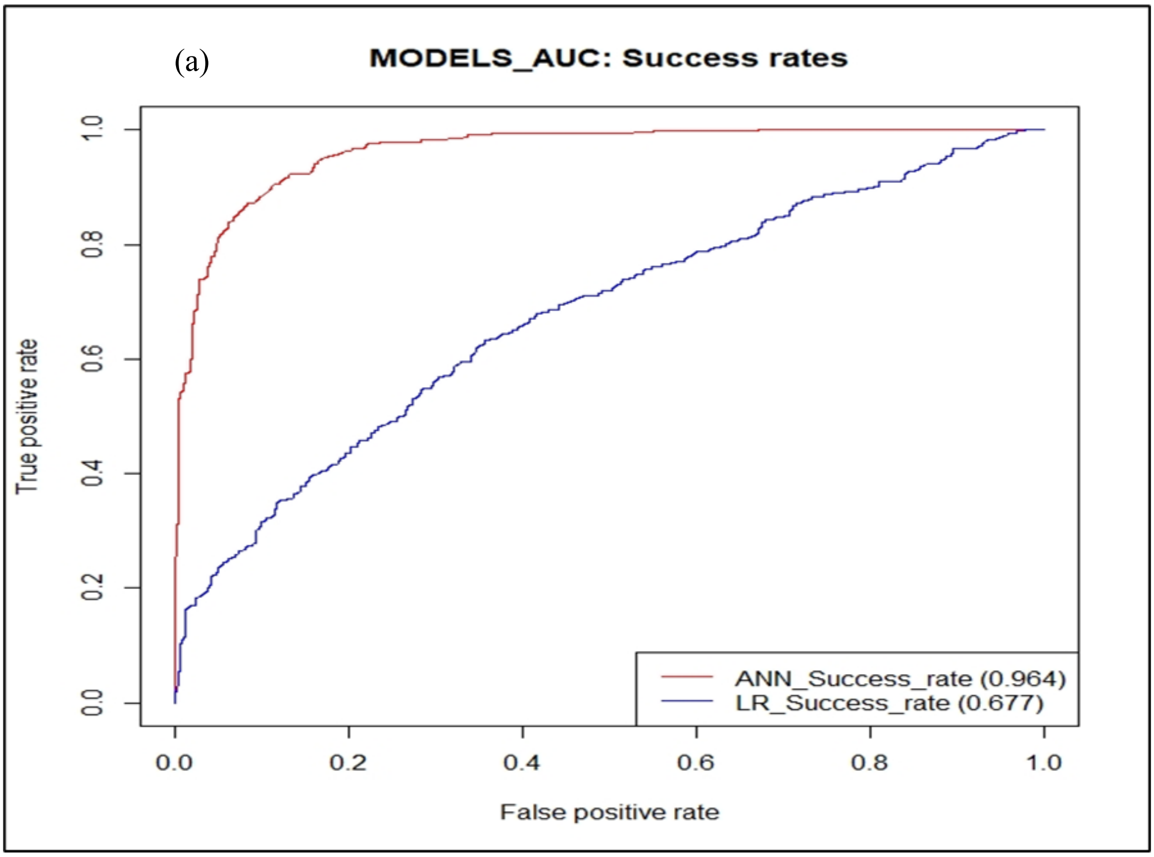


Figure 31 The susceptibility maps (a) ANN and (b) LR.

6.10 Model validation and accuracy assessment

Flood training and testing datasets helped validate the flood susceptibility models. Approximately 70% of the data (train set) was used for training, while 30% (test set) for validation. The model's authenticity in forecasting flood-prone locations was determined using the area under the curve (AUC) analysis and receiver operating characteristic (ROC) analysis.

The receiver operating characteristic (ROC) curve is valuable for defining a model's performance's predictive ability and effectiveness. The ROC analysis includes a chart comparing the fraction of true positives in a positive sample set to the fraction of false positives in a negative sample set as the bias threshold changes. The Receiver Operating Characteristic (ROC) is a metric that measures a system's ability to predict the sequence of events accurately. The AUC is a metric that displays the overall performance of the models and the total number of categorization levels. A model with a higher AUC is good at determining future events (Casas et al.,2010; Tuokkola et al., 2016).



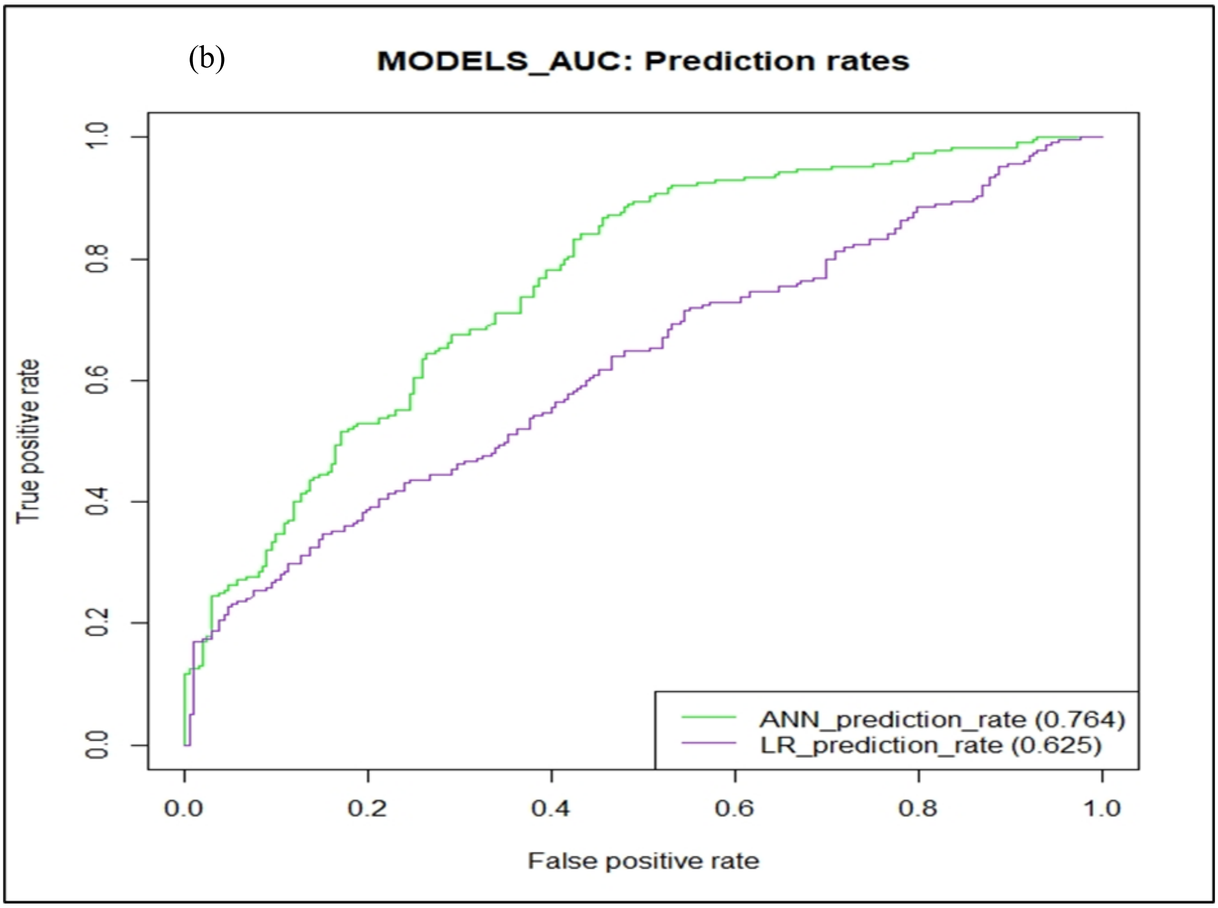


Figure 32 The validation plots- ROC and AUC (a) success rate and (b) prediction rate.

As shown in Figure 32a, the AUC of the ANN model (0.964) is significantly larger than the LR model (0.677). Since the training data is used to assess the model's performance success, it is not adequate to use the same data to test the predictive power of the models. However, in terms of prediction rate outcomes, the ANN model outperforms the LR model, with AUCs of 0.764 and 0.625, exhibiting higher prediction accuracy (Figure 32b).

6.11 Discussion

Identifying flood-prone areas is a common approach to developing flood mitigation strategies to ensure suitable, timely, and relevant priority settings for the most vulnerable area. In this study, we compared the success rates and predictive abilities of two machine learning models: ANN and LR, in estimating flood-prone areas in Nigeria. The results show that the ANN model performs better than the LR model in success and predictive ability.

The results of both models agree with the conclusions of several flooding susceptibility mapping studies, suggesting that the ANN model can effectively estimate flood-prone locations. Furthermore, our findings back up prior research by proving that machine learning algorithms can reliably and accurately identify flood-prone locations. The approach based on the ANN model has numerous advantages that make it suitable for dealing with a wide range of issues and situations. For example, even though many of the interconnections between inputs and outputs in real life are non-linear and complicated, the ANN can reflect non-linear and intricate connections between inputs and outputs. Similarly, the ANN has no restrictions on the number of input parameters, enabling it to forecast a wide range of outcomes effectively.

According to our findings, high-risk flood zones are primarily found in areas with extensive human activity, such as cultivated and settled land areas, and are more prevalent. In addition, the most vulnerable areas to flooding were those along coastlines and water bodies, highlighting the urgent need to develop flood mitigation measures and structural defences to offer complete flood protection for individuals and assets. Thereby highlighting the importance of a periodic flood susceptibility assessment study to help develop and implement improved flood prevention strategies in Nigeria. Due to the absence of detailed meteorological data for some regions of Nigeria, reliance on only hydrological techniques to successfully handle flooding issues may be problematic. As a result, using machine learning algorithms to identify flood-prone locations is a positive step forward. Furthermore, the generated flood susceptibility maps can identify regions where contingency plans are needed and aid disaster preparedness and emergency plans.

6.11.1 Variable importance in flood susceptibility

Variable importance refers to assigning a score to each model's input parameters; the score indicates the "significance" of each element in the model's results. A higher score indicates that a particular characteristic substantially affects the model's ability to predict a specific variable. The variable importance can be utilised to determine how the variables relate to the target attribute. It also aids in determining which features are unnecessary for the model. The relative contributions of the input elements to flood susceptibility are shown in Figure 33.

According to the results of relative importance estimation, the most critical factors determining flood vulnerability were soil and topographic components. As indicated in Figure 33, the curvature is the most influential factor. Curve number, SPI, aspect, land cover, and roughness are the most critical criteria in our study (Figure 33). On the other hand, elevation, slope, distance to the railway, and TWI have low significant values, similar to the ANN generalised weights plot and logistic regression coefficient values. According to the results, the top five most essential conditioning elements are curvature (18.86%), curve number (12.48%), land cover (12.47%), SPI (12.03%), and aspect (11.08).

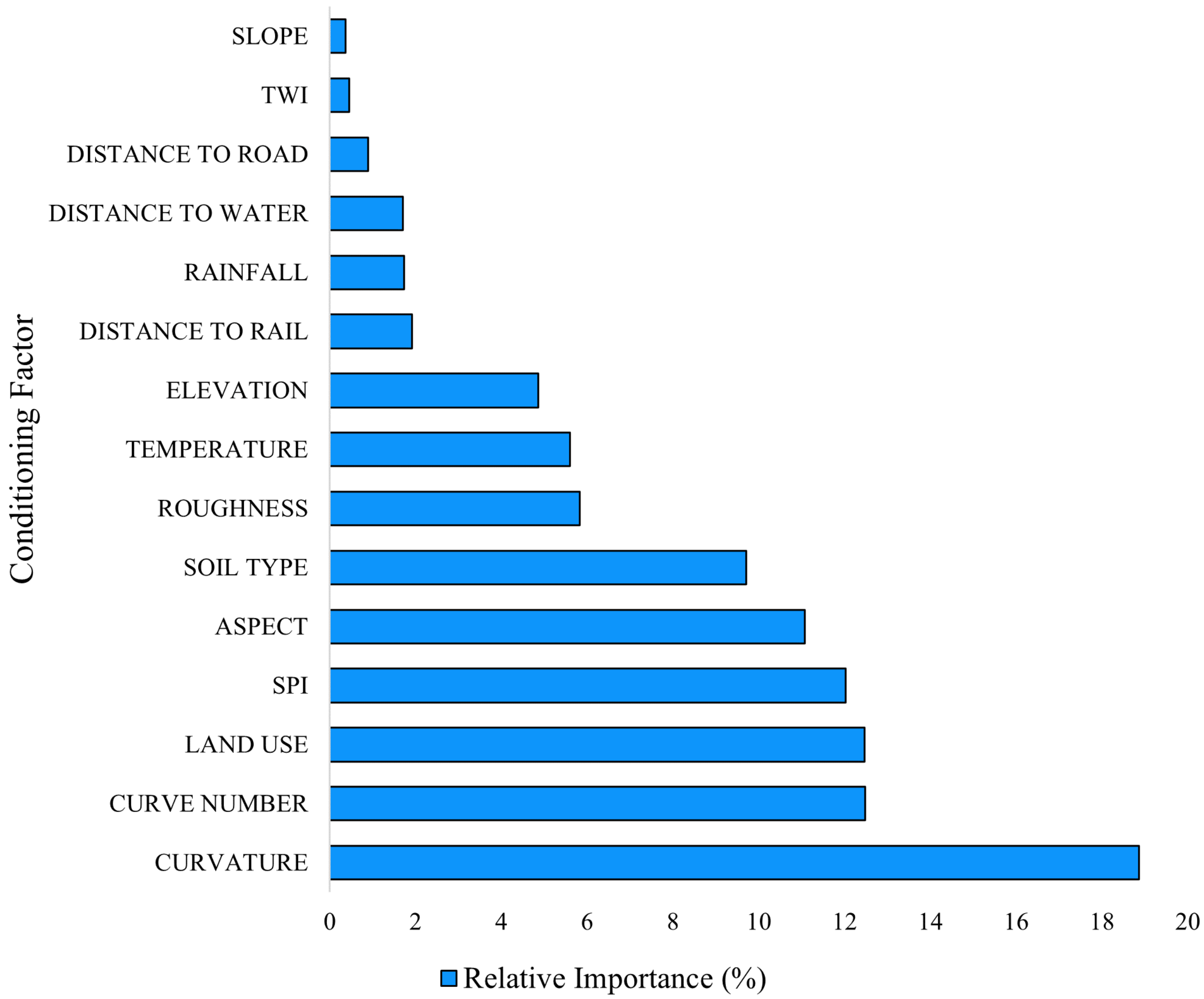


Figure 33 The relative importance of the selected conditioning factors

6.11.2 Analysis of flood susceptibility model results

Figure 34 displays the classification of both model susceptibility mapping results.

- The LR model: The distribution of flood susceptibility are as follows - very high (18.47 %); high risk (18.8 %); medium risk (21.3 %); low risk (20.60 %); and very low (20.90 %), respectively.

- The ANN model: In the ANN model (Figure 34), the respective percentages for the very low (6.5 per cent), low (2.3 per cent), moderate (26.07 per cent), high (4.1 per cent), and very high classes are 6.5 per cent, 23.45 per cent, low (4.1 per cent), and 39.88 per cent.

The areas along rivers Niger, Benue and the southern coasts have an exceptionally high risk of flooding, as shown by both models' flood susceptibility maps. The regions surrounding the main river basins and flow pathways of the Niger and Benue rivers were potentially tough to hit, where flooding was particularly severe. The two models' geographic distribution patterns of flood-prone locations are equal to sites classified as high or very high risk. However, the LR model's percentage (18.47 per cent) is lower than the ANN model's percentage (20 per cent) (39.88 per cent). Although the ANN model has higher accuracy and reliability, the LR model produces a more balanced output than the latter. It also explains why the ANN model is sensitive to anticipating possible outcomes. By comparing the two models, we may better understand the variations in modelling results.

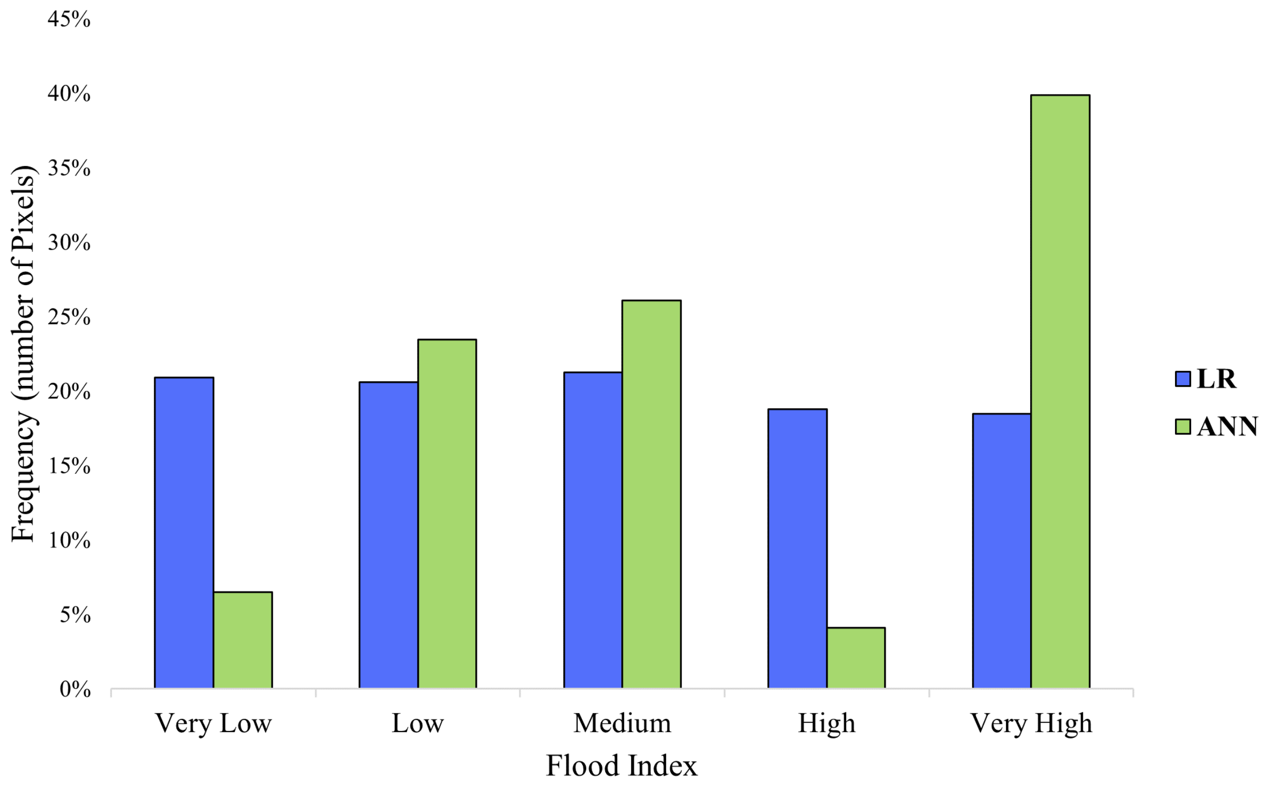


Figure 34 The flood susceptibility classification under the two models

6.11.3 Condition factors correlation

After the initial modelling, the correlation analysis determines the complex relationships between the conditioning factors. Two measurements of multicollinearity, the variance inflation factor (VIF) and Pearson's correlation coefficient, were utilised (Table 24). The results of the estimation are shown below. Multicollinearity exists between the variables in question. When the VIF is above 5, multicollinearity exists. In this study's case, the highest VIF value is 2.248 (Table 23), indicating that the selected conditioning variables have no collinearity, as represented by the VIF values.

Table 24 The Pearson's correlation and multicollinearity results for the conditioning factors

Conditioning factor	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	1.00														
2	-0.03	1.00													
3	0.58	-0.01	1.00												
4	0.04	0.00	-0.06	1.00											
5	0.02	-0.03	0.05	-0.02	1.00										
6	-0.03	0.03	-0.01	0.34	0.01	1.00									
7	-0.03	0.01	-0.05	-0.65	0.10	0.20	1.00								
8	0.00	0.04	0.04	0.36	-0.04	0.07	0.22	1.00							
9	0.03	-0.01	0.02	0.02	-0.02	0.02	0.14	-0.01	1.00						
10	0.00	-0.04	-0.05	-0.18	-0.13	0.20	-0.06	0.08	0.14	1.00					
11	0.20	-0.03	-0.11	0.01	0.00	0.04	0.00	-0.07	0.01	0.01	1.00				
12	-0.04	-0.04	-0.02	0.06	-0.01	-0.03	0.09	0.00	0.03	0.00	0.02	1.00			
13	0.05	-0.36	0.00	-0.07	-0.02	-0.01	-0.04	-0.06	0.10	-0.05	-0.08	-0.03	1.00		
14	-0.05	0.08	0.03	-0.10	-0.13	0.00	-0.33	-0.09	0.02	0.05	0.00	0.02	-0.04	1.00	
15	0.16	-0.02	-0.10	0.04	0.03	0.03	0.10	0.01	-0.02	-0.02	0.05	-0.01	0.00	0.17	1.00
VIF	1.64	1.18	1.56	2.25	1.09	1.24	2.13	1.27	1.08	1.12	1.06	1.02	1.21	1.25	1.07

1-curve number; 2-Slope; 3-Soil type; 4-Elevation; 5-Land use; 6-Roughness; 7-Rainfall; 8-Distance to water; 9-Distance to the road; 10- Distance to the railway; 11-Curvature; 12-Aspect; 13-TWI; 14-Temperature; 14-SPI

The findings shed light on the links between the various conditioning factors examined for inclusion in model development. Based on the analysis, the curve number and soil type had the highest correlation (0 .583), demonstrating that soil type affects surface runoffs.

6.11.4 Performance of the ANN and LR models

The metrics used to evaluate the performance of both models are the mean squared error (MSE), root mean square error (RMSE), accuracy and the area under the curve (AUC) (Table 25). The mean square error (MSE) and root mean square error (RMSE) in the ANN training were 0.047 and 0.217, respectively, whereas, in the testing, the values were 0.035 and 0.188. (Table 20). In the LR model, the MSE and RMSE for the training dataset were 0.195 and 0.442, respectively. On the other hand, the values derived from the testing dataset were 0.107 and 0.327.

Table 25 The model performance results

Model parameters	ANN		LR	
	Training	Testing	Training	Testing
MSE	0.047	0.0354	0.195	0.107
RMSE	0.217	0.188	0.442	0.327
AUC	0.964	0.764	0.677	0.625
Accuracy	0.907	0.875	0.772	0.784

Chapter 7 Population, land use changes and flood risks

7.1 Historical Flood risk exposure

Nigerias' vulnerability to flooding is evaluated on a spatial scale by intersecting datasets on flood hazards, land use, population, and socioeconomic parameter distribution. Similar studies have been done to estimate the land use, population, and economic exposure to flood hazards worldwide, adopting a local regional-based assessment of land use and population exposure. However, this study goes beyond the national level assessment but highlights flood risks at a district level, allowing for an easier understanding of the level of exposure at the micro level to allow for the streamlined development of mitigation plans. Furthermore, by intersecting the population and related socio-economic statistics with the flood hazards maps, it is easier to estimate the spatial distributions of the population at risk of flooding Figure 35. In addition to the total population, the disparities between the capital stock (US$ million) and income categories in urban and rural areas were estimated to highlight the disparities in exposure levels to floods.

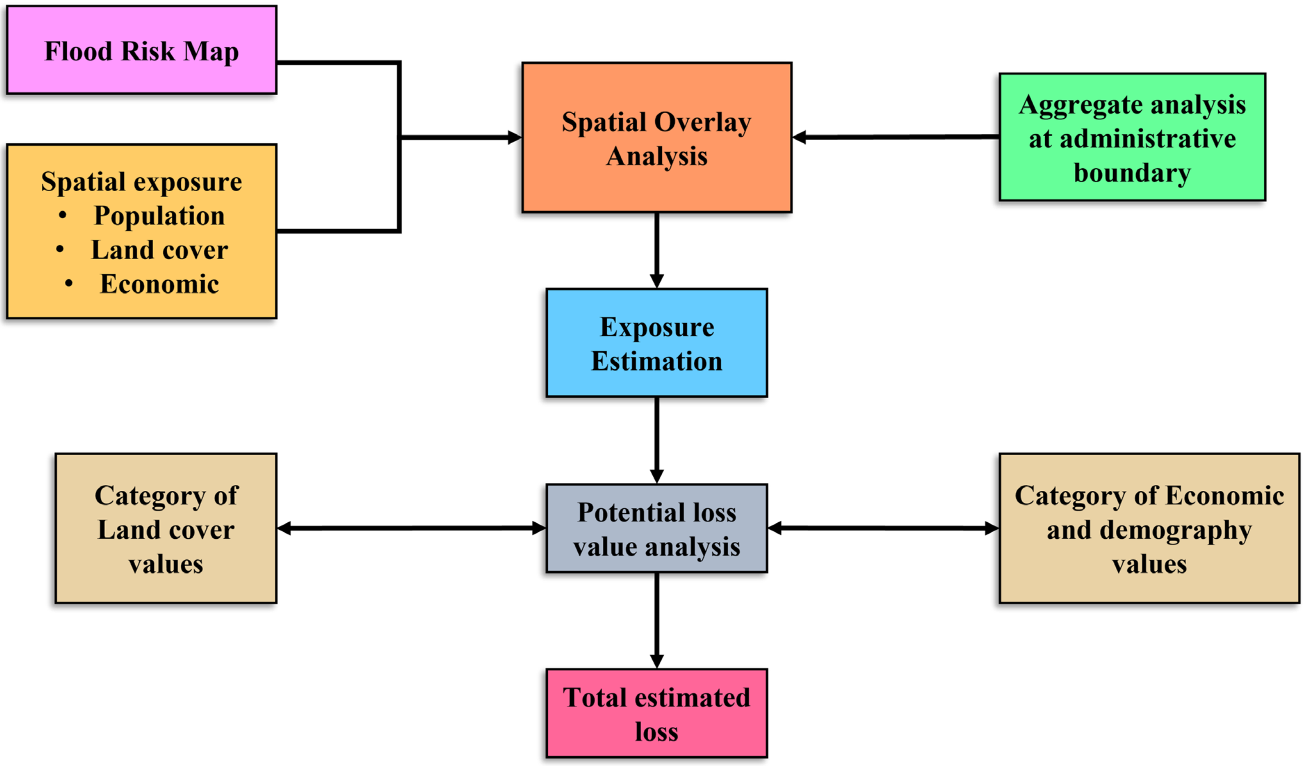


Figure 35 Flowchart for estimating the people and land cover exposed to flooding risks

7.2 Exposure estimation

7.2.1 Population exposed

The total population exposed (T_p) to flood risk is calculated by intersecting the overall population distribution (P) with flood risk (F_h) maps using the raster calculator function in QGIS. The sum of the total exposed population is expressed as

$$TP_i = P_i \times F_i \tag{22}$$

where:
TP_i is the sum of the total population in the flood zones
P_i: the total population in each administrative boundary
F_i; the flood risk map
i is the index of the location

The initial five categories (low, low/medium, medium, high, and extreme) presented in the dataset were reclassified into low and high groups. First, we looked at how many people were exposed to low and high-risk floods across the 20-year study intervals. Then, as a percentage of the overall population, we calculated the ratio of flood-affected people. Finally, the ratio of the population susceptible to floods is examined to gain meaningful information on which areas within municipal limits should be prioritised for flood management. The ratio of the exposed population is expressed as,

$$TP_{Ri} = \frac{TP_i}{P_i} \tag{23}$$

Where TP_R is the ratio of population in the flood zones, T_p Is the total population in the flood zones, and P is the total population within the study area.

7.2.2 Disparities between the exposed population

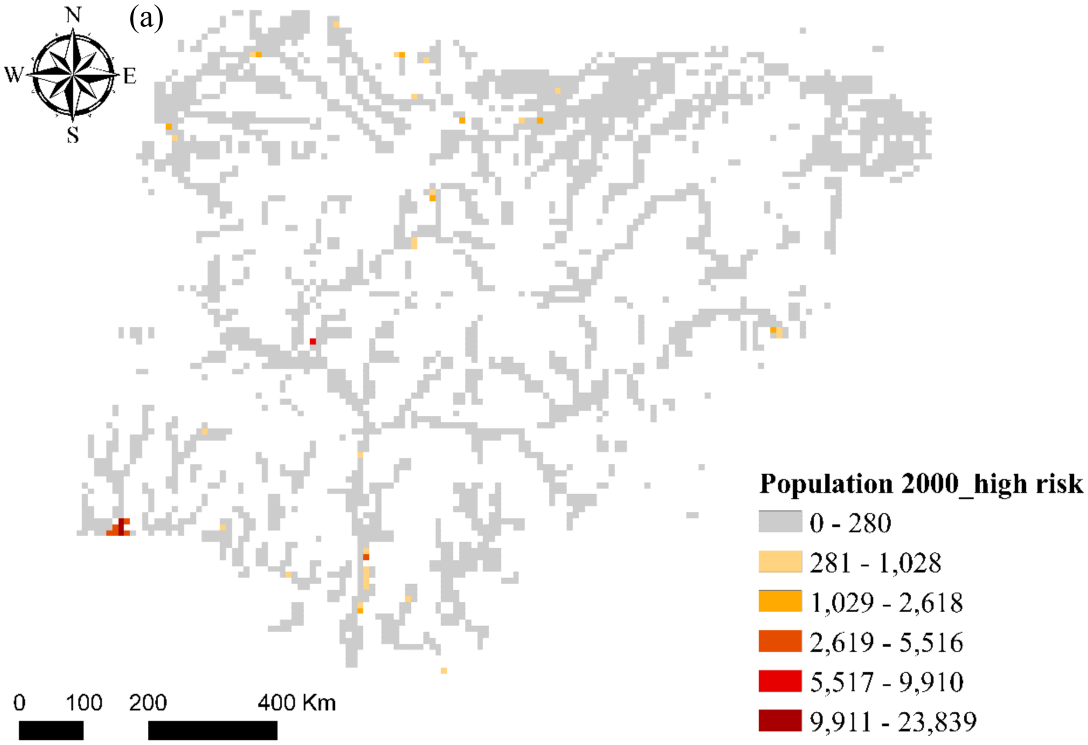
The ratio of flood-affected populations in urban and rural areas compares the exposure discrepancies between rural and urban populations. The premise is that observing the distribution of exposed people between rural and urban areas would reveal which areas are most vulnerable to flooding and will raise awareness about which areas should be prioritised for flood prevention. Although urban regions typically have a higher population density than rural areas, it is assumed that if the percentage of the population exposed to flood hazards in urban areas surpasses that of rural areas, then flood response is low. As a result, flood zones are not being avoided for development, and the sensitivity to existing flood hazards is low. Similarly, based on the current GDP (US$ 2015 estimate), the difference in per capita income between flood zones and exposed populations is compared using the income distribution under two main groups- low and medium, across all flood risk zones.

7.3 Risk exposure

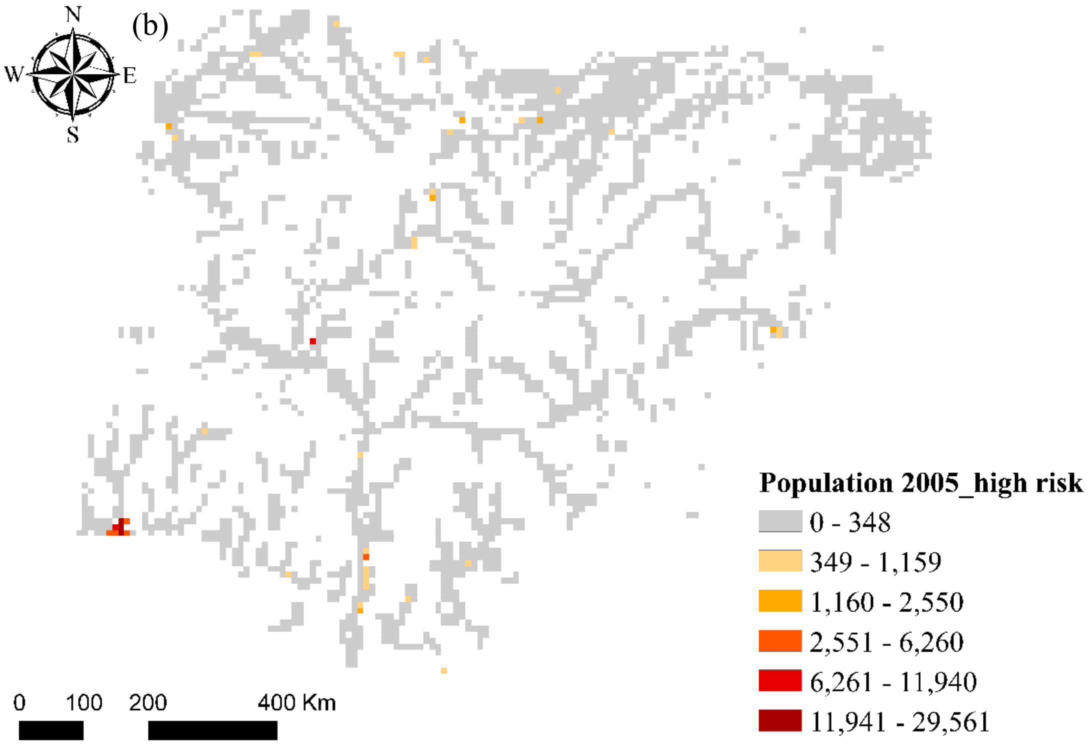
7.3.1 Historical Population exposure

Between 2000 and 2020, the number of persons exposed to flood hazards increased, according to the data estimates. Flooding has affected 118.8 million people (53.8 per cent of Nigeria's population) since 2000, up from 29.7 million in 2000 (Figure 36). In 2000, roughly 13.4 million individuals lived in high-risk flood zones out of the total number of people exposed to flood threats. By 2020, the figure had risen to almost 24.7 million persons (8.3% of Nigeria's population). Over 20 years, the population increased by 11.3 million people. Between 2010 and 2020, the number of people exposed to flood hazards increased significantly.

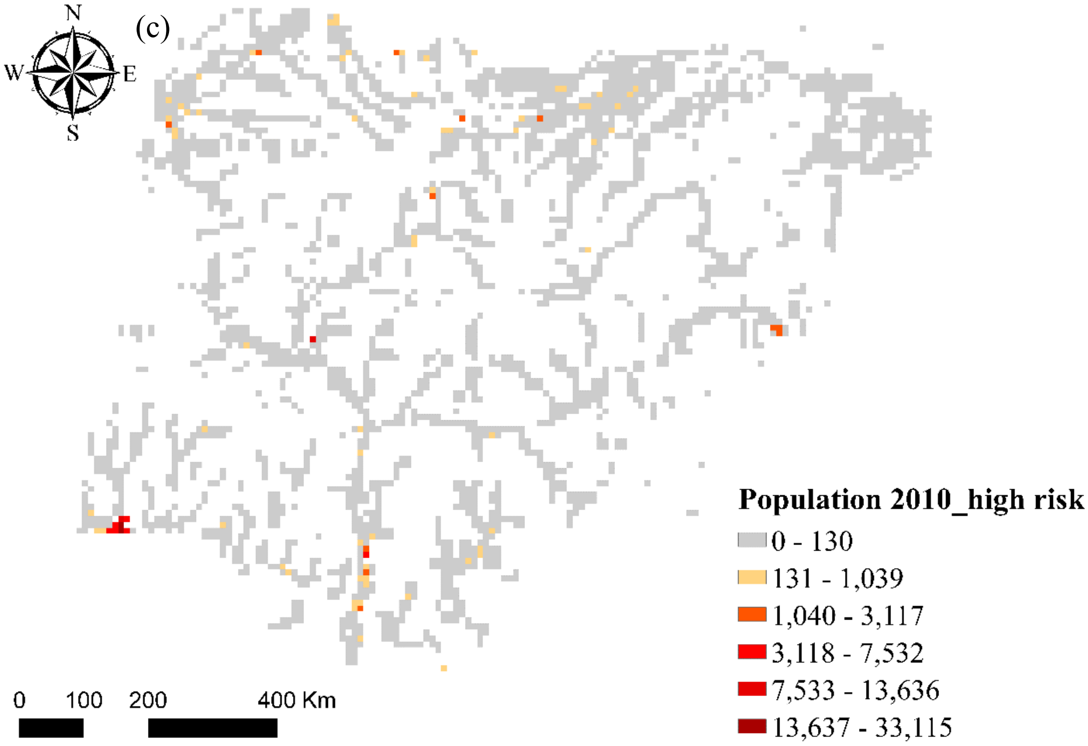
Over time, the total estimated population in flood zones has remained concentrated in states with big cities and clusters of mid-sized urban areas. The top 10 states with the highest number of exposed persons as of the 2020 estimates were Bauchi, Borno, Kaduna, Katsina, Lagos, Niger, Ogun, Osun, and Oyo. Lagos had the more significant share of the exposed population (27.9%) due to its high density and proximity to the coast and other water bodies. Similarly, the same trend among the nine other states shows that regions close to a water body and increased precipitation levels resulting from climate change significantly impact exposure to flood hazards. Therefore, we assumed that the rise in exposed populations could be attributed to various factors, including increased population growth, migration due to booming economic activities, and weather conditions resulting from climate change.



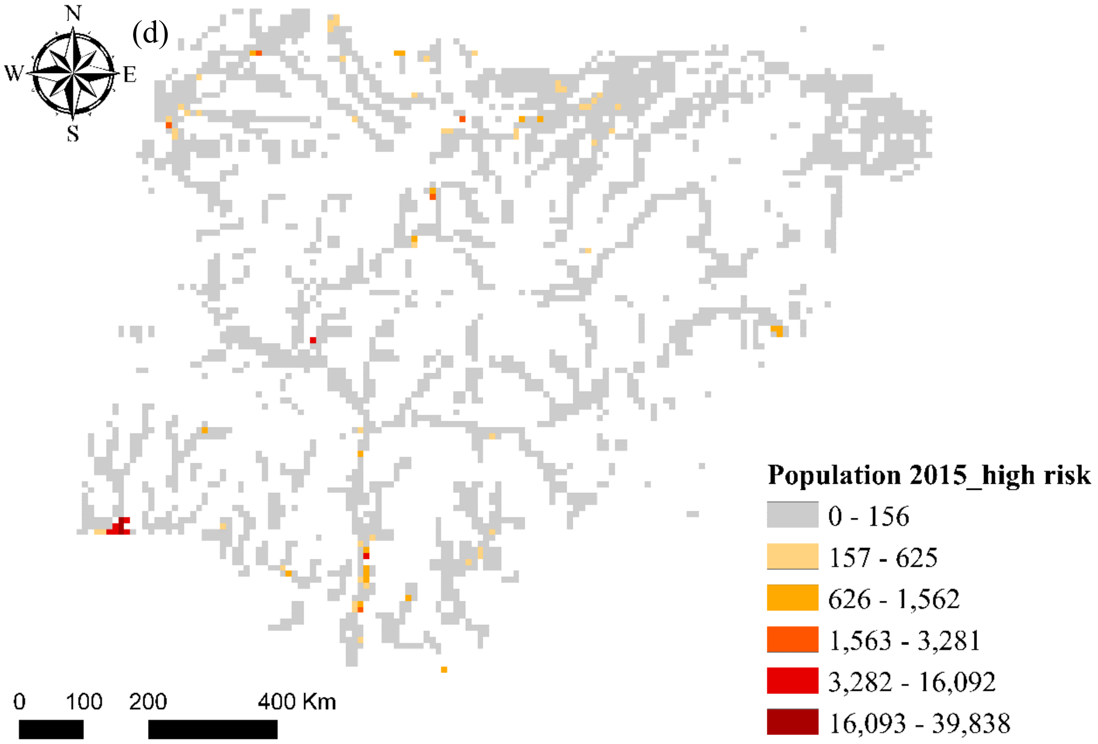
N
W
E
S
(a)
Population 2000_high risk
0 - 280
281 - 1,028
1,029 - 2,618
2,619 - 5,516
5,517 - 9,910
9,911 - 23,839
0
100
200
400 Km



N
W
E
S
(b)
Population 2005_high risk
0 - 348
349 - 1,159
1,160 - 2,550
2,551 - 6,260
6,261 - 11,940
11,941 - 29,561
0
100
200
400 Km



N
W
E
S
(c)
Population 2010_high risk
0 - 130
131 - 1,039
1,040 - 3,117
3,118 - 7,532
7,533 - 13,636
13,637 - 33,115
0
100
200
400 Km



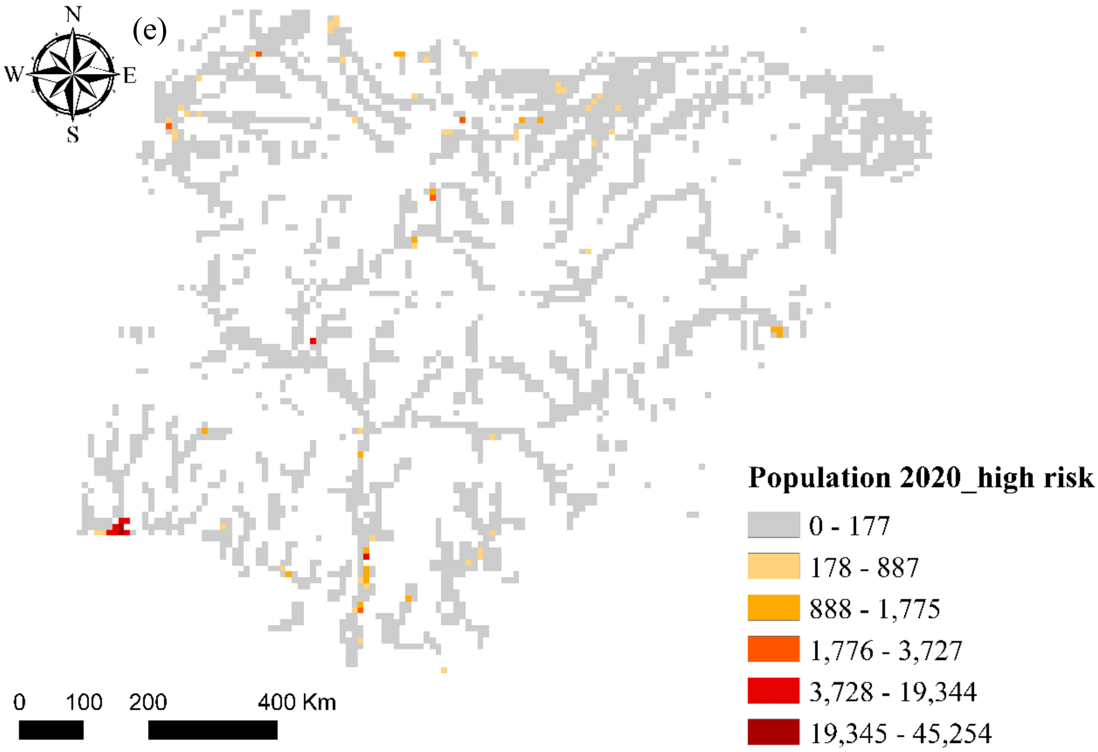
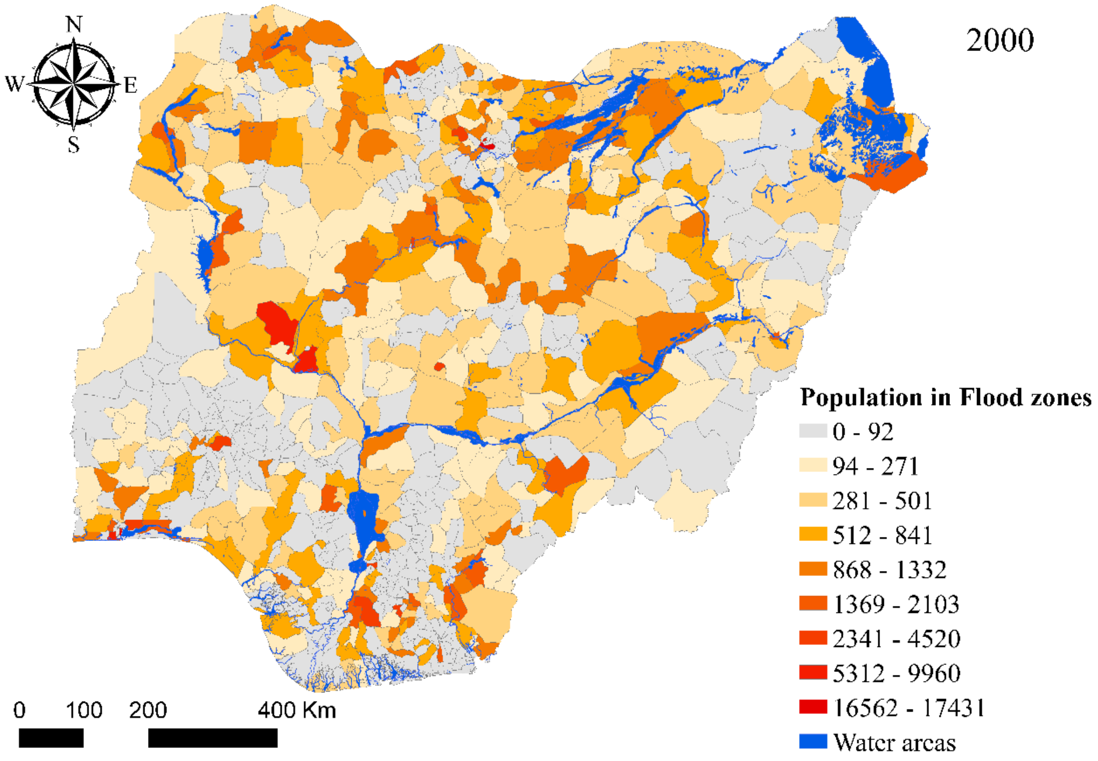
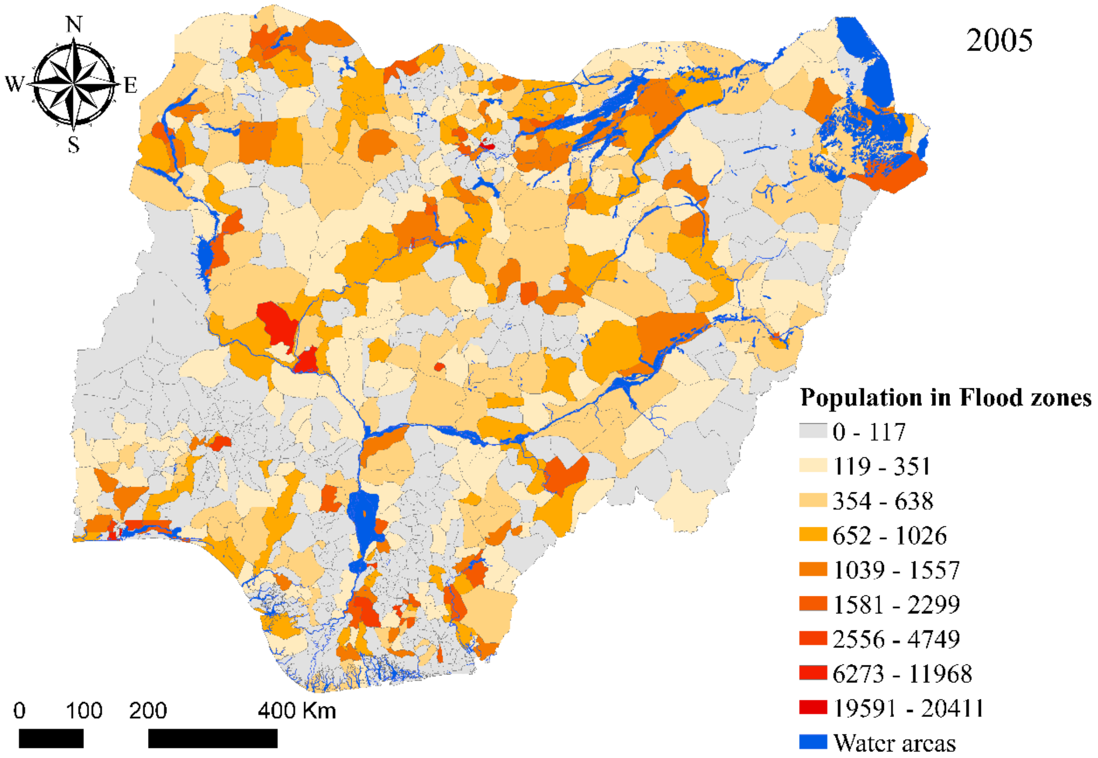


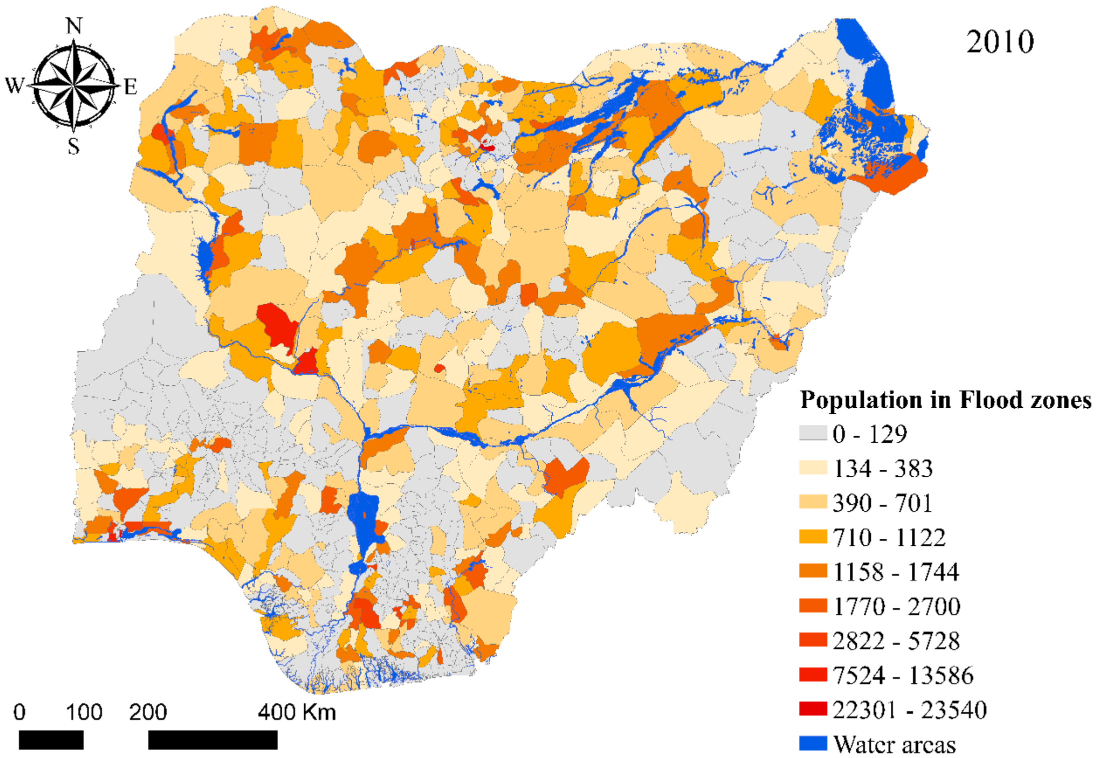
Figure 36 Spatial distribution of population exposed to high flood risks at a national scale (a) 2000; (b) 2005; (c) 2010; (d) 2015; (e) 2020.

After analysing areas exposed to high-risk floods, the regional distribution of flood-prone groups from 2000 to 2020 was made possible by additional spatial analysis of the people in flood zones. The result (Figure 37) shows which administrative districts have substantial flood exposure and how the number of persons exposed per region has changed over 20 years. Policymakers and government agencies can comprehend the extent and severity of flood exposure groups and provide appropriate flood hazard mitigation options, thanks to the spatial analysis of exposure distribution.





N
W
E
S
2005
Population in Flood zones
0 - 117
119 - 351
354 - 638
652 - 1026
1039 - 1557
1581 - 2299
2556 - 4749
6273 - 11968
19591 - 20411
Water areas
0 100 200 400 Km



N
W
E
S
2010
Population in Flood zones
0 - 129
134 - 383
390 - 701
710 - 1122
1158 - 1744
1770 - 2700
2822 - 5728
7524 - 13586
22301 - 23540
Water areas
0 100 200 400 Km

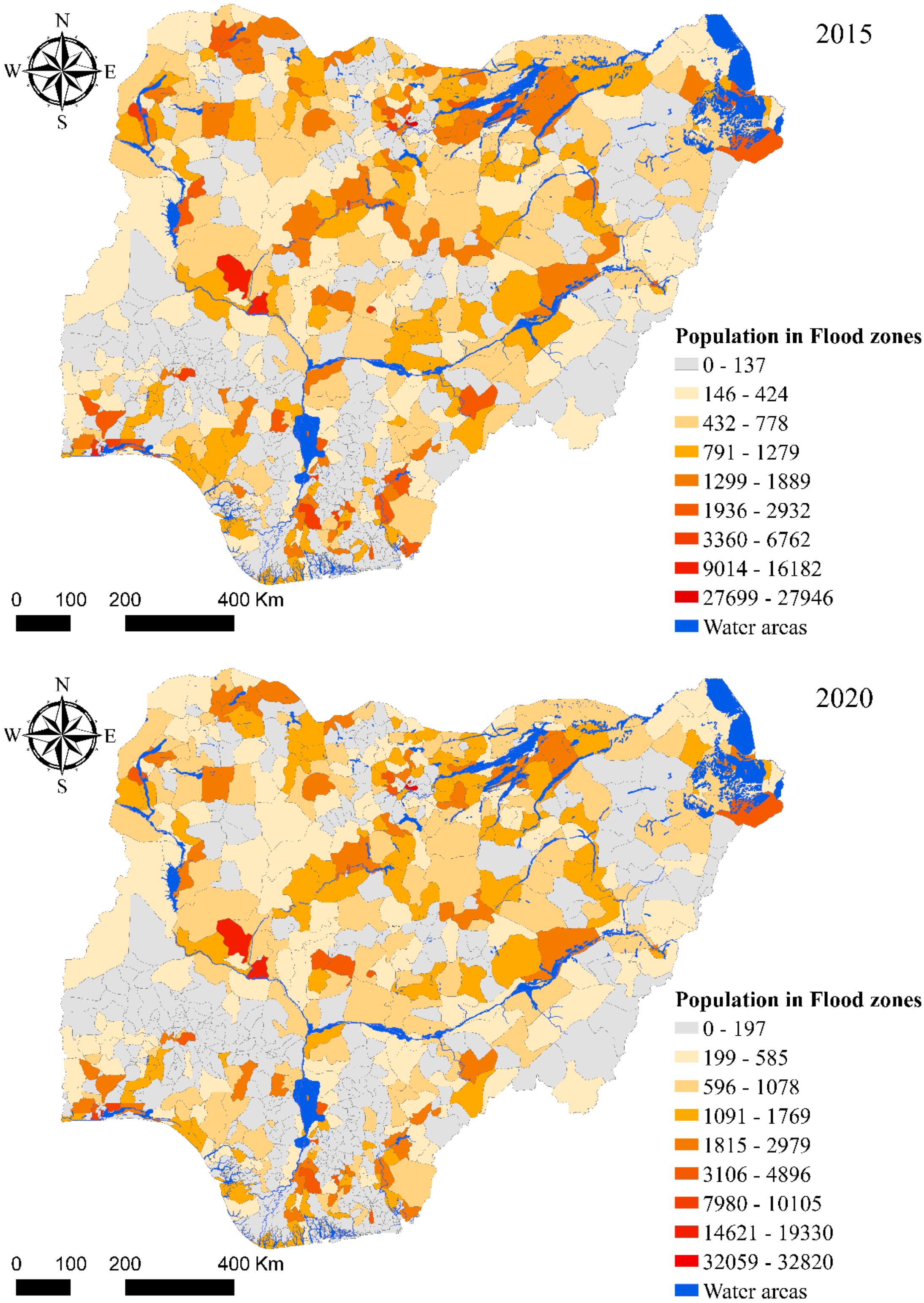


Figure 37 Spatial distribution of population exposed to flood risks per administrative district (a) 2000; (b) 2005; (c) 2010; (d) 2015; (e) 2020.

According to the findings, the number of persons exposed to high-risk flood threats continues to rise (Figure 37). The rising number of people exposed to high-risk floods can be attributed to a lack of proper flood knowledge and preparedness or a lack of responsiveness. If a rise in the number of individuals exposed is due to a lack of information and planning, the exposed population will continue to rise, posing a threat to Nigeria's natural, social, and economic development. On the other hand, if the growth in the exposed population is due to a lack of response to existing hazards and climate change, the findings will successfully provide indisputable evidence that will motivate disaster risk and climate change policymakers to mitigate against significant future loss.

7.3.2 Income exposure per population distribution

After successfully measuring the total population exposed to flood dangers, further analysis to distinguish between urban and rural areas; next, based on the population distribution, further segmentation according to income categories was implemented based on the differences in per capita income between rural and urban areas (Figure 38). Based on the US$ 2015 estimates, the per capita income group places Nigeria in the middle-income category. Even within the middle-income globalised standard, Nigeria has two major income classes: low and middle income. Finally, based on available economic data patterns for Nigeria, the socio-economic data is divided into two categories.

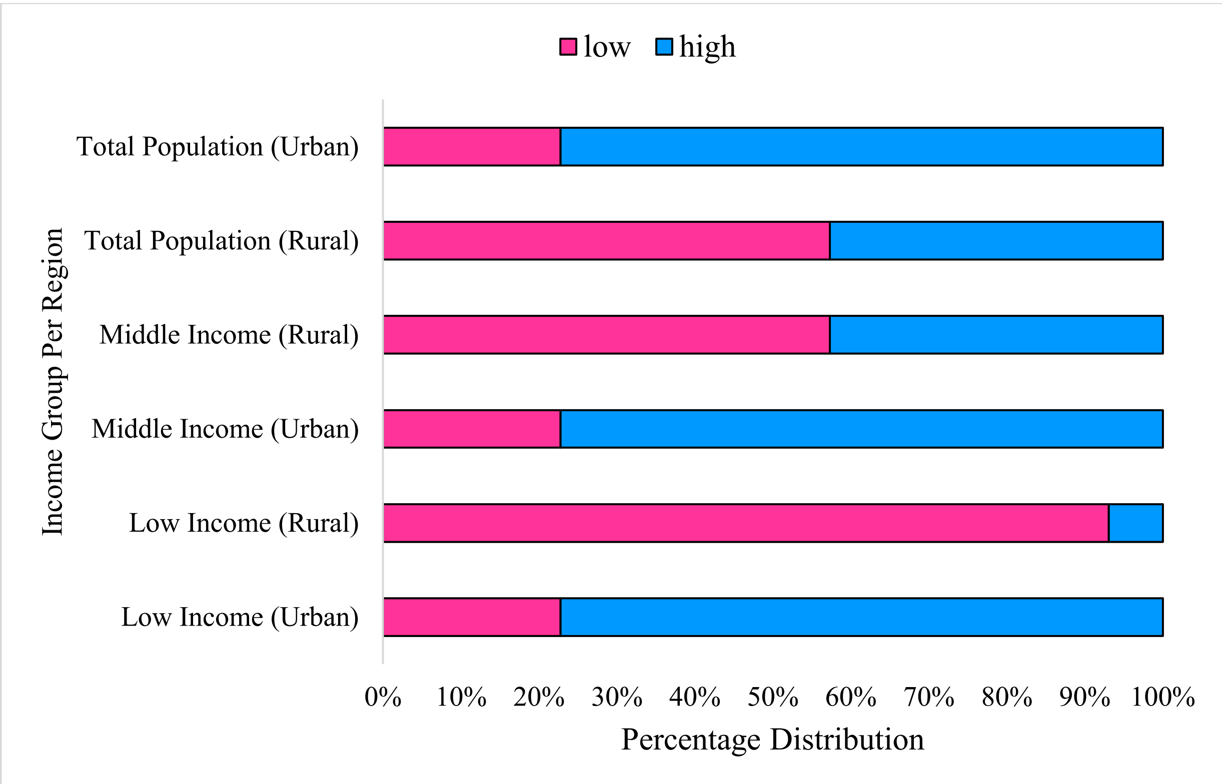


Figure 38 disparity between the urban and rural population per income group at risk of flood

According to the findings (Figure 38), urban areas have more residents living in high-risk flood zones (72 per cent) within the flood risk zones. However, 42 per cent of residents were in high-risk zones in rural areas. The findings further explain why urban dwellers are disproportionately vulnerable to flooding than their rural counterparts. If urban areas continue to grow and prosper economically, there is a greater chance of population growth in flood zones due to rural-urban migration. As a result, urban regions have a higher concentration of residents living in flood zones than rural areas. In addition, the per capita income distribution in urban and rural areas reveals that, regardless of income category, urban residents were more vulnerable to flooding than their rural counterparts in the same socioeconomic groupings (Figure 38).

7.3.3 Value of infrastructure exposure per population distribution

A similar trend was seen when examining total capital stock exposed to flood dangers based on per capita incomes in rural and urban areas (Figure 39). In high-risk flood zones, the ratio of urban stock to rural stock is much higher. Middle-income residents disproportionately hold the amount of capital stock exposed in metropolitan areas. The capital stock exposed to low-risk flood hazards in low-income urban areas is estimated at US$2634.6 million, while the capital stock exposed to high-risk flood hazards is US$9831.4 million. On the other hand, the middle-income group's capital stock is roughly US$3878.12 million for low-risk zones and US$14471.66 million for high-risk zones. As a result, the ratio of low and intermediate per capita income groups is exposed to low-risk flood dangers compared to their rural counterparts.

Nonetheless, because metropolitan regions house a substantial amount of Nigeria's population and infrastructure, the study's findings can be better explained as more significant capital stock is concentrated in urban regions. Furthermore, the analysis reveals that, regardless of per capita income, potential economic damage from flood hazards in a disaster is much more considerable in urban regions than in rural areas. A higher concentration of exposed infrastructure is expected as urban areas contribute and contain more to the socio-economic growth of Nigeria; however, the scary part of the result is that, without proper flood risk management strategies, the expected damage from a flood disaster occurrence would be enormous and impact all sectors of the society. The findings point to a lack of preparedness for floods and the urgent need to strengthen flood planning and mitigation, particularly in metropolitan areas (Figure 39).

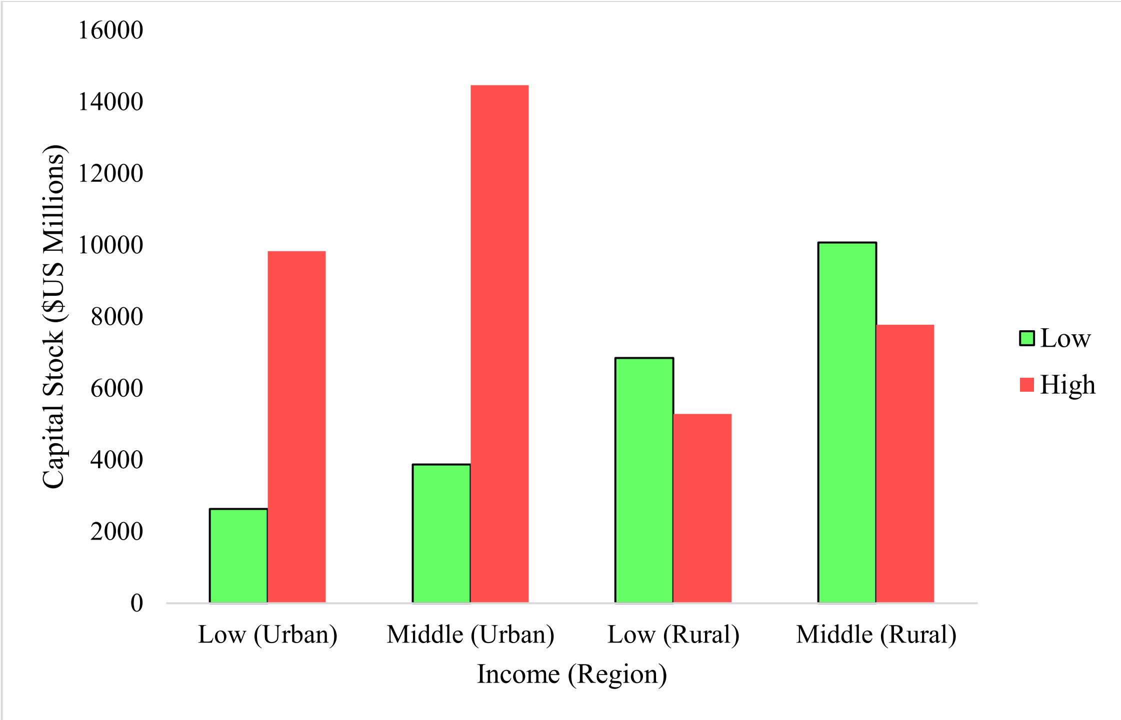


Figure 39 Income disparity between the per capital stock exposed to flood in rural and urban areas (US. $ million).

7.3.4 Land cover exposure

To calculate the total land area vulnerable to flooding, the historical land use distribution is superimposed with the historical flood risk map using the zonal statistics function in R to highlight the spatial distribution of the land cover types on flood hazards exposure. The result illustrates that settlement, cultivated, and forest land areas have the largest share of flood hazard exposure. An estimated 559,452 km^2 (53.11 per cent of the total land area) is exposed to some level of flood hazard. The most significant proportion of the exposed land area belongs to cultivated land (400,764 km^2), followed by forest land (143,596 km^2) and finally settlement land (15,092 km^2) respectively (Table 26). Further analysis of the distribution of the three land use categories under the varied flood risk levels highlights the disparities in an exposure. For example, Settlement land contains the largest share of land use cover within the very risk category, with an estimated 1,102 km^2.

Table 26 Distribution of the land cover areas exposed to flood risks (Historic)

Flood Risk (Level)	Land use (km^2)		
	Forest	Cultivated	Settlement
Very Low	52,383	92,799	1,199
Low	60,677	185,528	4,215
Medium	29,514	110,348	3,682
High	1,022	11,881	4,894
Very High	0	208	1,102
Total coverage area	143,596	400,764	15,092
Total percentage of Land Cover	53.36	83.29	29.36

7.4 Future land use changes and simulated flood risk areas

In estimating the impacts of future land use change on flood risk exposure, the study compared the distribution of land use change patterns under the three developed scenarios to understand how each socio-economic pathway would influence flood risk. Based on the analysis, under the BAU, exposed forest land to flood risk is estimated at 75,586 km^2, while the Market-oriented ad conversation scenario had an estimate of 83,304 km^2 and 64, 739 km^2 respectively. However, in the settlement land area, under the BAU, the exposed area is 18,271 km^2 , 19,744 km^2 for the market-oriented and 21,006 km^2 in the conservation scenario. The least exposed land use demand scenario for cultivated land areas is market-oriented, highlighting a lower land area than the BAU and conservation scenarios (Table 27).

The BAU development scenario is designed to maintain the existing socio-economic trends in Nigeria and shows that the areas at risk to flooding will remain dominant in the agriculture land areas in the estimated future. Similarly, as the settlement areas continue to expand significantly in urban areas with a higher ratio of flooding risk, Nigeria would continue to witness an increase in the number of residents exposed to flooding. As such, current land development patterns are unsustainable and require a comprehensive flood mitigation plan to reduce the effects of a flood disaster and significant economic loss.

In the conservation scenario designed to ensure forestry and biodiversity protection, the total land areas exposed to flood risks were significantly higher in areas within the settlement land use type. However, the estimated results were relatively similar to the exposed agricultural land areas under the BAU scenario. Similarly, despite the improvement in forest cover and a reduction in agricultural land expansion due to restrictions on forest conversion, a large percentage of the agricultural land remained within the flood risk zones, while forest areas in the flood zones were less than the two other scenarios. The result from the conservation scenario indicates that for Nigeria, relying on a conservative approach to development may not be the best possible strategy from the viewpoint of flood disaster risk reduction despite its advantage in achieving sustainable development and environmental protection.

The market-oriented scenario performed significantly better than the other scenarios (BAU and conservation). The total land area exposed to flooding in the Market-oriented scenario is slightly lower, especially within the agricultural areas, indicating the Market-oriented scenario may be a better fit for future land use development as it improves socio-economic conditions and slightly diminishes the ratio of exposure and vulnerability to flooding risks (Figure 40). The reduction in total flood risk areas in the market-oriented scenario is mainly due to improved socio-economic conditions that promote investment in better technology and industrial services required for the development. In turn, it reduced the conversion of forest land, especially those within the flood risk zones. Another reason for the reduction in forest area being converted to agricultural land stems from improved socio-economic conditions leading to increased productivity of agricultural land areas.

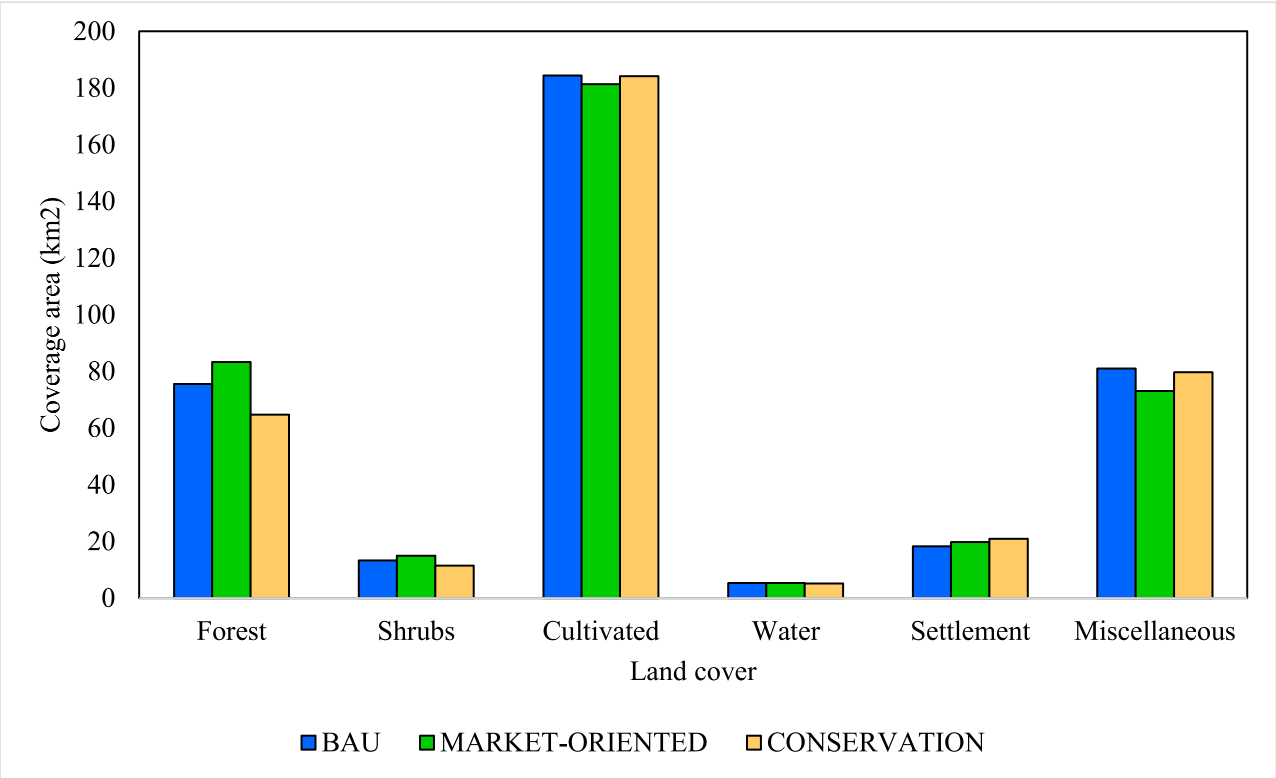


Figure 40 Distribution of total risk areas within the land use types under the three developed scenarios

Table 27 Distribution of the land cover areas exposed to flood risks under the three land use scenarios

BAU					
Land cover	Very Low	Low	Medium	High	Very High
Forest	16,719	14,876	12,336	5,193	26,462
Shrubs	1,660	1,713	2,004	1,310	6,647
Cultivated	25,551	24,673	24,304	11,959	97,841
Water	542	708	846	445	2,763
Settlement	2,664	2,915	2,944	1,298	8,450
Miscellaneous	12,071	11,911	11,143	6,180	39,676
MARKET-ORIENTED					
Land cover	Very Low	Low	Medium	High	Very High
Forest	17,507	16,337	13,844	5,700	29,916
Shrubs	1,826	1,928	2,245	1,440	7,554
Cultivated	25,143	24,086	23,757	11,734	96,638
Water	542	708	846	445	2,763
Settlement	2,787	3,133	3,208	1,395	9,221
Miscellaneous	11,402	10,604	9,677	5,671	35,747
CONSERVATION					
Land cover	Very Low	Low	Medium	High	Very High
Forest	16,845	14,960	1,001	5,238	26,695
Shrubs	1,449	1,514	1,778	1,187	5,649
Cultivated	25,373	24,529	24,212	11,931	98,078
Water	549	712	827	440	2,662
Settlement	2,993	3,325	3,379	1,486	9,823
Miscellaneous	11,998	11,756	10,939	6,102	38,932

Chapter 8 Conclusion

8.1 Introduction

The primary goal of this study was to investigate the underlying effects of land use changes on flood susceptibility in Nigeria. The study experimentally analysed the causes of land use change, anticipated future land demand patterns based on alternative potential development trajectories, the disparities of flood susceptibility between regions and income groups, predicted the areas at risk of flooding and anticipated the areas at risk under each developed land use scenario in Nigeria, representing medium and low-income populations. In addition to analysing flood vulnerability based on historical data, the study used a set of conditioning factors to anticipate probable flood susceptibility areas and demystify the underlying causes of flooding. The findings show how the physical, economic, demographic, technological, and biophysical factors influence Nigeria's land use and flood risks. A combination of GIS, statistics, system dynamics and machine learning modelling techniques helped gain insight into the factors that affect land use and its vulnerability to flooding hazards.

This chapter explains the objectives mentioned in Chapter 1 and the achievements based on the research questions and the contribution to knowledge about the drivers of land use change, the areas prone to flooding and the unequal distribution of flood vulnerability in Nigeria. Next, chapters 2 and 3 summarised existing literature on the causes of land use change, flood risk assessment and methods used in the study. Finally, chapters 4, 5, 6 and 7 provided the results of the analysis findings and their implications.

8.2 An overview of the objectives, achievements and contribution to knowledge

The first objective was to assess the indicators and factors that drove land use change and build a framework for assessing the likelihood of specific land use changes contributing to flooding hazards in Nigeria. The study further identified useful indicators and significant factors impacting land use changes with the help of a relevant literature review. Finally, various biophysical, economic, technological, and demographic variables to determine how natural and socio-economic factors interact and impact land usage. The final results illustrate that the factors of land use change included in the research framework include the Gross Domestic Product, Migration rate, Population density, Poverty ratio, Distance to Road, soil type, and precipitation, among the respective indicators.

The second objective looked into the relationship between changes in a specific land use type, their drivers, and flood hazards in Nigeria. These components aid in testing the theory that changes in land use due to various socio-economic influences could significantly impact the magnitude of flood risk. The observed results describe how the probability of a unit change in one land use category affects the magnitude of the existing flood hazard.

Since the study investigates the drivers of land use change and their effect on the level of existing flood risk, the third objective is to estimate the distribution of persons and land use vulnerable to flood hazards. The intent behind the objective is to help raise awareness and preparedness for flood hazards and understand the underlying causes of disparity of vulnerability in the study area. In addition, the knowledge obtained should assist in developing focus discussions with policy and planning officials at various levels of government and highlight where what and who needs immediate mitigation.

The next objective involves utilising the drivers of land use change to simulate future land use demand under multiple developmental scenarios. The driving force behind the objective originates from how an individual land use change can impact the risk of flooding highlighted in the second objective result. In addition, it would help to estimate how depending on the land use pattern, how much would be exposed to flooding and what nature of development would reduce the overall vulnerability of people and infrastructure—three developmental pathways based on perceived changes in the socio-economic characters and land use policies.

The fourth goal is to anticipate locations at risk of flooding and categorise them depending on their severity level using land use information, flood incidence data, historical flood risk information, and other specified conditioning factors. The analysis outcome helped accentuate the other factors influencing flood risk levels apart from the existing land use. The result equally showcased what regions are susceptible to flooding, which can increase the overall vulnerability and lead to significant economic loss when combined with the possible land use changes. If the areas predicted to have a high probability of flooding happen to accommodate a large extent of human settlement and infrastructure, then the impact on the environmental, social and economic character would be significantly affected.

The final objective investigates the relationship between future land use changes and the simulated flood susceptible areas. The intent is to estimate the effects of future land use changes under diverse growth scenarios and the impact on flood susceptibility and exposure. Furthermore, the section investigates flood risk changes under each land use scenario, estimating and showcasing the disparity in exposure levels under each land use. Finally, reflecting on the future developmental path, which would have the lowest exposure and vulnerability levels, assists planning and development officials in formulating and adopting appropriate policies that promote economic growth, limit environmental degradation and address flood risks.

8.3 Answers to the research questions

Question 1: What factors are responsible for land use changes?

The study successfully identified the factors that influence land use changes. The findings revealed that the drivers of land use change originated from various factors, including biophysical, economic, demographic, and technological indicators. From the results, the gross regional product (GDP), temperature, migration, poverty ratio, and population density were the primary drivers of land use changes in Nigeria. The gross regional product, population density and migration have the most significant impact on land use change.

Question 2: How do the individual land use and changes impact flooding risks?

According to the findings, land use changes and the factors that drive them to play a substantial role in the amount of risk connected with natural disasters. In a natural disaster, such as flooding, the disruption to Nigeria's social, environmental, and economic infrastructure would be considerably reduced if suitable policies to restrict land use conversion and promote sustainable land use management were introduced and implemented. The findings also indicate that the built human settlements cover many medium, high, and extreme risk zones. As a result, this research successfully highlights the importance of developing and promoting effective land use management systems that consider natural and social systems for land use changes and existing disasters to promote resilience, adaptive capacity and maintain a sustainable society. The methodology used in this study exemplifies that utilising and recognising different techniques in proposing solutions to Nigeria's land use and disaster difficulties is critical. Furthermore, it enables the collation of vital information to accomplish flood risk management in Nigeria.

Question 3: How can the changes from natural and socio-economic indicators impact the future land use demand?

The study used the results of the critical drivers of land use change, which include demographic, economic, and land use policy variables, to address how changes in natural and socio-economic indicators influence future demand for land use. Three developmental scenarios highlighting the variations in the socio-economic indicators with the system dynamics modelling framework helped simulate land use demand under the BAU, market-oriented and conservation scenarios.

The study effectively simulated the spatial distribution of land use in Nigeria's business-as-usual, market-oriented, and conservation scenarios in 2040 using the SD and FLUS models. The existing state of affairs is unsustainable, as evidenced by trends in land use classification, which show that cultivated land is expanding at an alarming rate at the expense of other land use categories. For example, cultivated land increased from 26 to 42 per cent of total land area between 2000 and 2020. In the meantime, miscellaneous land fell from 39 to 28 per cent of total land area, while settlement land climbed from 0.8 to 1.3 per cent. According to the future land use simulation results, Nigeria's share of agricultural land will expand by roughly 35 per cent by 2040 under a business-as-usual (BAU) development scenario.

Furthermore, it is more probable that the new agricultural land will come from the conversions of other land cover types, which will decline by roughly 60 per cent by 2040. The rate of cultivated land growth in the market-oriented scenario, on the other hand, is slower than in the BAU scenario, in which cultivated land expands by almost 23 per cent in 2040. The resultant effect on the market-oriented situation is that when socio-economic conditions are favourable, investment rates rise, and productivity levels grow, there is less demand for agricultural land. Furthermore, settlement and forest land areas also increase by 46 per cent and 6 per cent, respectively. Compared to the BAU scenario, the conservation scenario sees forest land expand by 11 per cent, cultivated land stabilise at 4 per cent, settlement areas grow at a slower rate of 25 per cent, and grassland areas shrink by 7 per cent.

Moreover, the study shows that placing limitations on land use through the creation and enforcement of stricter land use rules, as anticipated in the market-oriented and conservation scenarios, can strengthen the long-term sustainability of land use. The study also demonstrated the impact of demographic and economic changes on Nigeria's long-term development. It claims that improving socio-economic conditions is necessary before implementing sustainable land use methods. We now know how socio-economic changes will impact land use patterns. The information will allow the development, optimisation, and prioritisation of regions requiring great attention to reduce environmental deterioration and ensure long-term progress.

Question 4: How do the existing natural and socio-ecological factors impact flooding risks, and what areas have the highest risks?

Flooding is a common occurrence that poses a severe threat to human lives and critical infrastructure. The first step in limiting the level of destruction caused by flooding disasters is to create flood susceptibility maps. Combined with a flood susceptibility map, it can aid in identifying flood-prone areas by categorising the likelihood of flood occurrence based on various parameters. The study used two machine learning models in conjunction with geographic information systems (GIS) to successfully demonstrate the locations in Nigeria that were most vulnerable to flooding.

As part of the effort to successfully develop the flood susceptibility map, we selected 15 flood conditioning factors. The first instance produced a flood inventory map utilising historical flood occurrence data spanning 1985 to 2020. As a result, it was possible to identify and collect flood episodes and separate the generated data into two datasets: a training dataset and a validation dataset, with 70 per cent of the data used for training and the remaining 30 per cent used for validation.

The model's outcomes also highlighted which parameters had the most significant relative importance and places most likely to flood. Both machine learning algorithms can predict flood-prone locations based on the findings. Consequently, the study's flood susceptibility maps highlight its usefulness in Nigeria's flood risk management and land use planning, which is essential in preventing flood disasters in Nigeria. Furthermore, based on the data, we can quickly identify areas with high flood susceptibility and stimulate the development of policies and infrastructure to prevent the potential impacts of flooding.

Question 5: How do land use changes impact people and infrastructure's vulnerability in flood-prone areas?

To fully grasp the relationship between land use changes and the simulated flood risk areas, the study further estimated how future land use demand would influence the vulnerability levels. The question equally aimed to answer and serve as a policy guideline for future land use development and its implications on flood risk. The potential flood risk areas were categorised using the three simulated land use patterns to compare how each scenario differs in vulnerability. The results show that the Market-oriented scenario produced the lowest overall land area susceptible to flood hazards compared to the other developed scenarios. The areas exposed to flood risks illuminated the importance of effective land use policies on flood risk mitigation in each scenario. Although the differences in risk exposure between the scenarios were not extremely obvious, they successful showcased an avenue to improving land use development strategies to limit the level of exposure to flood risk, especially in highly susceptible areas. Furthermore, in terms of the distribution under each risk category, the market-oriented scenario is highlighted as the best alternative development scenario to mitigate flood risks and ensure socio-economic growth and development.

8.4 Strengths, limitations and future research

8.4.1 Strengths

The research has simplified the relationship between various socio-economic drivers, land use changes, and flood risk effects in Nigeria. However, in many cities in Nigeria, flood mitigation planning and risk assessment are not getting enough attention. Understanding what prompts land use changes and how it indirectly increases the vulnerability to flooding risks through hazard and risk mapping has not been prioritised in land use planning and policy formation and is still a long way from being integrated into flood risk management studies.

This study utilised open-source datasets, existing literature and web resources to fill the data shortage and deficiencies gaps. These data were integrated with current data by preprocessing, digitalising, transforming and revising. Another advantage of the study is its development of an initial database for land use and flood risk change for Nigeria, which hopes to offer a good reference for further land use changes and risk management studies. Similarly, the research has introduced and adopted innovative methods and tools for flood risk assessment. Some highlights of the research strengths include,

- We are developing practical methods for forecasting land use patterns by measuring the relationship between socioeconomic variables and land-use demand changes.
- Integrating machine learning algorithms helped improve land use change accuracy and precision in spatial pattern prediction.
- Enabled access to how land use serves an integral part in FRM and devised solutions to improve land use planning policies as a means of minimising future substantial damage
- The capacity to predict flood susceptibility areas without using advanced hydrological models, typically required to use large amounts of data that are not always readily available, is a significant advantage.
- In addition, machine learning approaches to predict flood susceptibility areas has the advantage of covering considerably larger areas than hydrological models, which are often limited in their ability to cover large areas.
- Finally, machine learning models can be adopted and replicated in numerous locations, even though data is limited.

8.4.2 Limitations

The limitations of the research are the availability of locally sourced statistical and GIS data, which made it challenging and forced the reliance on numerous global data warehouses, that required in-depth cleaning, processing and validation before they could be used in the research. Another limitation is that the study focused solely on Nigeria and made no comparison with other sub-Saharan African or developing countries with similar land use and socio-economic characteristics. Finally, the research utilised cross-checking and triangulation to decrease bias, which led to a review of relevant literature to understand how to limit scientific data disparity.

8.4.3 Future research

Develop methods for enhancing land use and natural resource assessment studies by enhancing methods for collecting high-resolution data, integrating sophisticated remote sensing techniques, and using machine learning applications. To further investigate the theoretical foundation built in the study to evaluate a more expansive collection of case studies in African cities that concentrate on changes in land use and other factors that influence the disproportionate occurrence of flood vulnerability. Conduct further research on the factors that determine changes in land use and the effect these changes have on a population's susceptibility to flooding hazards. Finally, allow a greater understanding of the factors responsible for the disparities in the populations and infrastructure at risk at various scales.

Acknowledgements

I express sincere gratitude to the Ministry of Education, Culture, Sports, Science, and Technology (MEXT) and the selection panel of the Japanese Embassy in Nigeria for the opportunity to study in Japan over the past five years. Through their belief and financial support, I could acquire a Master's and Doctoral degree from a top-rated Japanese University.

Special thanks to my Supervisor: Associate Professor Shirakawa, for the support and guidance throughout my study at Nagoya University. I have gained insights on how to research better and work smarter from all the comments and suggestions throughout these five years. I am most grateful. I would also like to thank the reviewers of my doctoral dissertation, Professors Tanikawa and Nakamura, for their suggestions and guidance in improving my research presentation and dissertation finalisation.

Outside Nagoya University, Professor Olotuah and Dr Attoye from the Federal University of Technology, Akure, Nigeria, also provided recommendations, moral support and encouragement before my arrival and during my stay in Japan. I am blessed to have had such words of encouragement in my time of need.

I would also give a special thanks to my members of my immediate family Dr Ikponmwosa Igbinovia and Osasikemwen Ighile, Andrew Igbinovia and my parents for their never-ending support. Cheers to You. I thank everyone, including those not mentioned in this acknowledgement. Your impact has been felt, and it is a memory that cannot be forgotten.

References

Abah, R.; Clement. An application of Geographic Information System in mapping flood risk zones in a north central city in Nigeria. African Journal of Environmental Science and Technology. **2013**: 7. 365-371. 10.5897/AJEST12.182.

Abubakar, T.; Azra, E. A.; Mohammed, C. Selecting Suitable Drainage Pattern to Minimize Flooding in Sangere Village Using GIS and Remote Sensing. Global Journal of Geological Sciences. **2013**:10. 10.4314/gjgs.v10i2.1.

Adelekan, I. Vulnerability of poor urban coastal communities to flooding in Lagos, Nigeria. Environment and Urbanisation. **2009**. Fifth Urban Research Symposium https://doi.org/10.1177/0956247810380141.

Adelekan, I.; Olajide-Taiwo, L.; Ayorinde, A.; Ajayi, D.; Babajide, S. Building Urban Resilience: Assessing Urban and Peri-urban Agriculture in Ibadan, Nigeria. **2014** .Padgham, J. and J. Jabbour.

Adelekan, I.; Asiyanbi, A. Flood risk perception in flood-affected communities in Lagos, Nigeria. Natural Hazards, **2016**: 80(1), 445-469. Retrieved 1 28, 2021, from https://link.springer.com/article/10.1007/s11069-015-1977-2.

Agarwal, C.; Green, G. M.; Grove, M.; Evans, T. P.; Schweik, C. A Review and Assessment of Land-Use Change Models. Dynamics of Space, Time, and Human Choice. **2002.**

Ahmadlou, M.; Al_Fugara, A. A.; Al-Shabeeb, A.; Arora, A.; Al-Adamat, R.; Quoc, P. Q.; Al-Ansari, N.; Nguyen, H. D.; Nguyen, L.; Hedieh, S. Flood susceptibility mapping and assessment using a novel deep learning model combining multilayer perceptron and autoencoder neural networks. J. Flood Risk Manag., **2020**: 13. 1-22. https://doi.org/10.1111/jfr3.12683.

Ajayi, O.; Agbola, S.; Olokesusi, B.; Wahab, B.; Gbadegesin, M.; Taiwo, D.; Olutade, O. Flood management in an urban setting: a case study of Ibadan metropolis. Special Publication of the Nigerian Association of Hydrological Sciences., **2012**: 65-81.Viewed 13 June 2014 from http://www.journal.unaab.edu.ng/index.php/NAHS/article/viewFile/914/882.

Al-Juaidi, A. E. M.; Nassar, A. M.; Al-Juaidi, O. E. M. Evaluation of flood susceptibility mapping using logistic regression and GIS conditioning factors. Arabian J. of Geosci. **2018**: 11: 765. https://doi.org/10.1007/s12517-018-4095-0.

Althuwaynee, O. F. First Simplified Step-by-Step Artificial Neural Network Methodology in R for Prediction Mapping using GIS Data. Udemy, **2021**: Available at: https://www.udemy.com/course/how-to-use-ann-for-prediction-mapping-using-gis-data/learn/lecture/14033471.

Anson, M. J. P.; Fabozzi, F. J.; Jones, F. J. The Handbook of Traditional and Alternative Investment Vehicles: Investment Characteristics and Strategies. **2010**. New Jersey: John Wiley & Sons. ISBN:9781118258248. DOI:10.1002/9781118258248.

Arabameri, A.; Saha, S.; Mukherjee, K.; Blaschke, T.; Chen, W.; Ngo, P. T. T.; Band, S. S. Modeling Spatial Flood using Novel Ensemble Artificial Intelligence Approaches in Northern Iran. Remote Sensing. **2020**: 12(20):3423. https://doi.org/10.3390/rs12203423 .

Arima E. Y. A Spatial Probit Econometric Model of Land Change: The Case of Infrastructure Development in Western Amazonia, Peru. PLoS One. **2016**. Mar 24;11(3):e0152058. doi: 10.1371/journal.pone.0152058. PMID: 27010739; PMCID: PMC4806871.

Arsanjani, J. J.; Helbich, M.; Kainz, W.; Boloorani, A. D. Integration of logistic regression, Markov chain and cellular automata models to simulate urban expansion. Int. J. Appl. Earth Obs. Geoinf., **2013**: No. 21, 265–275.

Assis Dias, M. C.; Saito, S. M.; Alvalá, R. C.; Stenner, C.; Pinho, G.; Nobre, C. A.; Fonseca, M. R.; Santos, C.; Amadeu, P.; Silva, D.; Lima, C. O.; Ribeiro, J.; Nascimento, F.; Corrêa, C. Estimation of exposed population to landslides and floods risk areas in Brazil, on an intra-urban scale. International Journal of Disaster Risk Reduction., **2018:** 31(6), 449–459. https://doi.org/10.1016/j.ijdrr.2018.06.002

Atkinson, P. M.; Massari, R. Generalised linear modelling of susceptibility to landsliding in the central Apennines, Italy. Comput. Geosci., **1998**: 24(4):373–385. https://doi.org/10.1016/S0098-3004(97)00117-9

Ayalew, L.; Yamagishi, H. The application of GIS-based logistic regression for landslide susceptibility mapping in the Kakuda-Yahiko Mountains, Central Japan. J. Geomorph., **2005**: (65) 15-31. https://doi.org/10.1016/j.geomorph.2004.06.010.

Bai, S. B.; Wang, J.; Lu, G. N.; Zhou, P.G.; Hou, S. S.; Xu, S. N. GIS-based logistic regression for landslide susceptibility mapping of the Zhongxian segment in the Three Gorges area, China. Geomorph., **2010:** 115 (1), 23–31.

Bakhtyari, M.; Pirasteh, S.; Pradhan, B.; Mahmud, A. R.; Moradi, A. An artificial neural network model for flood simulation using GIS: Johor River Basin, Malaysia. Env. Earth. sci., **2012**: 1-14. https://doi.org/10.1007/s12665-011-1504-z .

Barredo, J.; Engelen, G. Land Use Scenario Modeling for Flood Risk Mitigation. Sustainability., **2010**: 2. 10.3390/su2051327.

Beckers, A.; Dewals, B.; Erpicum, S. Contribution of land use changes to future flood damage along the river Meuse in the Walloon region. Nat Hazards Earth Syst Sci., **2013**: 13:2301–2318. https://doi.org/10. 5194/nhess-13-2301-2013

Belsley, D. A. A guide to using the collinearity diagnostics. Comput. Econ., **1991**: 4 (1), 33–50.

Booth, G. D.; Niccolucci, M.J.; Schuster, E.G. Identifying proxy sets in multiple linear regression: an aid to better coefficient interpretation. **1994**. In: Research Paper INT (USA).

Braimoh, A.; Onishi, T. Spatial determinants of urban land use change in Lagos, Nigeria. Land Use Policy., **2007**: 24. 502-515. 10.1016/j.landusepol.2006.09.001.

Brakenridge, G. R. Global Active Archive of Large Flood Events. Dartmouth Flood Observatory, University of Colorado, USA. http://floodobservatory.colorado.edu/Archives/ (Accessed July 2021).

Brown, D.; Verburg, P.; Pontius, R.; Lange, M. Opportunities to improve impact, integration, and evaluation of land change models. Current Opinion in Environmental Sustainability., **2013**: 5(5), 452-457. 10.1016/j.cosust.2013.07.012.

Budiyono, Y.; Aerts, J. C. J. H.; Tollenaar, D.; Ward, P. J. River flood risk in Jakarta under scenarios of future change. Natural Hazards and Earth System Sciences., **2016**. 16(3), 757–774. https://doi.org/10.5194/nhess-16-757-2016

Bui, D.T.; Hoang, N.D.; Martínez-Álvarez, F.; Ngo, P.-T.T.; Hoa, P.V.; Pham, T.D.; Samui, P.; Costache, R.; A novel deep learning neural network approach for predicting flash flood susceptibility: a case study at a high frequency tropical storm area. Sci. Total Environ. **2019**; 701, 134413. https://doi.org/10.1016/j.scitotenv.2019.134413

Campolo, M.; Soldati, A.; Andreussi, P. Artificial neural network approach to flood forecasting in the River Arno, Hydro. Sci. J., **2003**; 48:3, 381-398, DOI: 10.1623/hysj.48.3.381.45286.

Cao, C.; Xu, P.; Wang, Y.; Chen, L.; Zheng, L.; Niu, C. Flash flood hazard susceptibility mapping using frequency ratio and statistical index methods in coalmine subsidence areas. Sustainability., **2016**: (8) 9. doi: 10.3390/su8090948.

Casas, A.; Lane, S. N.; Yu, D.; Benito, G. A Method for Parameterising Roughness and Topographic Sub-grid Scale Effects in Hydraulic Modelling from LiDAR Data. Hydrol. Earth Syst. Sci., **2010.** 14, 1567–1579, https://doi.org/10.5194/hess-14-1567-2010.

Casella, G.; Fienberg, S.; Olkin, I. An Introduction to Statistical Learning. In Design **2006**. Vol. 102. https://doi.org/10.1016/j.peva.2007.06.006.

Chen, Y.; Yu, B. Impacts of climate and land-use changes on floods in an urban catchment in southeast Queensland, Australia. Climate and Land Surface Changes in Hydrology., **2013**. Griffith School of Engineering, Griffith University, Nathan, pp 23-29.

Choubin, B.; Moradi, E.; Golshan, M.; Adamowski, J.; Sajedi-Hosseini, F.; Mosavi, A. An ensemble prediction of flood susceptibility using multivariate discriminant analysis, classification and regression trees, and support vector machines. Sci. Total Environ. **2019**; 651, 2087–2096. https://doi.org/10.1016/j.scitotenv.2018.10.064

Chung, C.J.; Fabbri, A.G. Predicting landslides for risk analysis—spatial models tested by a cross-validation technique. Geomorph. **2008**; 94 (3), 438–452. https://doi.org/10.1016/j.geomorph.2006.12.036

CLUE Model; Verburg and Overmars, Landscape Ecology., **2009**: 24(9) 1167-1181.

Coker, A.; Awokola, O.; Olomolaiye, P.; Booth, C. Challenges of urban housing quality and its associations with neighbourhood environments: Insights and experiences of Ibadan City, Nigeria. Journal of Environmental Health Research., **2008**: 7(1), 21-30.

Danso-Amoako, E.; Scholz, M.; Kalimeris, N.; Yang, Q.; Shao, J. Predicting dam failure risk for sustainable flood retention basins: A generic case study for the wider greater Manchester area. Comput. Environ. Urban Syst., **2012**, 36, 423–433.

Devkota, K. C.; Regmi, A.; Pourghasemi, H. R.; Yoshida, K.; Pradhan, B.; Ryu, I.C.; Dhital, M. R.; Althuwaynee, O.F. Landslide susceptibility mapping using certainty factor, index of entropy and logistic regression models in GIS and their comparison at Mugling–Narayanghat road section in Nepal Himalaya. Nat. Hazards., **2013**: 65(1)135–165. https://doi.org/10.1007/s11069-012-0347-6.

Dharmasiri, L. M. Measuring Agricultural Productivity Using the Average Productivity Index (API). Sri Lanka Journal of Advanced Social Studies., **2006**: 1. 10.4038/sljass.v1i2.4855.

Diaz, J. H. Global climate changes, natural disasters, and travel health risks. J. Travel. Med., **2006**; Nov-Dec;13(6):361-72. https://doi.org/10.1111/j.1708-8305.2006.00072.x.PMID:17107430.

Dodangeh, E.; Choubin, B.; Eigdir, A. N.; Nabipour, N.; Panahi, M.; Shamshirband, S.; Mosavi, A. Integrated machine learning methods with resampling algorithms for flood susceptibility prediction, Sci.Total. Environ., **2019**: Vol. 705, 2020, https://doi.org/10.1016/j.scitotenv.2019.135983.

Dormann, C.F.; Elith, J.; Bacher, S.; Buchmann, C.; Carl, G.; Carré, G.; Marquéz, J.R.G.; Gruber, B.; Lafourcade, B.; Leitão, P.J. Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. Ecography., **2013**: 36 (1), 27–46.

Falah, F.; Rahmati, O.; Rostami, M.; Ahmadisharaf, E.; Daliakopoulos, I. N.; Pourghasemi, H. R. Artificial Neural Networks for Flood Susceptibility Mapping in Data-Scarce Urban Areas. Spatial Modeling in GIS and R for Earth and Environmental Sciences, Editor 1, Pourghasemi, H. R., Gokceoglu, C. Elsevier, **2019**, pp. 323-336. https://doi.org/10.1016/B978-0-12-815226-3.00014-4.

Fantin-Cruz, I.; Pedrollo, O.; Castro, N. M.; Girard, P.; Zeilhofer, P.; Hamilton, S. K. Historical reconstruction of floodplain inundation in the Pantanal (Brazil) using neural networks. **2011**. J. Hydrol. 399 (3–4), 376–384.

Fasona M. J. Land Degradation and Environmental Change in Ondo State, South-West Nigeria. **2007**.

Felzer, B. S.; Ember, C. R.; Cheng, R.; Jiang, M. The Relationships of Extreme Precipitation and Temperature Events with Ethnographic Reports of Droughts and Floods in Nonindustrial Societies, **2020**. Weather, Climate, and Society, 12(1), 135-148. Retrieved 17 March 2022, from https://journals.ametsoc.org/view/journals/wcas/12/1/wcas-d-19-0045.1.xml

Feng, Y.; Yang, Q.; Hong, Z.; Cui, L. Modelling coastal land-use change by incorporating spatial autocorrelation into cellular automata models. Geocarto Int. **2018**b. 33, 470–488.

Floodlist. Available online: https://floodlist.com/africa/nigeria-floods-october-2020.

Furtună, P.; Holobâcă, I. H. Forest fires study using remote sensing and meteorological indicators. Study case. Geographia Technica, **2013**: 18(2), 23–37.

Guha-Sapir, D.; Hoyois, P. H.; Below, R. Annual Disaster Statistical Review 2015: The Numbers and Trends. Brussels: CRED; **2016**. Available on http://www.cred.be/sites/default/files/ADSR_2015.pdf

Günther, F.; Fritsch, S. neuralnet: Training of Neural Networks. R Journal. **2010**; 2. https://doi.org/10.32614/RJ-2010-006 .

Habahbeh, A.; Fadiya, S.; Akkaya, M. Factors influencing SMEs CloudERP adoption: A test with Generalised Linear Model and Artificial Neural Network. Data in Brief., **2018**: 20. https://doi.org/10.1016/j.dib.2018.07.012.

Han, H.; Yang, C.; Jinping, S (2015). Scenario Simulation and the Prediction of Land Use and Land Cover Change in Beijing, China. Sustainability.**, 2015**: 7, 4260-4279.

Han, H.; Yang, C.; Jinping, S. Scenario Simulation and the Prediction of Land Use and Land Cover Change in Beijing, China. Sustainability. **2015**, 7, 4260-4279.

Harfoot, M.; Tittensor, D. P.; Newbold, T.; McInerny, G.; Smith, M. J.; Scharlemann, J. P. W. Integrated assessment models for ecologists: the present and the future. Global Ecology and Biogeography., **2014**: 23(2), 124–143. Available at: http://doi.wiley.com/10.1111/geb.12100 [Accessed May 03, 2021].

Harrington, D. W, Simon, L. V. Designing a Simulation Scenario. [Updated 2020 Oct 3]. In: StatPearls [Internet]. Treasure Island (FL): StatPearls Publishing; **2020** Jan-. Available from: https://www.ncbi.nlm.nih.gov/books/NBK547670/

Hawken, P. Drawdown: The Most Comprehensive Plan Ever Proposed to Reverse Global Warming. Penguin Books, **2017**: https://www.drawdown.org/solutions/sustainable-intensification-for-smallholders.

Haynes, K.; Coates, L.; Van Den Honert, R.; Gissing, A.; Bird, D.; Dimer De Oliveira, F.; D'arcy, R.; Smith, C.; Radford, D. Exploring the circumstances surrounding flood fatalities in Australia—1900–2015 and the implications for policy and practice. Environ. Sci. Pol. **2017**: 76, 165–176.

Heistermann, M.; Müller, C.; Ronneberger, K. Land in sight? Achievements, deficits and potentials of continental to global scale land-use modelling. Agriculture, Ecosystems & Environment., **2006**:114(2-4), 141–158. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0167880905005475 [Accessed April 27, 2021].

Hong, H.; Tsangaratos, P.; Ilia, I.; Liu, J.; Zhu, A. X.; Chen, W. Application of fuzzy weight of evidence and data mining techniques in construction of flood susceptibility map of Poyang County, China. Sci. Total Environ., **2018**: vol. 625, pp. 575–588. doi: 10.1016/j.scitotenv.2017.12.256.

Huo, J.; Shi, Z.; Zhu, W.; Xue, H.; Chen, X. A Multi-Scenario Simulation and Optimization of Land Use with a Markov–FLUS Coupling Model: A Case Study in Xiong'an New Area, China. Sustainability., **2022**: 14, 2425. https://doi.org/10.3390/su14042425.

Huong, H. T. L.; Pathirana, A. Urbanisation and climate change impacts on future urban flooding in Can Tho city, Vietnam. Hydrology and Earth System Sciences., **2013**:17(1), 379–394. https://doi.org/10.5194/hess-17-379-2013.

Idowu, I. A. An Assessment of Land Use/ Land Cover Changes in A Section of Niger Delta, Nigeria. Zaria, Kaduna, Nigeria: Department of Geography., **2012**. Ahmadu Bello University.

Ighile E. H.; Shirakawa. H. A Study on The Effects of Land Use Change on Flooding Risks in Nigeria. *Geographia Technica., **2020**:Vol 15, Issue no.1, pp. 91-101.* http://technicalgeography.org/pdf/1_2020/08_ighile.pdf.

Intrator, O.; Intrator, N. Interpreting Neural-Network Results: A Simulation Study. Comput. Stats & Data Analysis., **2001**: 37, 373-393. https://doi.org/10.1016/S0167-9473(01)00016-0.

IPCC. The physical science basis. Contribution of working group I to the fifth assessment report of the intergovernmental panel on climate change. In T. F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex, 172 & P. M. Midgley (Eds.), **2013**: (pp. 1535). Cambridge, UK: The Intergovernmental panel on Climate Change.

Irwin, E. G.; Geoghegan, J. Theory, data, methods: developing spatially explicit economic models of land use change. Agriculture Ecosystems & Environment., **2001**:85, 7–23

Ishaku, H. T.; Majid, M. R. X-Raying Rainfall Pattern and Variability in Northeastern Nigeria: Impacts on Access to Water Supply. Wat. Res. Protection., **2010**: 2, 952-959 https://doi.org/10.4236/jwarp.2010.211113.

Islam, A.R.M.T.; Talukdar, .S; Mahato, S.; Kundu, S.; Eibek, K. U.; Pham, Q. B; Kuriqi, A.; Linh, N.T.T. Flood susceptibility modelling using advanced ensemble machine learning models. Geosci. Frontiers, **2021.** Volume 12, Issue 3. https://doi.org/10.1016/j.gsf.2020.09.006.

Jaafari, A.; Najafi, A.; Rezaeian, J.; Sattarian, A. Modeling erosion and sediment delivery from unpaved roads in the north mountainous forest of Iran. GEM – Int. J. Geomaths., **2015**: 6 (2), 343–356. https://doi.org/10.1007/s13137-014-0062-4.

Jamali, B.; Bach, P. M.; Deletic, A. Rainwater harvesting for urban flood management – An integrated modelling framework, Water Res., Volume 171, **2020**, 115372. https://doi.org/10.1016/j.watres.2019.115372.

Janizadeh, S.; Avand, M.; Jaafari, A.; Phong, T.V.; Bayat, M.; Ahmadisharaf, E.; Prakash, I.; Pham, B.T.; Lee, S. Prediction success of machine learning methods for flash flood susceptibility mapping in the Tafresh watershed, Iran. Sustainability, **2019**: 11 (19), 5426. https://doi.org/10.3390/su11195426.

Jongman, B.; Ward, P.J.; Aerts, C. J. Global Exposure to River and Coastal Flooding: Long Term Trends and Changes." Global Environmental Change., **2012**: 22 (4):823–835. https://doi.org/10.1016/j.gloenvcha.2012.07.004

Josephat, M. Deforestation in Uganda: Population Increase, Forests Loss and Climate Change. Environmental Risk Assessment and Remediation, **2018**: 02(02), 46–50. https://doi.org/10.4066/2529-8046.100040.

Kabari, L.G.; Mazi, Y. C. Rain–Induced Flood Prediction for Niger Delta Sub-Region of Nigeria Using Neural Networks. Volume 5, Issue 9, **2020**; pp 1124 -1130. DOI: http://dx.doi.org/10.24018/ejers.2020.5.9.2114.

Kaelbling, L. P.; Littman, M. L.; Moore, A. W. "Reinforcement Learning: A Survey". Journal of Artificial Intelligence Research. **1996**. 4: 237–285. arXiv:cs/9605103. doi:10.1613/jair.301. S2CID 1708582. Archived from the original on 2001-11-20.

Kellens, W.; Terpstra, T.; De Maeyer, P. Perception and communication of flood risks: a systematic review of empirical research. Risk Anal., **2013**: 33(1):24–49

Khan, M. M. H.; Bryceson, I.; Kolivras, K. N.; Faruque, F.; Rahman, M. M.; Haque, U. Natural disasters and land-use/land-cover change in the southwest coastal areas of Bangladesh. Regional Environmental Change., **2014**: 15(2), 241–250. https://doi.org/10.1007/s10113-014-0642-8

Khoirunisa, N.; Ku, C.-Y.; Liu, C.-Y. A GIS-Based Artificial Neural Network Model for Flood Susceptibility Assessment. Int. J. Environ. Res. Public Health., **2021**: 18, 1072. https://doi.org/10.3390/ijerph18031072 .

Khosravi, K.; Pham, B.T.; Chapi, K.; Shirzadi, A.; Shahabi, H.; Revhaug, I.; Prakash, I.; Bui, D.T. A comparative assessment of decision trees algorithms for flash flood susceptibility modelling at Haraz watershed, northern Iran, Sci. Total. Environ, Vol. 627, **2018**,PP 744-755,https://doi.org/10.1016/j.scitotenv.2018.01.266.

Kia, M.B.; Pirasteh, S.; Pradhan, B.; Mahmud, A. R.; Sulaiman, W. N. A.; Moradi, A. An artificial neural network model for flood simulation using GIS: Johor River Basin, Malaysia., Environ. Earth Sci. **2012**: 67 (1), 251–264.

Kidron, G. J.; Karnieli, A.; Benenson, I.; Grinblat, Y. Simulating land-use degradation in West Africa with the ALADYN model. J. Arid. Environ., **2015**: No.112, 52–63.

Kim, I.; Heung, C. Development of integrated modelling framework of land use changes and ecosystem services in mountainous watersheds, **2017**.

Kim, S.; Matsumi, Y.; Pan, S.; Mase, H. A real-time forecast model using artificial neural network for after-runner storm surges on the Tottori Coast, Japan. Ocean Eng. **2016**: 122, 44–53. https://doi.org/10.1016/j.oceaneng.2016.06.017

Klemešová, K.; Kolář, M.; Andráško, I. Using gis in the flood management – flood maps (Troubky, Czech Republic). Geographia Technica, **2014**: 9(2), 44–53.

Komolafe, A.; Adegboyega, S.; Akinluyi, F. A Review of Flood Risk Analysis in Nigeria. American journal of environmental sciences., **2015**: 11. 157 -166. 10.3844/ajessp.2015.157.166.

Lambin. E. F.; Rounsevell, M. D. A.; Geist, H. J. Are agricultural land-use models able to predict changes in land-use intensity? Agriculture Ecosystems & Environment. **2000**; 82(1), 321–331.

Lars, B. Review of Land-use models., **2014**

Lavell, A.; Lopez-Marrero, T. Disaster risk management in Latin America and the Caribbean: Four decades of evolution and change, 1970–2010. **2014**: London: Earthscan.

Lee, J.; Kim, B. Scenario-Based Real-Time Flood Prediction with Logistic Regression. Water. **2021**; 13. 1191. 10.3390/w13091191.

Lee, S.; Kim, J. C.; Jung, H. S.; Lee, M. J.; Lee. S. Spatial prediction of flood susceptibility using random-forest and boosted-tree models in Seoul metropolitan city, Korea, Geomatics, Nat. Hazards and risk, **2017**: 8:2, 1185-1203, https://doi.org/10.1080/19475705.2017.1308971.

Lin, L.; Di, L.; Tang, J.; Yu, E.; Zhang, C.; Rahman, M.S.; Shrestha, R.; Kang, L. Improvement and Validation of NASA/MODIS NRT Global Flood Mapping. Remote Sens. **2019**: 11, 205. https://doi.org/10.3390/rs11020205.

Lin, W.; Sun, Y.; Nijhuis, S.; Wang, Z. Scenario-based flood risk assessment for urbanising deltas using future land-use simulation (FLUS): Guangzhou Metropolitan Area as a case study. Science of the Total Environment, **2020**:739, 139899.

Liu, Q.; Fang, L.; Yu, G.; Wang, D.; Xiao, CL.; Wang, K. Detection of DNA base modifications by deep recurrent neural network on Oxford Nanopore sequencing data. Nat. Commun., **2019**: 4 June;10(1):2449. https://doi.org/10.1038/s41467-019-10168-2. PMID: 31164644; PMCID: PMC6547721.

Liu, Q.; Wu, Y. Supervised Learning. Encyclopedia of the Sciences of Learning, **2012**. https://doi.org/10.1007/978-1-4419-1428-6.

Lu, R.C.; Huang, X.J.; Zuo, TH; Xiao, S.S.; Zhao, X.F.; Zhang, X.Y. Land Use Scenarios Simulation Based on CLUE-S and Markov Composite Model—A Case Study of Taihu Lake Rim in Jiangsu Province. Sci. Geol. Sinica, **2009**: 29, 577–581.

Luu, C.; Bui, Q.D.; Costache, R.; Nguyen, T.T.; Phong, T. V.; Le, H. V.; Pham, B. T. Flood-prone area mapping using machine learning techniques: a case study of Quang Binh province, Vietnam. Nat. Hazards., **2021**: 108, pp.3229–3251. https://doi.org/10.1007/s11069-021-04821-7

Maantay, J.; Maroko, A. (2009). Mapping urban risk: Flood hazards, race, & environmental justice in New York. Applied Geography., **2009**: 29(1), 111–124. https://doi.org/10.1016/j.apgeog.2008.08.002

Mahmoud, S. H.; Gan, T. Y. Urbanization and climate change implications in flood risk management: Developing an efficient decision support system for flood susceptibility mapping. Sci. Total Environ., **2018**: vol. 636, pp. 152–167. doi: 10.1016/j.scitotenv.2018.04.282.

Mekanik, F.; Imteaz, M.; Gato-Trinidad, S.; Elmahdi, A. Multiple regression and artificial neural network for long-term rainfall forecasting using large scale climate modes. J. Hydrol., **2013**: 503, 11–21. https://doi.org/10.1016/j.jhydrol.2013.08.035

Meshram, S.G.; Singh, V.P.; Kisi, O. Application of Artificial Neural Networks, Support Vector Machine and Multiple Model-ANN to Sediment Yield Prediction. Water. Resour. Manage., **2020**: 34, 4561–4575. https://doi.org/10.1007/s11269-020-02672-8

Meyer, W. B.; Turner, B. L. Human Population Growth and Global Land-Use/Cover Change. Annual Review of Ecology and Systematics. **2003.** https://doi.org/10.1146/annurev.es.23.110192.000351

Mojaddadi, H.; Pradhan, B.; Nampak, H.; Ahmad, N.; Ghazali, A. H. Ensemble machine-learning-based geospatial approach for flood risk assessment using multisensory remote-sensing data and GIS. Geomat. Nat. Haz. Risk., **2017**: 1–23.

Mosavi, A.; Ozturk, P.; Chau, K. Flood Prediction Using Machine Learning Models: Literature Review. Water., **2018**: 10, 1536. https://doi.org/10.3390/w10111536.

Moss, R. H.; Edmonds, J. A.; Hibbard, K. A.; Manning, M. R.; Rose, S. K.; van Vuuren, D. P.; Carter, T. R.; Emori, S.; Kainuma, M.; Kram, T.; Meehl, G. A.; Mitchell, J. F. B.; Nakicenovic, N.; Riahi, K.; Smith, S. J.; Stouffer, R. J.; Thomson, A. M.; Weyant, J. P.; Wilbanks, T. J. The next generation of scenarios for climate change research and assessment. Nature., **2010**: 463(7282), 747–56. Available at: http://www.ncbi.nlm.nih.gov/pubmed/20148028 [Accessed May 03, 2021].

National Bureau of Statistics, Nigeria. https://www.nigerianstat.gov.ng/

Nelson, R.; Kokic, P.; Crimp, S.; Meinke, H.; Howden. S. M. The Vulnerability of Australian Rural Communities to Climate Variability and Change: Part I—Conceptualising and Measuring Vulnerability." Environmental Science & Policy., **2009**:13 (1):8–17. https://doi.org/10.1016/j.envsci.2009.09.006

Nigeria Floods Situation Report No. 2. Available online: https://reliefweb.int/report/nigeria/floods-situation-report-no-2-15-november-2012 (accessed on 21 July 2021).

Nkeki, F.; Henah, P.; Ojeh, V. Geospatial Techniques for the Assessment and Analysis of Flood Risk along the Niger-Benue Basin in Nigeria. Journal of Geographic Information System, Vol. 5 No. 2, **2013**, pp. 123-135. doi: 10.4236/jgis.2013.52013.

O'Brien, R. M. A caution regarding rules of thumb for variance inflation factors. Qual. Quant., **2007**: 41 (5), 673–690.

Odufuwa, B. O.; Oludare, A.; Johnson O. O.; Aloysius, B. Floods of Fury in Nigerian Cities. Journal of Sustainable Development., **2012**: 5. 69-79. 10.5539/jsd.v5n7p69. https://doi.org/10.5539/jsd.v5n7p69.

Ojigi, M. L.; Abdulkadir, F. I.; Aderoju, M. O. Geospatial mapping and analysis of the 2012 flood disaster in central parts of Nigeria. Proceedings of the 8th National GIS Symposium, **2013**:Apr. 15-17, Dammam, Saudi Arabia.

Oladokun, V. O.; Proverbs, D. Flood risk management in Nigeria: A review of the challenges and opportunities. International Journal of Safety and Security Engineering., **2016**: 6(3), 485–497. https://doi.org/10.2495/SAFE-V6-N3-485-497

Olanrewaju, C.; Chitakira, M.; Olanrewaju, O. A.; Louw, E. Impacts of flood disasters in Nigeria: A critical evaluation of health implications and management, Jamba: J. Dis. Risk Studies, **2019**:11(1). https://doi.org/10.4102/jamba.v11i1.557.

Olden, J. D.; Joy, M. K.; Death R. G. An accurate comparison of methods for quantifying variable importance in artificial neural networks using simulated data. **2004**. J. Ecol. Model 178:389-397.

Olorunfemi, F. B.; Adebimpe, R. U. Sustainable Disaster Risk Reduction in Nigeria: Lessons for Developing Countries. African Research Review. **2011.** https://doi.org/10.4314/afrrev.v2i2.41050

Ortiz-García, E. G; Salcedo-Sanz, S; Casanova-Mateo, C. Accurate precipitation prediction with support vector classifiers: A study including novel predictive variables and observational data, Atmospheric Research, Volume 139, **2014**, pp. 128-136, https://doi.org/10.1016/j.atmosres.2014.01.012.

Oruonye, E. D. The Challenges of Urban Flood Disaster Management in Nigeria: A Case Study of Jalingo Lga, Taraba State Nigeria. International Journal of Recent Scientific, **2012**: 3(1):37-42. http://www.recentscientific.com/sites/default/files/Download_152.pdf.

Panahi, M.; Jaafari, A.; Shirzadi, A.; Shahabi, H.; Rahmati, O.; Omidvar, E.; Lee, S.; Bui, D. T. Deep learning neural networks for spatially explicit prediction of flash flood probability, Geosci. Frontiers, Volume 12, Issue 3, **2021**, 101076, ISSN 1674-9871, https://doi.org/10.1016/j.gsf.2020.09.007.

Parker, D.C.; Manson, S.M.; Janssen, M.A.; Hoffmann, M.J.; Deadman, P. Multi-agent systems for the simulation of land-use and land-cover change: A review. Ann. Assoc. Am. Geogr. **2003**, 93, 314–337.

Paterson Guma, I.; Rwashana, A.; Oyo, B. A System Dynamics Model of Land-use Change for Climate Change Adaptation: The Case of Uganda. **2021**:191-198. 10.5220/0010342101910198.

Pei, B.; Pan, T. Land use system dynamic modelling: literature review and future research direction in China. Prog. Geogr., **2010**: No. 29, 1060–1066.

Pelling, M. The vulnerability of cities: natural disasters and social resilience. **2003**. London: Earthscan from Routledge.

Pelling, M. (2011). The vulnerability of cities to disasters and climate change: a conceptual framework Coping with Global Environmental Change, Disasters and Security **2011**: (pp. 549-558).

Pelling, M.; Wisner, B. Disaster risk reduction: Cases from urban Africa. **2012**. New York: Routledge.

Peter, E., Samuel, D., & Olatunji, B. Land Use Change Modelling In Developing Countries: Issues And Prospects. International Journal of Geography and Geology., **2012**: 1(1), 23–41.

Pourghasemi, H.; Moradi, H.; Aghda, S.F. Landslide susceptibility mapping by binary logistic regression, analytical hierarchy process, and statistical index models and assessment of their performances. Nat. Hazards., **2013**: 69 (1), 749–779.

Qiang, Y. Disparities of population exposed to flood hazards in theiUnited States. Journal of Environmental Management, **2019**: 232(August), 295–304. https://doi.org/10.1016/j.jenvman.2018.11.039.

Qiang, Y.; Nina S. N.; Lam, H. C.; Lei Z. Changes in Exposure to Flood Hazards in the United States. Annals of the American Association of Geographers., **2017**: 107 (6):1332–50. https://doi.org/10.1080/24694452.2017.1320214.

Rahman, M.; Ningsheng, C.; Islam, M.M. Flood Susceptibility Assessment in Bangladesh Using Machine Learning and Multi-criteria Decision Analysis. Earth. Syst. Environ., 2019; 3, 585–601. https://doi.org/10.1007/s41748-019-00123-y.

Rasmussen, L. V.; Rasmussen, K.; Reenberg, A.; Proud, S. A system dynamics approach to land use changes in agro-pastoral systems on the desert margins of Sahel. Agricultural Systems., **2012**:107, 56–64. https://doi.org/10.1016/j.agsy.2011.12.002.

Razavi Termeh, S.V.; Kornejady, A.; Pourghasemi, H. R.; Keesstra, S. Flood susceptibility mapping using novel ensembles of adaptive neuro-fuzzy inference system and metaheuristic algorithms," Sci. Total Environ., **2018**: vol. 615, pp. 438–451, doi: 10.1016/j.scitotenv.2017.09.262.

Rosa, I. M. D.; Ahmed, S. E.; Ewers, R. M. The transparency, reliability and utility of tropical rainforest land-use and land cover change models. Global change biology., **2014**: 20(6), 1707–22. http://www.ncbi.nlm.nih.gov/pubmed/24399778 [Accessed April 20, 2021].

Rose, E. D.; Johnson, A. O.; Abubakar, I. Flood hazard assessment of river DEP floodplains in North-Central Nigeria. Int. J. Water Resources Environ. Eng., **2014** (6) 67-72. DOI: 10.5897/IJWREE2013.0457.

Rosegrant, M.W.; Paisner, M. S.; Meijer, S.; Witcover, J. 2020 Global food outlook: trends, alternatives and choices. International Food Policy Research Institute. Washington, DC. **2021.** Available at: http://www.fcrn.org.uk/sites/default/files/fpr30_0.pdf.

Ross, C.; Prihodko, L.; Anchang, J.; HYSOGs250m, global gridded hydrologic soil groups for curve-number-based runoff modelling. Sci. Data, **2018**; 5, 180091. https://doi.org/10.1038/sdata.2018.91.

Schuerman, J. Principal Components Analysis. Multivariate Analysis in the Human Services. **1983**. Springer, Netherlands.84.

Seo, Y.; Kim, S. River Stage Forecasting Using Wavelet Packet Decomposition and Data-driven Models. Procedia Eng., **2016**: 154, 1225–1230. https://doi.org/10.1016/j.proeng.2016.07.439.

Shuster, W.; Bonta, J.; Thurston, H.; Warnemuende, E.; Smith, D. Impacts of Impervious Surface on Watershed Hydrology: A Review. Urban Water J. **2005**; 2. 263-275. https://doi.org/10.1080/15730620500386529.

Siregar, P. G.; Supriatna, J.; Koestoer, R. H.; Harmantyo, D. System dynamics modelling of land use change in West Kalimantan, Indonesia. Biotropia., **2018**: 25(2), 103–111. https://doi.org/10.11598/btb.2018.25.2.792.

Skidmore, A. K.; Turner, B. J.; Brinkhof, W.; Knowles, E. Performance of a neural network: mapping forests using GIS and remotely sensed data. Photogrammetric. Eng. & rem. Sensing., **1997**: 63(5), pp.501-514.

Sojobi, A. O.; Balogun, I. I.; Salami, A. W. Climate change in Lagos State, Nigeria: what really changed? Environmental Monitoring and Assessment. **2015.** https://doi.org/10.1007/s10661-016-5549-z.

Strickland, J. Neural networks using R. Available at: https://bicorner.com/2015/05/13/neural-networks-using-r/ (Assessed 6 August 2021).

Suardiwerianto, Y. Flash flood modelling using data-driven models: Case studies of Kathmandu Valley (Nepal) and Yuna Catchment (Dominican Republic). Thesis Master of Science, UNESCO-IHE Institute for Water Education, Delft, **2017**. Available at: https://ihedelftrepository.contentdm.oclc.org/digital/collection/masters2/id/103719.

Szwagrzyk, M.; Kaim, D.; Price, B.; Wypych, A.; Grabska, E.; Kozak, J. Impact of forecasted land use changes on flood risk in the Polish Carpathians. Natural Hazards., **2018**: 94(1), 227–240. https://doi.org/10.1007/s11069-018-3384-y.

Tanoue, M.; Hirabayashi, Y.; Ikeuchi, H. Global-scale River flood vulnerability in the last 50 years. Sci Rep 6, 36021 **2016**. https://doi.org/10.1038/srep36021.

Tehrany, M. S.; Jones, S.; Shabani, F. Identifying the essential flood conditioning factors for flood prone area mapping using machine learning techniques, CATENA, Volume 175, **2019**, Pages 174-192, ISSN 0341-8162. https://doi.org/10.1016/j.catena.2018.12.011.

Tehrany, M. S; Kumar, L; and Shabani, F. A novel GIS-based ensemble technique for flood susceptibility mapping using evidential belief function and support vector machine: Brisbane, Australia. PeerJ, vol. **2019**, no. 10, 2019, doi: 10.7717/peerj.7653.

Tehrany, M.S.; Pradhan, B.; Jebur, M.N. Flood susceptibility mapping using a novel ensemble weights-of-evidence and support vector machine models in GIS. J. Hydrol., **2014**; 512, 332–343. https://doi.org/10.1016/j.jhydrol.2014.03.008.

Tellman, B.; Sullivan, J.A.; Kuhn, C. Satellite imaging reveals increased proportion of population exposed to floods. Nature., **2021**:596, 80–86 https://doi.org/10.1038/s41586-021-03695-w.

Tien Bui, D.; Tuan, T.A.; Klempe, H.; Pradhan, B.; Revhaug, I. Spatial prediction models for shallow landslide hazards: a comparative assessment of the efficacy of support vector machines, artificial neural networks, kernel logistic regression, and logistic model tree. Landslides., **2016**: 13 (2), 361–378.

Trisurat, Y.; Shirakawa, H.; Johnston, J. Land-Use/Land-Cover Change from Socio-Economic Drivers and Their Impact on Biodiversity in Nan Province, Thailand. Sustainability., **2019**: 11. 649. 10.3390/su11030649.

Tuokkola, T.; Koikkalainen, J.; Parkkola, R.; Karrasch, M.; Lötjönen, J.; Rinne J.O. Visual rating method and tensor-based morphometry in the diagnosis of mild cognitive impairment and Alzheimer's disease: a comparative magnetic resonance imaging study. Acta Radiologica. **2016**; 57(3):348-355. https://doi.org/10.1177/0284185115584656.

Uc, N.; Malcolm, W.; Brian, B. Flooding and Flood Risk Reduction in Nigeria: Cardinal Gaps. Journal of Geography & Natural Disasters., **2015**: 5(1), 1-12. Retrieved 1 28, 2021, from https://longdom.org/open-access/flooding-and-flood-risk-reduction-in-nigeria-cardinal-gaps-2167-0587-1000136.pdf

Uddin, K.; Matin, M. A.; Meyer, F. J. Operational flood mapping using multi-temporal Sentinel-1 SAR images: A case study from Bangladesh. Remote Sens., vol. 11, no. 13, **2019**, doi: 10.3390/rs11131581.

Ullah, K.; Zhang, J. GIS-based flood hazard mapping using relative frequency ratio method: A case study of Panjkora River Basin, eastern Hindu Kush, Pakistan. PLoS ONE. **2020**; 15(3): e0229153. https://doi.org/10.1371/journal. pone.0229153.

UNECA- United Nations Economic Commission for Africa: Background Guide. **2015.** THE 2015 GREATER WASHINGTON CONFERENCE ON INTERNATIONAL AFFAIRS.

UNEP GRID Global Risk Data Platform. Accessed from http://preview.grid.unep.ch/

UNISDR. Disaster risk reduction and resilience in the 2030 agenda for sustainable development. **2015.** October 1–21. http://www.unisdr.org/files/46052_disasterriskreductioninthe2030agend.pdf

USGS. Land-Cover/Land-Use-Land-Cover-And-Trends-Nigeria Retrieved 02 27, 2018, From Https://Eros.Usgs.Gov/Westafrica/Land-Cover/Land-Use-Land-Cover-And-Trends-Nigeria. **2015.**

Valipour, M.; Banihabib, M.E.; Behbahani, S.M.R. Comparison of the ARMA, ARIMA, and the autoregressive artificial neural network models in forecasting the monthly inflow of Dez dam reservoir. J. Hydrol. **2013**, 476,433–441. https://doi.org/10.1016/j.jhydrol.2012.11.017.

Van Soesbergen, Arnout. A review of land use change models. **2016.**

Veldkamp, A.; Fresco, L. O. CLUE : a conceptual model to study the conversion of land use and its effects. Ecological Modelling., **1996**: 85(2-3), 253-270. https://doi.org/10.1016/0304-3800(94)00151-0

Verburg, P.H.; Schot, P.P.; Dijst, M.J.; Veldkamp, A. Land use change modelling: Current practice and research priorities. Geojournal., **2004**: 61, 309–324.

Wagenaar, D.; Curran, A.; Balbi, M.; Bhardwaj, A.; Soden, R.; Hartato, E.; Mestav Sarica, G.; Ruangpan, L.; Molinario, G.; Lallemant, D. Invited perspectives: How machine learning will change flood risk and impact assessment. Nat. Hazards and Earth Sys. Sci, **2020**, 20(4), 1149–1161. https://doi.org/10.5194/nhess-20-1149-2020

Wang, Y.; Fang, Z.; Hong, H.; Peng, L. Flood susceptibility mapping using convolutional neural network frameworks. J. Hydrol., vol. 582, no, p. 124-482, **2020**, doi: 10.1016/j.jhydrol.2019.124482.

Wasko, C. Review: Can temperature be used to inform changes to flood extremes with global warming? Phil. Trans. R. Soc.A. **2021**. 37920190551 20190551. http://doi.org/10.1098/rsta.2019.0551

Wing, O. E. J.; Bates, P. D.; Smith, A. M.; Sampson, C. C.; Johnson, K. A.; Fargione, J.; Morefield, P. Estimates of Present and Future Flood Risk in the Conterminous United States. Environmental Research Letters., **2018**: 13 (3): 034023. https://doi.org/10.1088/1748-9326/aaac65.

Wisner, B. A personal account of activist political ecology. In Tom Perreault, Gavin Bridge, & J. McCarthy (Eds.), The Routledge Handbook of Political Ecology., **2015** (pp. 53- 63). London: Routledge.

Wood, E.; Tappan, G.; Hadj, A. Understanding the drivers of agricultural land use change in south-central Senegal. J. Arid Environ., **2004**: 59, 565–582. https://doi:10.1016/j.jaridenv.2004.03.022

Woodrow, K.; Lindsay, J. B.; Berg, A. A. Evaluating DEM conditioning techniques, elevation source data, and grid resolution for field-scale hydrological parameter extraction. J. Hydrol., **2016**; 540, 1022–1029. https://doi.org/10.1016/j.jhydrol.2016.07.018

Xu, Z.; Li, J. Short-term inflow forecasting using an artificial neural network model. Hydrol. Process. **2002**, 16, 2423–2439.

Zhang Z. Neural networks: further insights into error function, generalised weights and others. Annals. Translat. medicine, **2016**; 4(16), 300. https://doi.org/10.21037/atm.2016.05.37

Zhang, Z.; Laakso, T.; Wang, Z.; Pulkkinen, S.; Ahopelto, S.; Virrantaus, K.; Li, Y.; Cai, X.; Zhang, C.; Vahala, R.; Sheng, Z. Comparative Study of AI-Based Methods-Application of Analysing Inflow and Infiltration in Sanitary Sewer Subcatchments. Sustainability, **2020**; 12(15), [6254]. https://doi.org/10.3390/su12156254.

Zhao, G.; Pang, B.; Xu, Z.; Yue, J.; Tu, T. Mapping flood susceptibility in mountainous areas on a national scale in China, Sci. Total Environ., Volume 615, **2018**, Pages 1133-1142, ISSN 0048-9697, https://doi.org/10.1016/j.scitotenv.2017.10.037.

Zhao, G.; Pang, B.; Xu, Z.; Peng, D.; Xu, L. Assessment of urban flood susceptibility using semi-supervised machine learning model. Sci. Total Environ., volume 659, **2019**, pp. 940-949. https://doi.org/10.1016/j.scitotenv.2018.12.217.

Zhao, M.; Hendon, H.H. Representation, and prediction of the Indian Ocean dipole in the poama seasonal forecast model. Q. J. R. Meteorol. Soc. **2009**, 135, 337–352. https://doi.org/10.1002/qj.370.

APPENDIX

Appendix A: Land use demand estimates produced by the SD model under the three scenarios:

A1: Land use demand under the BAU scenario between 2020 and 2040

BAU						
Time	Cultivated	Forest	Shrubs	Water	Settlement	Miscellaneous
2020	3332670	1601930	550884	70845	107878	2173441
2021	3389523	1601380	550333	70137	110329	2115947
2022	3446698	1600830	549783	69435	112682	2058220
2023	3504211	1600280	549233	68741	114941	2000243
2024	3562039	1599730	548684	68053	117109	1942033
2025	3620177	1599180	548135	67373	119191	1883592
2026	3678632	1598630	547587	66699	121190	1824910
2027	3737374	1598090	547039	66032	123108	1766005
2028	3796435	1597540	546492	65372	124950	1706860
2029	3855775	1596990	545946	64718	126718	1647501
2030	3915401	1596450	545400	64071	128415	1587911
2031	3975309	1595900	544855	63430	130045	1528109
2032	4035498	1595360	544310	62796	131609	1468075
2033	4095966	1594810	543765	62168	133111	1407828
2034	4156687	1594270	543222	61546	134553	1347369
2035	4217673	1593730	542678	60931	135937	1286699
2036	4278920	1593190	542136	60322	137265	1225816
2037	4340425	1592640	541594	59718	138541	1164730
2038	4402176	1592100	541052	59121	139765	1103434
2039	4464172	1591560	540511	58530	140941	1041935
2040	4526411	1591020	539970	57945	142069	980233

A2: Land use demand under the Market-oriented scenario between 2020 and 2040

MARKET-ORIENTED						
Time	Cultivated	Forest	Shrubs	Water	Settlement	Miscellaneous
2020	3332670	1601930	550884	70845	107878	2173441
2021	3376129	1607440	545375	70633	112780	2125292
2022	3419243	1612890	539921	70421	117290	2077883
2023	3461942	1618290	534522	70209	121439	2031246
2024	3504207	1623640	529177	69999	125256	1985369
2025	3545999	1628930	523885	69789	128768	1940277
2026	3587287	1634170	518646	69579	131999	1895966
2027	3628034	1639360	513460	69371	134971	1852452
2028	3668228	1644500	508325	69163	137706	1809727
2029	3707852	1649580	503242	68955	140221	1767798
2030	3746874	1654620	498210	68748	142536	1726660
2031	3785296	1659600	493228	68542	144665	1686317
2032	3823089	1664530	488295	68336	146624	1646774
2033	3860241	1669420	483412	68131	148427	1608017
2034	3896766	1674250	478578	67927	150085	1570042
2035	3932622	1679040	473792	67723	151610	1532861
2036	3967830	1683780	469054	67520	153014	1496450
2037	4002369	1688480	464364	67317	154305	1460812
2038	4036253	1693120	459720	67115	155493	1425946
2039	4069471	1697720	455123	66914	156585	1391835
2040	4102022	1702280	450572	66713	157591	1358470

A3: Land use demand under the Conservation scenario between 2020 and 2040

CONSERVATION						
Time	Cultivated	Forest	Shrubs	Water	Settlement	Miscellaneous
2020	3332670	1601930	550884	70845	107878	2173441
2021	3007770	1612950	539866	70774	109716	2496572
2022	2753899	1623750	529069	70703	111499	2748728
2023	2561760	1634330	518488	70633	113229	2939208
2024	2423142	1644700	508118	70562	114907	3076219
2025	2330726	1654860	497956	70492	116534	3167081
2026	2278056	1664820	487996	70421	118113	3218242
2027	2259446	1674580	478236	70351	119644	3235391
2028	2269852	1684140	468672	70280	121129	3223575
2029	2304816	1693520	459298	70210	122570	3187234
2030	2360453	1702700	450112	70140	123967	3130277
2031	2433304	1711700	441110	70070	125323	3056141
2032	2520356	1720530	432288	70000	126638	2967836
2033	2618993	1729170	423642	69930	127913	2868001
2034	2726886	1737640	415169	69860	129150	2758944
2035	2842018	1745950	406866	69790	130351	2642674
2036	2962655	1754090	398729	69720	131515	2520939
2037	3087290	1762060	390754	69650	132644	2395250
2038	3214583	1769880	382939	69581	133739	2266926
2039	3343433	1777530	375280	69511	134801	2137094
2040	3472857	1785040	367775	69442	135832	2006703

Appendix B:The estimated total population exposed to flood risk per district in Nigeria between 2000 and 2020

Total population exposed to high-risk flood 2000- 2020						
SN	District name	2000	2005	2010	2015	2020
1	Aba North	0	0	0	0	0
2	Aba South	0	0	0	0	0
3	Abadam	87	125	142	199	203
4	Abaji	52	75	125	160	256
5	Abak	0	0	0	0	0
6	Abakalik	281	286	262	407	422
7	Abeokuta South	0	0	0	0	0
8	AbeokutaNorth	1211	1478	1700	2393	2979
9	Abi	0	0	0	0	0
10	Aboh-Mba	2624	2772	3051	3776	4314
11	Abua/Odu	804	1223	1513	1641	2135
12	AbujaMun	332	577	945	1843	3165
13	Adavi	0	0	0	0	0
14	Ado	146	141	116	152	173
15	Ado-Ekiti	0	0	0	0	0
16	AdoOdo/Ota	738	1183	1448	1740	2021
17	Afijio	182	184	194	306	356
18	Afikpo	0	0	0	0	0
19	AfikpoSo	708	809	693	721	862
20	Agaie	291	331	376	489	574
21	Agatu	203	187	177	265	292
22	Agege	2033	2760	3556	3937	4811
23	Aguata	0	0	0	0	0
24	Agwara	180	176	191	260	304
25	Ahizu-Mb	0	0	0	0	0
26	Ahoada East	180	190	234	326	344
27	Ahoada West	628	800	792	965	1091
28	Ajaokuta	0	0	0	0	0

29	Ajeromi/Ifelodun	0	0	0	0	0
30	Ajingi	565	527	739	936	1124
31	Akamkpa	333	404	484	595	729
32	Akinyele	0	0	0	0	0
33	Akko	0	0	0	0	0
34	Akoko North-East	0	0	0	0	0
35	Akoko South-East	0	0	0	0	0
36	Akoko South-West	162	153	120	134	135
37	Akoko-Ed	0	0	0	0	0
38	AkokoNorthWest	0	0	0	0	0
39	Akpabuyo	1305	1303	1613	1983	2327
40	Akukutor	271	286	322	339	356
41	Akure North	73	90	99	101	103
42	Akure South	0	0	0	0	0
43	Akwanga	241	260	236	298	356
44	Albasu	1222	1536	1255	1480	2049
45	Aleiro	198	245	277	274	316
46	Alimosho	2005	3001	3330	3506	4896
47	Alkaleri	354	392	426	602	686
48	Amuwo Odofin	5312	6273	7524	9014	10105
49	Anambra East	219	244	224	188	221
50	Anambra West	498	638	804	985	1112
51	Anaocha	0	0	0	0	0
52	Andoni/O	0	0	0	0	0
53	Aninri	0	0	0	0	0
54	AniochaN	0	0	0	0	0
55	AniochaS	0	0	0	0	0
56	Anka	282	409	435	455	539
57	Ankpa	0	0	0	0	0
58	Apa	0	0	0	0	0
59	Apapa	0	0	0	0	0
60	Ardo-Kola	218	189	182	266	302

61	Arewa	370	414	513	627	728
62	Argungu	590	604	618	836	932
63	Arochukw	256	290	297	280	302
64	Asa	0	0	0	0	0
65	Asari-To	0	0	0	0	0
66	Askira/U	256	264	313	506	551
67	Atakumosa East	166	163	241	257	278
68	Atakumosa West	0	0	0	0	0
69	Atiba	4	4	3	4	4
70	Atisbo	0	0	0	0	0
71	Augie	239	324	417	435	451
72	Auyo	381	462	482	625	675
73	Awe	248	244	221	406	453
74	Awgu	0	0	0	0	0
75	AwkaNort	938	1140	1469	1450	1635
76	AwkaSout	0	0	0	0	0
77	Ayamelum	1278	1844	2377	2753	3738
78	Ayedaade	658	785	1004	1160	1331
79	Ayedire	571	575	824	969	1010
80	Babura	405	467	549	680	772
81	Badagary	999	1005	859	1228	1513
82	Bade	1007	1397	1550	1834	2257
83	Bagudo	398	492	512	572	671
84	Bagwai	2407	2012	2112	2649	3423
85	Bakassi	0	0	0	0	0
86	Bakori	0	0	0	0	0
87	Bakura	134	151	139	178	215
88	Balanga	841	963	1436	1563	1722
89	Bali	146	161	187	198	219
90	Bama	1616	1914	2242	2686	3261
91	Barkin Ladi	0	0	0	0	0
92	Baruten	125	109	114	196	221

93	Bassa	0	0	0	0	0
94	Bassa	1105	1127	1327	1422	1686
95	Batagarawa	0	0	0	0	0
96	Batsari	0	0	0	0	0
97	Bauchi	973	992	1055	1115	1285
98	Baure	1067	1062	1219	1401	1736
99	Bayo	203	196	213	252	283
100	Bebeji	0	0	0	0	0
101	Bekwarra	0	0	0	0	0
102	Bende	300	293	325	756	770
103	Biase	1375	1662	1938	2391	2661
104	Bichi	185	172	196	331	353
105	Bida	0	0	0	0	0
106	Billiri	0	0	0	0	0
107	Bindawa	0	0	0	0	0
108	Binji	0	0	0	0	0
109	Biriniwa	355	441	519	553	649
110	Birnin-G	194	254	290	300	318
111	BirninKe	1096	1140	1281	1799	2035
112	BirninKu	242	293	299	303	350
113	Birnin-Magaji/Kiyaw	642	862	1070	1088	1447
114	Biu	11	11	11	15	15
115	Bodinga	263	239	244	379	507
116	Bogoro	410	464	564	649	732
117	Boki	0	0	0	0	0
118	Bokkos	0	0	0	0	0
119	Boluwaduro	0	0	0	0	0
120	Bomadi	371	382	483	603	731
121	Bonny	0	0	0	0	0
122	Borgu	106	109	144	204	239
123	Boripe	535	659	552	778	1078
124	Borsari	587	764	775	935	1145

125	Bosso	31	44	56	77	92
126	Brass	410	430	588	1005	1230
127	Buji	539	625	723	767	877
128	Bukkuyum	602	756	834	899	1018
129	Bungudu	944	842	998	1219	1448
130	Bunkure	133	139	170	312	347
131	Bunza	1665	2299	2957	3532	4213
132	Buruku	631	722	666	830	917
133	Burutu	583	674	836	978	1254
134	Bwari	0	0	0	0	0
135	Calabar	149	144	151	168	164
136	Calabar South	0	0	0	0	0
137	Chanchaga	0	0	0	0	0
138	Charanchi	0	0	0	0	0
139	Chibok	0	0	0	0	0
140	Chikun	737	705	880	901	1199
141	Dala	6643	8366	12112	12072	15706
142	Damaturu	6	7	8	17	21
143	Damban	0	0	0	0	0
144	Dambatta	244	220	274	402	449
145	Damboa	353	426	451	601	709
146	Dandi	679	699	752	978	1125
147	Dandume	0	0	0	0	0
148	Dange-Shuni	76	67	71	83	101
149	Danja	0	0	0	0	0
150	Danko Wasagu	0	0	0	0	0
151	Danmusa	126	169	219	232	254
152	Darazo	164	178	174	219	229
153	Dass	0	0	0	0	0
154	Daura	974	820	864	1007	1174
155	DawakinK	0	0	0	0	0
156	DawakinT	905	917	2289	1978	2652

157	Degema	0	0	0	0	0
158	Dekina	262	362	487	514	623
159	Demsa	411	536	597	706	788
160	Dikwa	283	354	420	475	551
161	Doguwa	185	224	258	316	354
162	Doma	537	628	742	828	924
163	Donga	361	433	355	563	607
164	Dukku	464	484	514	697	793
165	Dunukofia	0	0	0	0	0
166	Dutse	1233	1352	1463	1759	2137
167	Dutsi	0	0	0	0	0
168	Dutsin-M	310	294	266	334	367
169	Eastern Obolo	0	0	0	0	0
170	Ebonyi	0	0	0	0	0
171	Edati	263	296	339	380	426
172	Ede North	0	0	0	0	0
173	Ede South	37	37	34	45	53
174	Edu	639	664	861	802	963
175	Efon	0	0	0	0	0
176	EgbadoNorth	187	187	253	286	370
177	EgbadoSouth	145	168	187	276	372
178	Egbeda	0	0	0	0	0
179	Egbedore	941	1072	1174	1861	2065
180	Egor	0	0	0	0	0
181	Ehime-Mb	0	0	0	0	0
182	Ejigbo	0	0	0	0	0
183	Ekeremor	132	136	145	388	460
184	Eket	0	0	0	0	0
185	Ekiti	22	27	32	34	34
186	EkitiEas	0	0	0	0	0
187	EkitiSouth-West	0	0	0	0	0
188	EkitiWest	0	0	0	0	0

189	Ekwusigo	0	0	0	0	0
190	Eleme	0	0	0	0	0
191	Emuoha	738	936	1030	1159	1319
192	Emure/Ise/Orun	0	0	0	0	0
193	Enugu East	0	0	0	0	0
194	Enugu North	0	0	0	0	0
195	EnuguSou	0	0	0	0	0
196	Epe	1563	1825	1854	2304	2552
197	EsanCent	0	0	0	0	0
198	EsanNort	0	0	0	0	0
199	EsanSout	68	53	46	70	80
200	EsanWest	0	0	0	0	0
201	Ese-Odo	779	769	794	1035	1132
202	Esit Eket	0	0	0	0	0
203	Essien-U	0	0	0	0	0
204	Etche	460	526	564	517	785
205	Ethiope West	0	0	0	0	0
206	EthiopeE	122	207	246	218	232
207	EtimEkpo	517	461	318	872	983
208	Etinan	1389	1980	2125	2932	3106
209	Eti-Osa	0	0	0	0	0
210	Etsako Central	489	438	445	532	737
211	EtsakoEa	673	636	622	846	975
212	EtsakoWe	1787	1888	2204	2164	2339
213	Etung	127	155	193	181	238
214	Ewekoro	0	0	0	0	0
215	Ezeagu	329	325	311	315	382
216	Ezinihit	0	0	0	0	0
217	Ezza North	0	0	0	0	0
218	Ezza South	0	0	0	0	0
219	Fagge	0	0	0	0	0
220	Fakai	168	189	198	228	269

221	Faskari	330	412	492	495	559
222	Fika	765	1108	1162	1151	1490
223	Fufore	335	398	413	424	467
224	Funakaye	998	1071	1414	1562	1709
225	Fune	293	322	407	533	622
226	Funtua	0	0	0	0	0
227	Gabasawa	0	0	0	0	0
228	Gada	446	458	513	576	656
229	Gagarawa	620	767	968	923	1146
230	Gamawa	779	960	1122	1331	1510
231	Gamjuwa	119	140	148	174	193
232	Ganye	0	0	0	0	0
233	Garki	592	714	820	915	1294
234	Garko	391	313	311	389	393
235	Garum Mallam	253	333	382	466	534
236	Gashaka	5	7	10	11	11
237	Gassol	539	546	619	797	899
238	Gaya	982	1317	1351	1464	1686
239	Gbako	540	561	644	737	901
240	Gboko	0	0	0	0	0
241	Gboyin	0	0	0	0	0
242	Geidam	473	522	613	871	1030
243	Gezawa	0	0	0	0	0
244	Giade	187	229	250	280	341
245	Girie	85	76	86	158	177
246	Giwa	171	179	189	336	385
247	Gokana	0	0	0	0	0
248	Gombe	0	0	0	0	0
249	Gombi	173	166	268	253	282
250	Goronyo	871	1256	1479	1485	1858
251	Gubio	369	377	431	550	656
252	Gudu	149	130	134	216	262

253	Gujba	34	46	46	53	58
254	Gulani	39	51	50	60	67
255	Guma	392	731	672	844	998
256	Gumel	0	0	0	0	0
257	Gummi	1235	1300	1472	1789	1995
258	Gurara	145	132	146	175	224
259	Guri	303	308	481	432	502
260	Gusau	401	380	458	545	643
261	Guyuk	161	176	410	363	422
262	Guzamala	190	219	347	372	451
263	Gwadabaw	1219	2292	1941	2019	2283
264	Gwagwala	440	821	1244	1689	3140
265	Gwale	0	0	0	0	0
266	Gwandu	426	417	525	588	662
267	Gwaram	728	739	1069	1158	1297
268	Gwarzo	339	294	478	696	710
269	Gwer East	218	190	175	249	281
270	GwerWest	255	228	231	485	547
271	Gwiwa	388	487	541	640	677
272	Gwoza	0	0	0	0	0
273	Hadejia	0	0	0	0	0
274	Hawul	70	76	85	94	106
275	Hong	55	59	56	93	99
276	IbadanNorth	0	0	0	0	0
277	IbadanNorth-East	0	0	0	0	0
278	IbadanNorth-West	0	0	0	0	0
279	IbadanSouth-East	0	0	0	0	0
280	IbadanSouth-West	0	0	0	0	0
281	Ibaji	1141	1391	1770	1952	2210
282	Ibarapa Central	525	612	710	809	956
283	Ibarapa East	362	383	426	466	528
284	Ibarapa North	151	241	355	294	366

285	Ibeju/Lekki	80	98	129	149	157
286	Ibeno	0	0	0	0	0
287	Ibesikpo Asutan	0	0	0	0	0
288	Ibi	347	356	378	509	552
289	Ibiono Ibom	0	0	0	0	0
290	Idah	186	180	134	137	153
291	Idanre	183	160	261	268	317
292	Ideato South	0	0	0	0	0
293	IdeatoNo	0	0	0	0	0
294	Idemili North	0	0	0	0	0
295	Idemili South	2641	2556	3136	3412	3766
296	Ido	74	66	74	110	140
297	Ido/Osi	0	0	0	0	0
298	Ifako/Ijaye	0	0	0	0	0
299	Ife East	0	0	0	0	0
300	Ife North	49	56	55	62	71
301	Ife South	0	0	0	0	0
302	IfeCentral	0	0	0	0	0
303	Ifedayo	0	0	0	0	0
304	Ifedore	0	0	0	0	0
305	Ifelodun	0	0	0	0	0
306	Ifelodun	80	96	104	93	99
307	Ifo	411	518	600	605	847
308	Igabi	1083	1157	1204	1761	1916
309	Igalamela-Odolu	287	256	267	309	353
310	Igbo-Eti	0	0	0	0	0
311	Igbo-eze North	0	0	0	0	0
312	Igbo-eze South	0	0	0	0	0
313	Igueben	0	0	0	0	0
314	Ihiala	794	936	1085	1135	1426
315	Ihitte/U	0	0	0	0	0
316	Ijebu North-East	0	0	0	0	0

317	IjebuEast	53	46	43	61	62
318	IjebuNorth	828	952	925	1166	1360
319	IjebuOde	0	0	0	0	0
320	Ijero	0	0	0	0	0
321	Ijumu	107	120	134	151	157
322	Ika	0	0	0	0	0
323	IkaNorth	0	0	0	0	0
324	Ikara	1174	1490	1856	1714	2286
325	IkaSouth	47	43	38	38	45
326	Ikeduru	0	0	0	0	0
327	Ikeja	0	0	0	0	0
328	Ikenne	0	0	0	0	0
329	Ikere	0	0	0	0	0
330	Ikole	0	0	0	0	0
331	Ikom	245	241	228	370	392
332	Ikono	0	0	0	0	0
333	Ikorodu	4520	4749	5728	6762	7980
334	Ikot-Aba	0	0	0	0	0
335	Ikot-Ekp	0	0	0	0	0
336	Ikpoba-Okha	451	555	649	646	786
337	Ikwerre	0	0	0	0	0
338	Ikwo	1161	1121	1320	2020	2169
339	Ikwuano	0	0	0	0	0
340	Ila	0	0	0	0	0
341	IlajeEseodo	636	774	970	1153	1485
342	Ilejemeje	0	0	0	0	0
343	IleOluji/Okeigbo	0	0	0	0	0
344	Ilesha East	0	0	0	0	0
345	Ilesha West	0	0	0	0	0
346	Illela	120	128	156	154	202
347	Ilorin East	24	27	29	26	29
348	Ilorin South	0	0	0	0	0

349	IlorinWe	0	0	0	0	0
350	Imeko-Afon	86	124	191	171	207
351	Ingawa	248	288	301	358	382
352	Ini	293	334	305	329	372
353	Ipokia	0	0	0	0	0
354	Irele	377	387	390	495	526
355	Irepo	41	30	31	48	64
356	Irepodun	0	0	0	0	0
357	Irepodun	0	0	0	0	0
358	Irepodun/Ifelodun	0	0	0	0	0
359	Irewole	734	638	1025	1019	1395
360	Isa	75	72	90	116	140
361	Ise/Orun	939	963	982	1374	1500
362	Iseyin	203	231	310	306	356
363	Ishielu	221	248	598	575	641
364	Isiala Ngwa North	501	560	806	1186	1472
365	Isiala Ngwa South	1199	1640	1959	2036	2255
366	IsialaMb	0	0	0	0	0
367	Isin	0	0	0	0	0
368	Isi-Uzo	0	0	0	0	0
369	Isokan	565	522	541	1004	1214
370	IsokoNor	0	0	0	0	0
371	IsokoSou	0	0	0	0	0
372	Isu	0	0	0	0	0
373	Isuikwua	0	0	0	0	0
374	Itas/Gad	237	271	308	330	421
375	Itesiwaju	102	102	96	113	125
376	Itu	0	0	0	0	0
377	Ivo	0	0	0	0	0
378	Iwajowa	0	0	0	0	0
379	Iwo	191	174	167	374	443
380	Izzi	418	490	468	690	804

381	Jaba	0	0	0	0	0
382	Jada	44	44	50	40	47
383	Jahun	929	977	1465	1353	1533
384	Jakusko	892	1039	1478	1723	2009
385	Jalingo	0	0	0	0	0
386	Jama'are	263	273	399	439	506
387	Jega	0	0	0	0	0
388	Jema'a	344	442	496	691	725
389	Jere	155	155	210	276	319
390	Jibia	2103	2055	2177	1754	2220
391	Jos East	1294	1794	1817	1889	1938
392	Jos North	0	0	0	0	0
393	Jos South	0	0	0	0	0
394	Kabba/Bu	0	0	0	0	0
395	Kabo	952	1735	1412	3605	4330
396	Kachia	362	413	520	555	630
397	Kaduna North	2767	2861	3028	3891	4363
398	Kaduna South	0	0	0	0	0
399	KafinHau	1140	1344	1681	1944	2254
400	Kafur	299	269	337	372	390
401	Kaga	22	22	24	38	43
402	Kagarko	40	45	40	40	45
403	Kaiama	11	9	9	11	11
404	Kaita	691	710	662	800	1045
405	Kajola	126	137	165	168	199
406	Kajuru	101	117	125	147	154
407	Kala/Balge	240	262	313	365	435
408	Kalgo	363	349	408	409	491
409	Kaltungo	309	382	582	539	628
410	Kanam	284	304	326	418	490
411	Kankara	416	634	717	759	826
412	Kanke	0	0	0	0	0

413	Kankiya	250	259	343	361	413
414	Kano	0	0	0	0	0
415	Karasuwa	293	351	358	459	563
416	Karaye	0	0	0	0	0
417	Karim-La	1099	1382	1550	1676	2217
418	Karu	391	442	482	616	753
419	Katagum	365	400	452	537	636
420	Katcha	634	702	834	895	1017
421	Katsina (Benue)	1381	1581	2000	2037	2310
422	Katsina (K)	549	377	374	585	540
423	Kaugama	306	312	482	504	538
424	Kaura	0	0	0	0	0
425	Kaura-Na	913	910	1398	1325	1554
426	Kauru	868	1026	1332	1487	1708
427	Kazaure	325	343	378	461	535
428	Keana	0	0	0	0	0
429	Kebbe	386	435	520	545	612
430	Keffi	2341	2876	2831	3546	3918
431	Khana	0	0	0	0	0
432	Kibiya	0	0	0	0	0
433	Kirfi	260	291	510	565	627
434	KiriKasa	0	0	0	0	0
435	Kiru	0	0	0	0	0
436	Kiyawa	937	1058	1362	1359	1556
437	Koko/Bes	163	258	355	345	383
438	Kokona	208	204	209	293	330
439	Kolokuma/Opokuma	0	0	0	0	0
440	Konduga	385	420	486	609	712
441	Konshish	324	358	597	553	616
442	Kontogur	12	14	18	22	26
443	Kosofe	0	0	0	0	0
444	Kotonkar	342	387	529	655	753

445	Kubau	652	753	926	1051	1135
446	Kudan	324	333	369	496	525
447	Kuje	124	143	279	535	994
448	Kukawa	115	104	111	176	214
449	Kumbotso	17431	19591	22301	27699	32820
450	Kunchi	657	633	831	881	1128
451	Kura	0	0	0	0	0
452	Kurfi	0	0	0	0	0
453	Kurmi	58	59	71	83	97
454	Kusada	229	295	366	488	470
455	Kwali	222	305	422	821	1250
456	Kwami	585	845	728	1121	1256
457	Kwande	613	715	826	1123	1246
458	Kware	1088	1074	1172	2366	2782
459	Kwaya Kusar	0	0	0	0	0
460	Lafia	464	521	764	968	1151
461	Lagelu	334	275	355	456	559
462	LagosIsland	0	0	0	0	0
463	Lake chad	123	126	123	276	322
464	Lamurde	111	180	245	215	248
465	Langtang North	0	0	0	0	0
466	Langtang South	111	143	151	133	150
467	Lapai	144	150	201	255	320
468	Lau	70	76	75	107	116
469	Lavun	7441	8853	10048	12286	14621
470	Lere	294	469	515	530	640
471	Logo	0	0	0	0	0
472	Lokoja	389	331	453	604	751
473	Machina	120	131	171	264	306
474	Madagali	0	0	0	0	0
475	Madobi	1105	1459	1100	1568	1665
476	Mafa	461	569	631	751	917

477	Magama	493	584	772	774	906
478	Magumeri	46	47	67	67	79
479	Mai'Adua	216	254	320	445	481
480	Maidugur	575	668	859	1110	1371
481	Maigatari	1072	959	1109	1661	1769
482	Maiha	0	0	0	0	0
483	Mainland	16562	20411	23540	27946	32059
484	Maiyama	496	704	931	847	976
485	Makarfi	592	864	809	1036	1138
486	Makoda	1121	1214	1501	1798	1990
487	Makurdi	241	303	545	419	436
488	MalamMad	423	570	587	734	844
489	Malumfashi	0	0	0	0	0
490	Mangu	94	108	150	174	206
491	Mani	0	0	0	0	0
492	Maradun	112	95	125	158	174
493	Mariga	164	164	160	347	395
494	Marte	1088	1385	1523	1936	2386
495	Maru	391	428	409	501	560
496	Mashegu	427	442	483	570	622
497	Mashi	0	0	0	0	0
498	Matazu	0	0	0	0	0
499	Mayo-Bel	255	263	283	307	347
500	Mbaitoli	0	0	0	0	0
501	Mbo	0	0	0	0	0
502	Michika	0	0	0	0	0
503	Miga	292	290	334	384	423
504	Mikang	0	0	0	0	0
505	Minjibir	384	806	1477	1179	1743
506	Misau	764	883	1082	1267	1390
507	Mkpat Enin	0	0	0	0	0
508	Moba	0	0	0	0	0

509	Mobbar	148	183	193	257	319
510	Mokwa	620	803	1014	1040	1238
511	Monguno	367	453	661	870	982
512	Mopa-Muro	146	181	166	146	176
513	Moro	239	267	307	365	425
514	Mubi North	123	126	198	169	180
515	Mubi South	0	0	0	0	0
516	Musawa	0	0	0	0	0
517	Mushin	0	0	0	0	0
518	Muya	157	213	291	302	350
519	Nafada	175	266	369	351	414
520	Nangere	0	0	0	0	0
521	Nasarawa	368	401	460	585	651
522	Nassaraw	0	0	0	0	0
523	Nassarawa Egon	514	529	458	545	596
524	Ndokwa East	249	294	315	353	391
525	Ndokwa West	97	63	69	74	74
526	Nembe	0	0	0	0	0
527	Ngala	644	749	794	998	1108
528	Nganzai	691	1042	993	1333	1483
529	Ngaski	1420	1681	2147	2551	2872
530	Ngor-Okp	252	247	194	466	556
531	Nguru	409	449	604	791	958
532	Ningi	315	354	439	551	641
533	Njaba	0	0	0	0	0
534	Njikoka	0	0	0	0	0
535	Nkanu East	0	0	0	0	0
536	Nkanu West	0	0	0	0	0
537	Nkwerre	0	0	0	0	0
538	NnewiNort	0	0	0	0	0
539	NnewiSou	622	766	977	907	1051
540	Nsit Atai	0	0	0	0	0

541	Nsit Ibom	0	0	0	0	0
542	Nsit Ubium	0	0	0	0	0
543	Nsukka	0	0	0	0	0
544	Numan	618	607	741	699	780
545	Nwangele	0	0	0	0	0
546	Obafemi-Owode	1221	1521	1877	2339	2608
547	Obanliku	0	0	0	0	0
548	Obi	0	0	0	0	0
549	Obi	494	778	837	885	925
550	Obio/Akp	0	0	0	0	0
551	Obokun	2595	2562	2700	3603	3962
552	Oboma Ngwa	0	0	0	0	0
553	Obot Akara	0	0	0	0	0
554	Obowo	1332	1766	1961	1858	1944
555	Obubra	1517	1748	1893	2067	2413
556	Obudu	110	120	214	255	298
557	Odeda	241	287	328	398	480
558	Odigbo	364	479	604	763	957
559	Odo0tin	0	0	0	0	0
560	Odogbolu	611	664	762	844	1173
561	Odukpani	741	730	653	1133	1395
562	Offa	0	0	0	0	0
563	Ofu	367	354	374	485	515
564	Ogba/Egbe	1566	1655	1787	1841	2116
565	Ogbadibo	0	0	0	0	0
566	Ogbaru	120	101	97	137	160
567	Ogbia	0	0	0	0	0
568	Ogbomosho North	0	0	0	0	0
569	Ogbomosho South	0	0	0	0	0
570	Ogoja	1125	1268	1202	1517	1815
571	Ogo-Oluw	126	131	122	147	162
572	Ogori/Magongo	0	0	0	0	0

573	Ogu/Bolo	0	0	0	0	0
574	OgunWaterside	142	185	221	243	282
575	Oguta	1325	1465	1677	1836	2186
576	Ohafia Abia	0	0	0	0	0
577	Ohaji/Eg	2500	2645	2822	3360	4335
578	Ohaozara	707	789	1075	1038	1142
579	Ohaukwu	0	0	0	0	0
580	Ohimini	0	0	0	0	0
581	Oji-River	0	0	0	0	0
582	Ojo	0	0	0	0	0
583	Oju	457	440	526	556	658
584	Oke-Ero	0	0	0	0	0
585	Okehi	100	76	75	103	112
586	Okene	0	0	0	0	0
587	Okigwe	0	0	0	0	0
588	Okitipupa	447	424	446	896	926
589	Okobo	0	0	0	0	0
590	Okpe	302	340	391	406	456
591	Okpokwu	0	0	0	0	0
592	Okrika	0	0	0	0	0
593	Olamabor	0	0	0	0	0
594	Ola-Oluwa	234	229	306	335	383
595	Olorunda	0	0	0	0	0
596	Olorunsogo	0	0	0	0	0
597	Oluyole	117	90	58	130	168
598	Omala	74	88	85	95	107
599	Omumma	1083	1120	1499	1747	2190
600	Ona-Ara	151	126	86	150	206
601	Ondo East	0	0	0	0	0
602	Ondo West	13	13	15	35	42
603	Onicha	0	0	0	0	0
604	Onitsha North	0	0	0	0	0

605	Onitsha South	0	0	0	0	0
606	Onna	0	0	0	0	0
607	Opobo/Nkoro	0	0	0	0	0
608	Oredo Edo	0	0	0	0	0
609	Orelope	0	0	0	0	0
610	Orhionmw	537	512	538	686	768
611	Oriade	0	0	0	0	0
612	Ori-Ire	0	0	0	0	0
613	Orlu	0	0	0	0	0
614	Orolu	0	0	0	0	0
615	Oron	0	0	0	0	0
616	Orsu	0	0	0	0	0
617	Oru East	0	0	0	0	0
618	Oru West	0	0	0	0	0
619	Oruk-Ana	649	624	805	923	1076
620	OrumbaNo	0	0	0	0	0
621	OrumbaSo	0	0	0	0	0
622	Ose	815	913	1265	1594	1964
623	Oshimili North	221	200	206	226	251
624	Oshimili South	987	848	1074	1023	1105
625	Oshodi/Isolo	0	0	0	0	0
626	Osisioma Ngwa	584	632	701	894	1042
627	Osogbo	1282	1557	1725	1961	2303
628	Oturkpo	251	263	278	365	417
629	OviaNort	702	724	848	955	1075
630	OviaSouth-West	435	560	625	857	1022
631	Owan East	203	186	180	182	194
632	OwanWest	45	44	49	63	64
633	Owerri Municipal	0	0	0	0	0
634	Owerri North	0	0	0	0	0
635	Owerri West	0	0	0	0	0
636	Owo	290	350	526	525	675

637	Oye	0	0	0	0	0
638	Oyi	750	976	1215	1369	1465
639	Oyigbo	978	1059	1158	1525	1618
640	Oyo East	92	209	336	281	336
641	Oyo West	0	0	0	0	0
642	Oyun	0	0	0	0	0
643	Paikoro	125	145	163	225	254
644	Pankshin	0	0	0	0	0
645	Patani	0	0	0	0	0
646	Pategi	261	253	276	423	450
647	Port Harcourt	0	0	0	0	0
648	Potiskum	0	0	0	0	0
649	Qua'anpa	353	469	576	638	700
650	Rabah	799	858	937	1327	1400
651	Rafi	222	289	357	372	454
652	Rano	325	377	441	580	627
653	Remo-North	96	76	59	106	139
654	Rijau	28	35	42	45	50
655	Rimi	0	0	0	0	0
656	RiminGad	255	237	506	525	570
657	Ringim	567	1107	785	1162	1263
658	Riyom	0	0	0	0	0
659	Rogo	295	277	285	253	296
660	Roni	249	248	280	339	398
661	Sabon Birni	1162	1489	1343	1538	1828
662	Sabon-Ga	1246	1141	1010	1401	1507
663	Sabuwa	0	0	0	0	0
664	Safana	485	573	607	711	778
665	Sagbama	0	0	0	0	0
666	Sakaba	106	119	121	171	174
667	Saki East	68	81	94	148	166
668	Saki West	0	0	0	0	0

669	Sandamu	0	0	0	0	0
670	Sanga	117	115	159	204	241
671	Sapele	1125	1153	1350	1424	1630
672	Sardauna	202	201	241	260	291
673	Shagamu	0	0	0	0	0
674	Shagari	54	53	57	74	85
675	Shanga	598	715	873	931	1100
676	Shani	340	403	586	625	728
677	Shanono	616	797	1023	1227	1337
678	Shelleng	206	191	164	170	173
679	Shendam	799	897	924	1035	1280
680	Shinkafi	372	344	402	615	653
681	Shira	133	149	166	244	315
682	Shiroro	874	1006	1215	1392	1611
683	Shomgom	0	0	0	0	0
684	Shomolu	9960	11968	13586	16182	19330
685	Silame	145	116	134	274	320
686	Soba	393	499	560	643	729
687	Sokoto North	0	0	0	0	0
688	Sokoto South	0	0	0	0	0
689	Song	151	163	175	237	248
690	Southern Ijaw	0	0	0	0	0
691	Suleja	0	0	0	0	0
692	Sule-Tan	636	752	827	929	1037
693	Sumaila	284	455	473	529	597
694	Suru	868	1208	1433	1487	1715
695	Surulere	0	0	0	0	0
696	Surulere	0	0	0	0	0
697	Tafa	0	0	0	0	0
698	Tafawa-B	1095	1416	1636	1700	1954
699	Tai	0	0	0	0	0
700	Takai	319	306	414	587	636

701	Takum	62	70	54	63	73
702	Talata-Mafara	0	0	0	0	0
703	Tambawal	494	595	729	756	879
704	Tangazar	92	134	191	205	232
705	Tarauni	0	0	0	0	0
706	Tarka	0	0	0	0	0
707	Tarmuwa	94	112	139	173	197
708	Taura	1990	2232	2315	2410	2717
709	Teungo	0	0	0	0	0
710	Tofa	0	0	0	0	0
711	Toro	396	511	574	686	834
712	Toto	56	69	92	73	97
713	Tsafe	1205	1107	1197	1693	2098
714	Tsanyawa	868	1007	995	1342	1493
715	Tundun Wada	428	558	683	869	1019
716	Tureta	116	96	90	129	149
717	Udenu	0	0	0	0	0
718	Udi	0	0	0	0	0
719	Udu	0	0	0	0	0
720	Udung Uko	0	0	0	0	0
721	Ughelli North	514	618	604	647	697
722	Ughelli South	89	92	77	103	112
723	Ugwunagbo	0	0	0	0	0
724	Uhunmwonde	0	0	0	0	0
725	Ukanafun	0	0	0	0	0
726	Ukum	0	0	0	0	0
727	Ukwa East	0	0	0	0	0
728	Ukwa West	330	312	600	636	691
729	Ukwuani	161	111	138	127	128
730	Umuahia North	1667	2020	2275	2089	2565
731	Umuahia South	937	975	1008	1002	1392
732	Umu-Nneochi	0	0	0	0	0

733	Ungogo	0	0	0	0	0
734	Unuimo	0	0	0	0	0
735	Uruan	0	0	0	0	0
736	UrueOffo	0	0	0	0	0
737	Ushongo	262	287	361	323	367
738	Ussa	269	241	253	446	511
739	Uvwie	0	0	0	0	0
740	Uyo	0	0	0	0	0
741	Uzo-Uwani	303	331	352	379	496
742	Vandeiky	0	0	0	0	0
743	Wamakko	934	928	915	960	1012
744	Wamba	27	32	24	46	51
745	Warawa	0	0	0	0	0
746	Warji	1051	1226	1246	1279	1445
747	Warri North	221	240	290	467	585
748	Warri South	0	0	0	0	0
749	Warri South-West	0	0	0	0	0
750	Wase	756	851	881	1111	1177
751	Wudil	220	234	224	265	270
752	Wukari	361	395	447	527	577
753	Wurno	1846	2047	2621	2505	2973
754	Wushishi	512	652	516	623	718
755	Yabo	223	251	297	418	450
756	Yagba East	28	37	53	50	53
757	Yagba West	98	121	141	150	202
758	Yakurr	874	901	876	1299	1412
759	Yala Cross	337	366	415	456	503
760	Yamaltu	635	744	841	998	1154
761	Yankwashi	674	724	806	976	1104
762	Yauri	247	290	340	347	407
763	Yenegoa	0	0	0	0	0
764	Yola North	1665	2152	2506	2556	2948

765	Yola South	571	783	1281	953	1120
766	Yorro	0	0	0	0	0
767	Yunusari	369	429	588	712	815
768	Yusufari	300	309	383	507	602
769	Zaki	899	1337	1617	1642	1850
770	Zango	183	210	276	281	317
771	ZangonKa	170	167	179	213	229
772	Zaria	1369	1693	1744	1590	1819
773	Zing	0	0	0	0	0
774	Zurmi	687	854	950	1127	1260
775	Zuru	0	0	0	0	0