UNIVERSITY OF GHANA COLLEGE OF HUMANITIES

POPULATION DYNAMICS, LAND USE/COVER CHANGE AND FLOOD RISK IN THE GREATER ACCRA METROPOLITAN AREA (GAMA)

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ACCEPTANCE

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DECLARATION

I hereby declare that this is my work and to the best of my knowledge contains no previously published work, which has not been duly acknowledged. This work has not been submitted elsewhere for a degree either in part or whole.

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ABSTRACT

Flood disasters have become universal, causing damage to human lives and properties. The occurrences of flood disasters also impede social and economic growth. Accra is facing floods and flood disasters annually with impacts on the poor and vulnerable which cannot be overemphasized. The relationship between population growth and land use/land cover (LULC) changes is well-documented. However, there is a dearth of knowledge on their joint effect on flood disaster risk in Ghana. Using a quantitative approach, this study examined the impact of changes in population growth and LULC on future flood risk of the Greater Accra Metropolitan Area (GAMA). The GAMA is an agglomeration of districts which are typically low-lying, coastal, and urbanized. The seven selected districts are Adenta, Ashaiman, Kpone Katamanso, La Dade-Kotopon, Ledzokuku-Krowor and Tema. Data used were multiple, including a cross-sectional survey, Geographical Information Systems (GIS) and remote sensing such as Landsat and NASA imagery, weather data, i.e., rainfall and temperature data from the Ghana Meteorological Authority and population census data from the Ghana Statistical Service (GSS). The land use/ land cover classes were determined using an unsupervised land use/land cover classification of historical Landsat imageries in an ERDAS software environment. Furthermore, an Ordinary Least Square (OLS) regression model was executed in ArcGIS to obtain the predictors of flood risk. In forecasting future flood risks, three scenarios- trend, liberalization, and self-sufficiency - were built based on assumptions on changes in LULC, population and economic growth. The Modules for Land Use Change Simulations (MOLUSCE) was used to project changes in LULC. This data used together with projected population, economic growth, and other predictors of flood risk in the OLS were used to forecast flood risk. Presently, almost half (45.2%) of GAMA is prone to high flood risk.

Predictors of flood risk included population, slope, rainfall, built-up spaces (human settlements), areas covered by impervious surfaces, wealth, and proximity of a building (human settlement) to a water body. In 2010, there was a 15.7% increase in the population of GAMA. Between 1990 and 2020, built-up area coverage increased by 31.9%. In the future, there is a possibility of exacerbated flood risk in GAMA given high population growth, rapid uncontrolled urbanization, and poor land use practices. Flood risk was forecasted for 2030, 2040 and 2050 and on average, medium flood risk was dominant. However, comparatively, under the trend scenario, high flood risk will be relatively pervasive in the future. Most parts of GAMA are likely to encounter medium flood risk which has the highest likelihood under the liberalization scenario. Low flood risk is more likely to be experienced under the self-sufficiency scenario especially at later dates as there were assumptions of high economic growth and prioritization of sustainability of the environment. This study has shown that there is high population growth in GAMA. There was evidence of accelerated changes in LULC visible in the spatial analysis of the city. The impact of changes in population growth and LULC might be dire if efficient planning of the urban space of GAMA is not expedited. Therefore, based on the forecast, the impacts of flood disasters in GAMA can be lowered in the future by employing appropriate policies and strategies for population growth and LULC. The improvement in land use by penalizing poor land use practices and promoting the building of space-saving accommodation types are recommended.

DEDICATION

To *my*

mother

Mrs. Faustina Enyonam Letsa,

your sacrifice is immense, and

my children

I love you

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LIST OF ABBREVIATIONS

ABBREVIATION		MEANING
AdMA	-	Adenta Municipal Assembly
AHP	-	Analytical Hierarchical Process
AIC	-	Akaike's Information Criterion
AMA	-	Accra Metropolitan Assembly
AshMA	-	Ashaiman Municipal Assembly
DTT	-	Demographic Transition Theory
GAMA	-	Greater Accra Metropolitan Assembly
GEE	-	Google Earth Engine
GHG	-	Greenhouse Gas
GIS	-	Geographic information Systems
GMet	-	Ghana Meteorological Agency
GSS	-	Ghana Statistical Service
ICSFM	-	Integrated Climate-Smart Flood Management
IDRC	-	International Development for Research Centre
KKDA	-	Kpone Katamanso District Assembly
LaDMA	-	La Dade-Kotopon Municipal Assembly
LeKMA	-	Ledzokuku-Krowor Municipal Assembly
LULC	-	Land Use Land Cover
LUSPA	-	Land Use and Spatial Planning Authority
MESTI	-	Ministry of Science, Technology, and Innovation
MLGRD	-	Ministry of Local Government, Decentralization and Rural Development
MMDAs	-	Metropolitan, Municipal and District Assemblies
NASA	-	National Aeronautics and Space Administration
OLS	-	Ordinary Least Square Regression
PHC	-	Population and Housing Census
SEDAC	-	Socioeconomic Data and Applications Center
SSA	-	Sub-Saharan Africa
TMA	-	Tema Metropolitan Assembly
VCM	-	Vicious Cycle model
VIF	-	Variance Inflation Factor

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CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

Flood disasters have become globally common that hinder social and economic growth. Their occurrences cause one of the commonest disasters that are highly destructive: loss of human lives, damage to properties, farms and businesses or livelihoods (Larbi, 2017; Hammond et al., 2014; Alderman et al., 2012). Floods dominated with 223 occurrences of the recorded 432 natural disasters worldwide by Emergency Event Database (EM-DAT) in 2021 (CRED, 2021). Forty-six trillion US Dollars is estimated to be lost globally due to exposure to global and coastal floods (Jongman et al., 2016). Between 1980 and 2018, in the USA alone, 241 weather and climate disasters with damages attributed to floods costing $123.5 billion were recorded (Smith, 2019).

The occurrence of floods is closely related to climate changes, Land Use Land Cover (LULC) changes and anthropogenic factors. The risk of flood increases due to global changes in climatic conditions and other human-induced changes of the environment (Castro & De Robles, 2019; Kundewicz et al., 2014; Bronstert, 2003). The increase in temperature implies increased moisture held in warmer air which results in intense rainfall events. The short intense rainfalls in recent years have been reported at inducing catastrophic floods globally (Blenkinsop et al., 2021; Tabari, 2020; Tarmizi et al., 2019). However, the discourse on floods also revolves around land which is a very important asset and a means to sustain the livelihoods of the population (Codjoe, 2004a). In catering for human needs, like food for instance, land is cultivated for farming and other agricultural processes. Accommodation, industry, roads and other forms of shelter and recreational spaces also make use of land. Changes in LULC are one of the main driving forces of global environmental change (Hegazy & Kaloop, 2015). Although populations are at the center of sustainable development and LULC, changes in LULC tend to increase the exposure of population to floods (Larbi, 2017; Poussin, 2016).

The rapid uncontrolled urbanization of cities mainly due to population growth implies an increase in demand for services, housing, transport, waste disposal and many more. The influence of population growth on land use is that vegetative cover will be cleared at a faster rate thereby increasing impervious surfaces (Brandt et al., 2017; Gyamfi et al., 2016; Zimmermann et al., 2016) and increased flood discharge (Yan & Edwards, 2012). Population change directly affects LULC change, causing changes in the intensity and structure of land use by changing the quality, structure, pattern, and product demand of land use (Li et al., 2015). Population dynamics, therefore, hold important implications for economic and social development and environmental sustainability (Bai et al., 2015). It is the changes in population attributable to births, deaths, and migration over time where attention is paid to the composition by sex and age. The rate of human activities has transformed the earth's surface to a large extent (Lambin et al., 2001). Humans and their activities are proximate determinants to change in land cover and tend to increase exposure to floods (Geist & Lambin, 2001).

In sub-Saharan Africa (SSA), flood risk is increasing, and the continent is rated the second hardest hit by flood disasters after Asia (Ansah et al., 2020; Ouikotan et al., 2017). Fatalities and economic losses from flood disasters are increasing in urban centres. Most African cities are highly populated and unplanned which over time, coupled with other factors increases the vulnerability of the population (Ramiaramanana & Teller, 2021). Rapid urbanization in the SSA and poor planning of spaces put the continent at a higher risk of natural disasters (Adelekan et al., 2015).

In Ghana, floods are annually occurring with adverse effects on livelihoods, property, infrastructure, and lives (Mensah and Ahadzie, 2020). Floods have been recorded throughout the country and Greater Accra, Volta, Central, Western and Eastern Regions are the most affected regions (Mensah and Ahadzie, 2020). Urban flooding in Ghana is caused by inadequate drainage systems, poor waste management, the loss of urban vegetation, and poor urban planning (Tasantab, 2019; Owusu-Ansah, 2016; Tabiri, 2015; Logah et al., 2014). Additionally, the country's planning system has struggled to effectively regulate urban physical development (Adarkwa, 2012), which has worsened the impact of flooding in cities.

Accra, records on floods date as far back as the 1930s with major floods causing disasters occurring in 1955, 1960, 2001, 2002, 2010, 2011 and 2015(Asumadu Sarkodie et al., 2015; Rain et al., 2011; Karley, 2009). These disasters in the coastal capital city have impacted lives and livelihoods (Asumadu-Sarkodie et al., 2017; Larbi, 2017). Poor planning of especially urban centres due to high rural-urban migration pressurizes the cities as slums develop at a fast pace (Ramiaramanana & Teller, 2021).

In order to safeguard the population, it is important that strategies of early warning, forecasting and prediction, adaptation and building resilience are clearly known and implemented. Flood risk management is therefore imperative using strategies to mitigate, adapt and forecast future occurrences (Bruner, 2021; Munawar, 2022). In order to explore uncertainties and alternative future occurrences of climate change and its underlying factors, the Intergovernmental Panel on Climate Change (IPCC) developed scenarios. A scenario is a coherent, internally consistent and plausible description of a possible future state of the world (IPCC, 2014). Future flood risks and the interaction with other factors such as population dynamics and land use land cover changes can be studied with the aid of various scenarios (Sayers et al., 2016). The availability of predictive models for flood-prone areas is necessary to aid in improving flood risk management and the resilience of the population (Lumbroso, 2020).

Ghana can take advantage of predictions and past experiences of floods to aggressively pursue flood risk adaptation (Tasantab et al., 2018). Therefore, this study forecasts flood risk using population and LULC variables with contextualized scenarios to explore uncertainties and forecast flood risk in seven districts in the Greater Accra Metropolitan Area. These districts were selected based on flood hazard mapping conducted in the entire Greater Accra region of Ghana which showed these districts as the high flood hazard zones in the metropolitan area. The forecasts will help improve the planning of urban spaces, improving LULC and population policies.

1.2 Statement of the Problem

More than half of global population growth between 2019 and 2050 is expected to occur in Africa (UN, 2019) although the land remains finite. Meanwhile, the continent is highly dependent on land and land resources (Antwi et al., 2016; Antwi Agyei et.al., 2012). Africa is still grappling with low technological advancement and stalling in the Demographic Transition Theory (DTT) (de Sherbinin & Bardy, 2015). The need for a study to explore relationships between population growth and LULC has been necessitated by the fast -growing cities in Sub-Saharan Africa. This is because the cities are facing challenges of rising inequality, poverty, exclusion and increasing residency in informal settlements (Titz & Chiotha, 2019). These place the continent as one of the worst-hit from climatic disaster such as floods. Generally, the rise in flood risk is attributable to socio-economic and climate changes coupled with population growth (Winesemus et al., 2016). The risk of flood events on the continent are increasing in frequency and intensity due to intensive and unplanned human settlements in flood-prone areas (Owuor & Mwiturubani, 2022; John, 2020; di Baldassarre et al., 2010)

Accra like other coastal zones is densely populated compared to hinterlands. The city exhibits higher rates of population growth and urbanization (Neumann et al., 2015). Coastal regions are typically low-lying and prone to floods (de Sherbinin & Bardy, 2015; Hallegatte et al., 2013). There is evidence of coastal population growth increasing the risk of flood which is exacerbated by urbanization, poor land use and inadequate planning (Kim & Newman, 2019). Urbanization can compound flood risk by an increase in runoffs as there will be an increase in impervious surfaces and removal of vegetation (Tellman et al., 2016). Fatalities from floods over the years, are worsening with Ghana amongst the worst affected countries in the sub-region (UN, 2009).

Land ownership and acquisition in Ghana is unique. Lands belong to chiefs, families, and individuals with a small proportion as state-owned lands; making acquisition and use of land difficult to regulate (Gyamera, 2018; Yeboah & Shaw, 2013). The Land Use and Spatial Planning Act, 2016 (ACT 925) was introduced as a revision and consolidation of laws on land use in Ghana. The aim was to ensure judicious land use, good planning and sustainable development through a decentralized system. However, there is still a problem with land use, caused by the increasing population, poor LULC practices and weak enforcement of land use regulations. For instance, destruction and conversion of wetlands, land encroachment, and the destruction of vegetation for infrastructural development are some of the poor land use practices that increase the risk of floods in urban spaces (Amoako & Inkoom, 2017; Yeboah & Obeng-Odoom, 2010).

Existing research have explored the relationship between population, changes in LULC and flood risk (Neves et al., 2022; Rahaman et al., 2020; Danumah et al., 2016). Others forecasted flood risk using population and LULC and relied on various modelling approaches such as Markov chains (Yapo et al., 2020), land change modeller (Näschen et al., 2019) and various hydrological modelling approaches (Maskrey et al., 2022; Neves et al., 2022; Tsakiri et al., 2014). However, these modelling approaches have not explicitly considered population dynamics as a driver of climate change in modelling using a scenario approach (Salman and Li, 2018). The use of scenarios is important in understanding the drivers of flood risk and enhancing flood risk mitigation efforts. Thus, the impact of population and LULC changes on flood risk in Ghana and how specified scenarios drive this relationship are therefore a problem worth investigating (Kim & Newman, 2019; Szwagrzyk et al.,2018).

In flood risk forecasting, the Intergovernmental Panel on Climate Change (IPCC, 2007) introduced families of scenarios. These scenarios make assumptions on anthropogenic influences and rates of emission of GHGs on climate change. Similarly, Price et al., (2017) developed LULC scenarios which is a subset of IPCC scenarios and was originally proposed by Verburg and Overmars, (2009) for flood forecasting. Szwargrzk et al., (2018) applied these three scenarios Trend, liberalization and self-sufficiency in forecasting flood risk in a developed settings where the population growth rate is slower and urban planning is advanced. However, there is scant literature in sub-Saharan Africa on how these scenarios have been applied to forecast flood risk. This study however utilizes these scenarios (Price et al., 2017) to an urban setting with high population growth and relatively poor LULC practices where floods are perennial. Altogether, this study contributes to the knowledge gap in examining the growth of the population and changes in LULC over time (1990-2020). Also, it also fills a methodological gap as it employs an analytical hierarchical process (AHP) to calculate flood risk and forecast flood risk by combining predictors of projected population and LULC under the three scenarios.

1.3 Research Questions

1. What is the trend of change in population and land use in the Greater Accra Metropolitan Area (GAMA): 1991-2000, 2001-2010, 2011-2020?
2. How is population growth and LULC associated with flood risk in GAMA?
3. How does projected population and land use/cover changes GAMA in 2030, 2040 and 2050 determine the risk of flooding?

1.4 Objectives to the study

The main objective of this study was to assess the impact of changes in population growth and LULC on future flood risk in the GAMA.

Specifically,

- to investigate the trend of population growth and LULC changes in GAMA: 1990-2000, 2000-2010 & 2010-2020
- to examine the predictors of flood risk in GAMA with variables of population and LULC.
- to forecast flood risk in GAMA (2030, 2040 and 2050) using population and LULC scenarios.

1.5 Rationale for the study

This study was important because it offered an insight into the trend of flooding in the Greater Accra Metropolitan Area (GAMA) with respect to the population growth and LULC changes. Also, vulnerability to floods has differentials by age and by sex (Llorente-Marrón et al. 2020) therefore, this study demonstrated the current nexus between the rate of population growth, land use, and land cover (LULC) changes and the risk of flood. Again, it forecasted future floods which will enable policymakers, the affected population and other stakeholders to plan appropriately regarding the management of floods. The study also highlighted the adverse role of some anthropogenic factors affecting flooding in the GAMA.

Also, loss of lives and properties is costly and impairs growth. Therefore, this study offered the platform to understand the variations in communities' experience of flooding in GAMA, in order to minimize losses and improve city planning through a forecast of flood risk. There were slight variations in characteristics of the selected municipalities - planning, livelihood activities, availability of natural assets, waste management strategies adopted and infrastructure - which are reflected in the results. The study is therefore geared at informing stakeholders to appropriately reduce the impact of flood disasters by building the adaptive capacity and resilience at community and individual levels and improving adaptation styles. It also provides enough data-driven evidence for policymakers to understand the interplay between demographic shifts and land use can help create more sustainable and resilient urban environments.

Finally, the novel methodological approach proposed by this research offers several key benefits to the scientific community. It provided an integrated analysis by providing a comprehensive framework that integrates datasets of population dynamics with LULC changes and flood risk, which are often studied in isolation. By analyzing these factors together, researchers can better understand how urbanization, population growth, and land-use transitions interact to exacerbate or mitigate flood risks. It also used modelling approaches and tools which are predictive. This unique approach could lead to the development of more accurate predictive models for flood risk assessment. By incorporating population trends and land use changes, these models will enable more precise forecasting of flood-prone areas, which is crucial for urban planning and disaster management.

1.6 Definition of Key Concepts

Population: The number of people living in a jurisdiction captured in a Population and Housing Census (PHC) at a particular time (census).

Flood: The overflowing of the normal confines of a stream or water body, or the accumulation of water over places that are normally not submerged. There are various types of floods, this includes flash floods, coastal floods, river/fluvial floods, glacial lake outbursts, urban floods, sewer floods and pluvial floods (IPCC, 2014)

Flooding: The overflowing of the normal confine of a water body (river, stream, lake, sea) or the accumulation of water in areas which are not normally submerged resulting from heavy precipitation where the volume of water exceeds the discharge capacity of drains (Douben, 2006).

Urban floods are types of floods that can result from overflows of rivers passing through them or overflow of local drainage (pluvial flooding) (WMO,2011).

Flood risk: The probability of occurrence of a flood and the aftermath if it occurred (United Nations & UNISDR, 2009; Meyer et al., 2007).

Land Use: The dominant purpose for which a parcel of land is used where human activities in a certain land cover type are either changed or maintained (Jansen & Gregorio, 1998). It is also defined as the utilization of the natural environment (land) by man to fulfil life's needs (Somantri & Nandi, 2018).

Land Cover: This is the observed physical cover of the land (IPCC, 2007). It is the physical covering of a parcel of land which may be natural or from human alteration.

Scenario: A scenario is a coherent, internally consistent, and plausible description of a possible future state of the world. Scenarios commonly are required in climate change impact, adaptation, and vulnerability assessments to provide alternative views of future conditions considered likely to influence a given system or activity (IPCC, 2007)

1.7 Organization of Chapters

The first chapter of this thesis is the introductory chapter which offered an insight into the study through the background of the study, statement of the problem, research questions and objectives, the rationale of the study and the organization of the entire work.

Chapter Two reviews the literature and presents the framework of the study. In this chapter, the theoretical underpinning of the study and the framework which adequately links population growth, land use/cover changes and risk of a flood are discussed backed by relevant literature.

Chapter Three is dedicated to describing the study area, design and detailed methods employed in the study. The chapter also presents the limitations to the study.

Chapter Four presents the descriptive statistics of the study. It describes the survey data by highlighting the demographics. This chapter also describes the evolution of GAMA from the initial districts forming the metropolis to the present state and composition.

In Chapter Five, the results of trends of change in LULC and population are presented. The changes in population and LULC from 1990 to 2020 are expounded in this chapter.

Chapter Six discussed findings from an Ordinary Least Square regression model were presented and discussed. The predictors of flood risk per the model in GAMA and the type of relationship, whether positive or negative and its implication to flood risk were shown.

In Chapter Seven, the flood risk forecast in GAMA for the years 2030, 2040 and 2050 was presented and discussed. These forecasts made under three different scenarios- trend, liberalization and self-sufficiency are examined by districts for their similarities and differences.

The final Chapter Eight ends the thesis with a summary of discussions, conclusions and recommendations

CHAPTER TWO

LITERATURE REVIEW, THEORETICAL UNDERPINNING AND CONCEPTUAL FRAMEWORK

2.1 Introduction

This chapter discusses literature relevant to the study of population dynamics, changes in LULC and risk of flood. The initial part explores the relationship between the population and environment, then how LULC is influenced by the population and their collective impact on flooding and the risk of flooding. The chapter ends by discussing theories and the conceptual framework guiding the study regarding the nexus of change in population growth, LULC and the risk of flooding.

2.2 Literature Review

2.2.1 The population, land use/land cover and the environment nexus

Lambin et al., 2001; Ojima et al., 1994 and Meyer & Turner, 1992 in diverse ways conceptualized the nexus of proximate causes and underlying driving forces of land use and land-cover changes. Proximate causes of land cover change are human activities (land uses) that directly affect the environment and thus constitute proximate sources of change (Geist & Lambin, 2001). The use of land by the population however has caused the removal of a vegetative cover mostly in the urban context where impervious surfaces increase therefore increasing the exposure of the population to flood (Feng et al., 2021; Wang et al., 2020; Chui & Ngai, 2016). Floods have become a global issue with differentials in people's vulnerability: exposure, sensitivity and adaptive capacity (Christian, 2016).

Floods, like drought and other climate-related occurrences, have serious implications on human lives and activities (World Bank, 2019) and therefore are of global concern. In 2017, the West African coast has been estimated to have lost $3.8 billion to erosion, flooding and pollution (Croitoru et al., 2020). Floods in Ghana date as far back as the 1930s when Accra began to urbanize (Karley, 2009). Notably, there were occurrences of floods in 1955, 1960, 1963, 1968, 1973, 1986, 1991, 1995, 1999, 2001, 2002, 2010, 2011 and 2015 (Asumadu-Sarkodie et al., 2017; Rain et al., 2011; Twumasi & Asomani-Boateng, 2002). Accra is a coastal city but extends inland and there are accounts of pervasive floods (Addo & Adeyemi, 2013). A flood disaster on June 3, 2015, coupled with a gas explosion claimed about 152 lives. This event is unique because it also raises issues pertaining to land use in the capital city where structures are situated: there are cases of buildings in waterways which tend to increase people's exposure to climate change (Yeboah & Obeng-Odoom, 2010; Karley, 2009).

The topography of Accra also plays a role in flooding, the risk of coastal inundation due to sea level rise among other factors has significantly contributed to its flood experiences. An analysis of the likely impacts of coastal inundation revealed that about 650,000 people, 926 buildings and a total area of about 0.80 km^2 of land are vulnerable to permanent inundation by the year 2100(Addo et al., 2011). Hence, being closer to the sea increases one's exposure to floods (Larbi, 2017).

Again, climate-driven land cover modifications interact with land use changes (Lambin et al., 2003), where because of poor planning especially there are cases of flooding (Rogger et al., 2017; Petrisor, 2016). Increasing populations coupled with poor planning, improper zoning, uncontrolled land use, lack of emergency services, poor sanitation and lack of early warning systems, in urban settings are challenges to several countries. These are situations exacerbating floods, especially the developing countries. Africa, though the continent with the least emission of greenhouse gases (GHG) and the most vulnerable to the effects of climate change (Amlalo & Oppong-Boadi, 2015; IPCC, 2007). The continent's vulnerability to climate change has been aggravated by poverty, climate and anthropogenic factors such as indiscriminate land degradation and improper waste management (Venkatesh, 2018).

2.2.2 Land use land cover changes and flooding

Land use increases exponentially with change in population density (Li et al., 2015) and studies have linked LULC changes to flooding (Szwagrzyk et al., 2018). Urbanization is a major driver of floods as the natural environment- such as forests and farmlands- are being converted and therefore increasing surface runoffs (Guzha et al., 2018; Szwagrzyk et al., 2018). The hydrological changes that result in urban flooding are long understood and quantified (Huong & Pathirana, 2013). Urbanization has caused the increase in impervious surfaces, poor infiltration and reduction of flow resistance. And in developing countries, the problem is compounded by inadequate and drainage systems and poor waste management (Amoako & Inkoom, 2017).

Land cover changes, for example, deforestation has proximate determinants classified into three main groups, agricultural expansion, wood extraction and infrastructural extension (Geist & Lambin, 2001), these activities are known as land use are population driven. Population growth due to high fertility may exacerbate resource scarcity in areas where a large proportion of the population already relies on natural resource-based livelihoods (Bremner et al., 2010). Land use change has a strong effect on floods as humans have heavily modified natural landscapes (Rogger et al., 2017). In Accra, the ever-increasing population and urbanization have caused massive changes in LULC.

Growing populations and urban expansion can worsen climate change conditions and enlarge hazard-impacted areas if land use changes are not planned adequately (Y. Kim & Newman, 2019). Meanwhile, around the world, more than 600 million people live in coastal areas that are 10 metres below sea level (Amlalo & Oppong-Boadi, 2015). The use of coastal zones for settlement purposes exposes the population to coastal flooding (Hauer et al., 2021; McMichael et al., 2020) as climate change is causing the rise in sea levels.

Therefore, various scenarios of urbanization have resulted and scientists emerging with models on land use- land use models (LCM) and land transformation models (LTM).

In June 1999, Ghana formulated a national land policy aimed at the judicious use of land and natural resources whilst providing economic gain for the Ghanaian society, sustainable resource management principles and maintaining viable ecosystems (MOLF, 1999). This policy was, however, identified as having some weaknesses which made it relatively ineffective. Some lapses identified included poor coordination, consultations and cooperation among public sector land agencies (Ministry of Land & Forestry, Ministry of Local Government, MMDAs, Ministry of Sanitation and Water Resources, etc.) weak land administration system marked by fragmented institutions, poor consultations with landowners, land boundary issues by customarily owned lands and general indiscipline in the acquisition and sale of lands. The National Land Policy was revised and in 2019, a Bill was placed before the legislature which was later sanctioned into an Act in 2020. The Land Act, 2020 (ACT 1036) was passed in December 2020. The Land Use and Spatial Planning Authority (LUSPA) was also established in 2016 to replace the Town and Country Planning unit which has been in existence since 1945. Their core mandate is to plan spatial, land use and human settlements for national development under the National Development Commission Act, 1994 (Act 479) and the National Development Planning Act, 1994 (Act 480). The Authority is also tasked to prepare and provide for technical human settlement planning, provide guidelines for spatial planning, and develop capacities of the district assemblies in land use, spatial planning, and human settlement management functions.

2.3 Flood forecasting and scenarios

2.3.1 Flood forecasting

Forecast or prediction of future climatic-related disasters such as floods has become crucial to aid in planning and disaster risk management. They tell the likelihood of future climate related events. In flood forecasting, data from previous, present and /or real-time are required (Ansah et al., 2020). The forecast of floods is linked to early warning systems geared at preparation, evacuation, and resilience-building (Jain et al., 2017; Tilford, 2007). Timely forecasts are beneficial to protection of the ecosystem, reduction of fatalities, reduction of cost of post-flood rehabilitation and improvements in provision of safer water infrastructure (Seneviratne et al., 2021; IPCC, 2019). Flood forecasting models can be classified as either deterministic or stochastic (WMO, 2011b).

There are inherent uncertainties in forecasting as models are built on data and scenarios (IPCC, 2007, 2014). Uncertainties in flood forecasting which may be due to input data, model uncertainty and model parameter uncertainty (Jain et al., 2018). They can however be quantified by components by model sensitivity evaluation, predictive uncertainty, and ensemble prediction systems (Jabbari & Bae, 2018; Paciorek et al., 2018; Coccia & Todini, 2011). Results of forecasts can also be evaluated to assess the robustness (Lott & Stott, 2016).

The increased probability of extreme precipitation is due to increasing anthropogenic forcing of climate change which birthed flood forecast research (Arduino et al., 2005). There are various models in flood forecasting, some of which are Global numerical weather prediction models (de Roo et al., 2003), statistical and correlation techniques e.g., Markov chains (CWC & NIDM, 2008), run off models in basins (CWC, 2013), flood forecasting systems (Marker, 2015) and many more. Floods are forecasted using scenarios which built usually based on historical data. Flood forecasts also consider various sectors

2.3.2 Scenarios

Scenarios are plausible representations of future occurrences of (IPCC, 2007). They are constructed based on data using model-based approaches, temporal and spatial analogues, incremental scenarios for sensitivity and expert judgement (IPCC, 2007). Climate scenarios developed by IPCC can be used the global, national, regional levels (IPCC, 2007). Though initially scenarios were thought as sequential, further studies have proved otherwise and parallel scenarios processes are in use currently (IPCC. 2014).

Some scenarios developed by the IPCC include socioeconomic, land use and land cover change, environmental, climate, sea-level rise and emissions scenarios (IPCC, 2007). Socioeconomic scenarios entail demographic, socioeconomic and technologies which influence anthropogenic GHG emissions. These scenarios focus on the population's vulnerability, sensitivity and adaptive capacity in relation to climate change (WMO, 2011). Socioeconomic scenarios have been studied to neglect the qualitative aspects (perception, lived experiences, etc.) in the process of building the scenario (Abeka et al., 2020). This scenario is fraught with high uncertainties especially in social and economic systems such as policy changes, economic booms, or dips (WMO, 2011).

The LULC change scenarios are essential because LULC change influences carbon fluxes and GHG emissions (IPCC, 2019). Also, a change in LULC affects the climate by determining vulnerability of ecosystem by altering its possible response (Lee et al., 2021). In LULC change scenarios, regional and sector-specific approaches can be used (Seneviratne et al., 2021; IPCC, 2014). Due to the diversity in land use practices, expert judgment and spatial modelling are dominant in this type of scenario -building.

Environmental scenarios are broad scenarios which consider environmental changes as imminent and consequential for climate change (Seneviratne et al., 2021). These scenarios are usually scale from subcontinental to global levels. Climate scenarios are focused on methodological issues in building plausible future climate models (Lee et al., 2021). Sea-level rise scenarios are used to examine impacts and adaptations to climate change in coastal regions (Mearns et al., 2001). The GHG emissions scenarios assess the impact of GHG on climate change (Kirtman et al., 2013). This is a scenario combined with four storylines describing the evolution of the world in the 21st century (Kirtman et al., 2013).

Due to the varied types of data needed in forecasting using scenarios of IPCC which usually are at larger scales, other scientists have also developed contextualized scenarios for modelling climate-related events- floods, flood risk, drought (Kim & Jehanzaib, 2020; Shan et al., 2019; Budiyono et al., 2016; Fischer-Kowalski et al., 2013; Verburg & Overmars, 2009). These scenarios though tend to fall under either one or more IPCC scenarios but modified (Budiyono et al., 2016). Scenarios are beneficial as they produce varied storylines and with data aid simulations and forecasts.

2.4 Theories

2.4.1 Population and environment

There are various theories linking population and environment, these theories have metamorphosized and transitioned through various lenses and push/ pull factors. Classical, neoclassical, dependency and intermediate theories of population and environment were discussed by Jolly (1994). Neoclassical economists postulate the neutrality of population growth on environmental alterations whilst classical economists report otherwise. Dependency theorists link environmental degradation to high population growth and expound their root causes as being similar. The intermediate theorists identified high population and population growth as a proximate determinant and exacerbating factor on the environment and its degradation.

Codjoe (2004) also discusses five classifications of theories of population and environment: linear, multiplicative, intermediate, development-dependency and complex.

The Malthus, (1872) and Boserupian (1965) theories linked population growth to food production in a linear manner. These theories postulated that a growing population implies an increase in food production by extending farmlands (Malthus) or intensification using technology (Boserup). The Malthusian theory postulates that population will outstrip food production because while the population is increasing geometrically, food production is increased arithmetically. Therefore, there will be control which will be either preventive or positive – abstinence, contraception and abortion. Otherwise, there will be social checks which are mainly vices- war, poverty, famine and diseases (Weeks, 2011). Boserup theorized that food production can match population growth when appropriate technologies employed in food production. Both theories were criticized in various ways, the main flaw of Malthusian theory is the relegation of technology in agriculture (Weeks, 2011; Weil & Wilde, 2009).

The use of technology though mentioned in Boserup's thesis has been critiqued that there may be ecological constraints such as leeching, farmers focused on maximizing profit: especially in developing countries, unfavourable land tenure systems, poor credit markets, poor technologies for tropics and unfavourable macroeconomic policies (Fischer-Kowalski et al., 2013; Codjoe, 2004b; Marquette, 1997).

The Neo-Malthusian theory was postulated similar to the Malthusian theory and popularized in the 1900s (Martinez-Alier & Masjuan, 2005). It differs from the initial Malthusian theory in two ways. First, is the use of contraception as birth control. And the second is the likelihood of overpopulation caused by the middle working class who was identified as the main source of moral degeneration as they end up as those who build slums. This theory is criticized for imposing planned parenthood on the low to middle-class meanwhile affluence consumes energy and produces waste at a far higher rate (Collins, 2002; Martinez-Alier & Masjuan, 2005).

Another population-environment theory is the multiplicative theory. The multiplicative relationship between population and environment includes other factors such as technology and affluence moderating the impact of population on the environment. This theory known as IPAT (Commoner, 1991; Ehrlich & Holdren, 1971), is $I = P \times A \times T$ where I is the total impact on the environment, P the population, A is the affluence or per capita consumption, and T is technology.

Populations have unique socializations and cultural practices and institutional factors which will influence their impact on the environment. These factors are therefore mediating the population-environment nexus. The dependency theory is also a classification by Jolly (1994), where the interplay has a root cause of poverty. Other theorists also expound on the nexus as complex: the interaction of human-driven systems and ecological systems resulting in a socio-ecological system (Codjoe, 2004a). The effects of the human environment are not unidirectional but reciprocal (de Sherbinin et al., 2007) for instance, human activities are depleting land cover through various land uses; construction of roads, buildings, agriculture and many others increase the susceptibility to floods. Floods in turn cause damage to human properties and lives, this observation caused scientists to arrive at the theory of the Vicious Cycle Model (VCM) (Brown et al., 1987). This theory postulates that prolonged high fertility implies impacts on the environment and the resources will continually decline, leading to degradation. Meanwhile, poverty causes high fertility which in turn causes environmental degradation. And because the environment is degraded, livelihoods are adversely affected which in turn causes poverty, hence the vicious cycle. The VCM is characteristic of developing countries and was however built based on previous theories; the Demographic Transition theory (DTT), Intergenerational wealth flows and tragedy of the commons (de Sherbinin et al., 2007).

The demographic transition theory was conceived by Thompson (1929) and finalized by Notestein (1945) is a description of global demographic trends and is typically made up of four stages. The first stage is characterized by high fertility and death rates which connote high natural increase. The fertility rates in the first stage, however, are noted to decrease with time. In the second stage of the transition, death rates begin to decrease together with decreasing birth rates. In the third stage, birth rates and death rates become persistently low. The fourth stage is characterized by below replacement fertility rates where fertility and mortality remain low and stagnant. The theory of intergenerational wealth flow holds that high fertility is beneficial as wealth flows from children to parents as they become older (Caldwell et al., 1982; Caldwell, 1977). Hardin (1968) propounded a theory- tragedy of commons - that, individuals acting rationally and independently deplete common resources because they act in self interest.

Most countries in sub-Saharan Africa (SSA) unlike the developed countries are in the latter of the second stage and early phase of the third stage. And co-evolving with the DTT is the land use transition theory (Foley et al., 2005), which has three nonlinear stages. The DTT links population growth and urbanization, showing how rapid population growth in early stages can lead to unsustainable land use practices like deforestation and settlement in flood-prone areas, increasing flood risk. As countries urbanize, particularly in low- and middle-income countries, unplanned urban growth in flood-prone areas further intensifies flood risks. The land use transition construct is a process of land use change in which the structural characteristic of the system transforms. It is a region-specific change in land morphology driven by innovation and socio-economic change (Long & Li, 2012; Lambin & Meyfroidt, 2010).

The DTT faces contemporary issues like stalled transitions (Schoumaker, 2019), urban-rural disparities (Nickayin et al., 2022), migration (Johnson, 2020), environmental degradation (Zhang, 2018; Lakshmana, 2016), and climate change (Rauscher, 2020). For instance, slow demographic transitions have been attributed to higher vulnerability to climate change (Dao et al., 2022) for which the DTT does not account. DTT was developed without considering climate change, a key factor that alters flood risks today by increasing the frequency and severity of floods, which can disrupt the demographic transition process. The model therefore requires more nuanced models that account for economic, social, cultural, and environmental variables that extend beyond the DTT's traditional scope.

The applicability of DTT varies across contexts. In low to middle-countries, rapid population growth, poor infrastructure, rapid urbanization without proper planning leads to increased vulnerability to floods (Dao et al., 2022; Ramiaramanana & Teller, 2021). High-income countries have been more successful in mitigating flood risks through strong governance and infrastructure. However, flood risk management and the corresponding social and political discourse are more likely to neglect the challenge of population decline (Clar et al., 2023). In climate-vulnerable regions like small island states, the theory falls short in addressing how environmental shocks like rising sea levels and storm surges can reshape demographic and flood risk dynamics (UN-DESA, 2024).

This study also adopts the VCM, to explore the relationship between the population, LULC and the risk of flooding. The study adopts the concept of the Petrişor et al., 2016 where a vicious cycle is produced by poor planning in an urbanized setting. This in effect adversely affects the environment resulting in environmental e.g., floods and social impacts which in turn cause harm to the population and livelihoods (Figure 1). This study notes the urban sprawl being experienced in Accra due to higher urban pressure (population and density), will result in fragmentation (Petrişor et al., 2016). The population in the various districts form the urbanization/ urban sprawl as in the model which by virtue of LULC changes impacts the green infrastructure. The impact of these is the decrease in the quality and quantity of the ecosystem, where the risk and occurrences of flooding increase. The cycle is completed by the adverse effect of a decrease (quality and quantity) of ecosystem services in the urban setting, a decrease in urban life quality.

The vicious cycle model provides valuable insights into the self-reinforcing relationship between floods and socio-economic vulnerability, especially in low-income, high-risk regions. Its strengths lie in illustrating how repeated floods exacerbate poverty, environmental degradation, and weak governance (Ssekibaala & Kasule, 2023; Petriosor et al., 2017). The VCM also accounts for social dimensions of flood risk such as marginalization, poverty, and governance (Petriosor et al., 2017). The model is also applicable developing countries as it explains how flood impacts in these regions are often magnified due to a lack of resources for flood management (Ssekibaala & Kasule, 2023).

Some limitations of the VCM include the overemphasis on poverty as the primary driver of flood risk (Petriosor et al., 2017). It has a limited focus on structural mitigation measures (Ssekibaala & Kasule, 2023) and also the assumption of a linear relationship (Petriosor et al., 2017). The VCM is applicable in different contexts, in low-income, developing nations**,** it is able to address issues of infrastructure is weak, governance is limited, and flood resilience is low. In these contexts, recurrent floods often drive communities into deeper poverty, degrading their ability to recover. It is also applicable especially in urban areas due to inadequate urban planning and large populations living in informal settlements (Petriosor et al., 2016). The VCM is also applicable to developed nations as they face increasing flood risks which they can manage. In the context of the advanced nations, the proposed virtuous cycle is likely to be achieved as policies and planning are well-implemented.

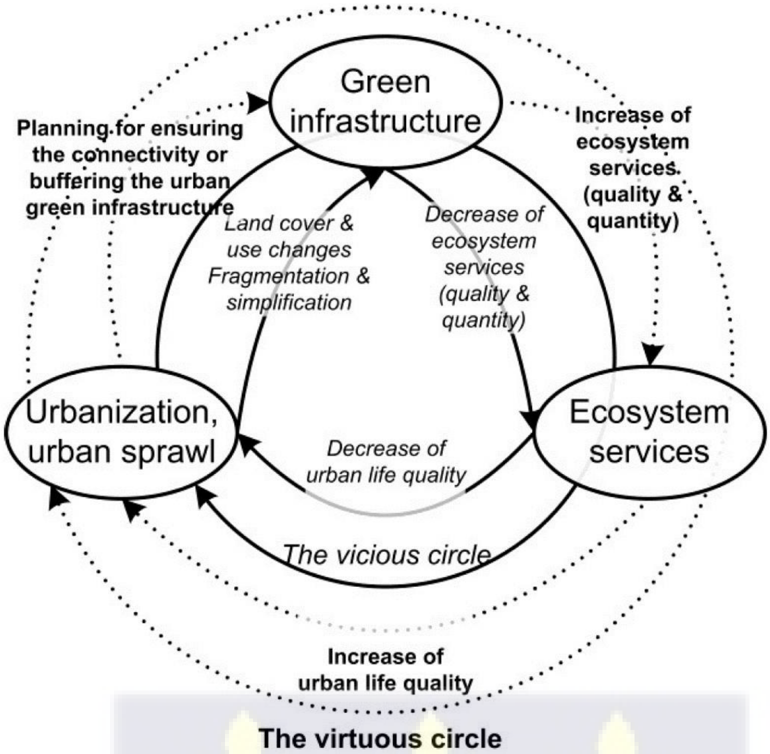


Figure 1: Vicious Cycle Model by Petrisor et al., 2016

Again, to forecast future risk, the study applied land use scenarios, an initial concept by Price et al., 2017. Scenarios can be generated using various approaches, namely: IPCC, Human Development, Risk and Adaptation Framework Approaches. Each approach is unique and considers certain variables as important in building scenarios. The IPCC approach models the implication of climatic and land cover changes. The Human Development approach models vulnerability as a product of both climatic and non-climatic stresses. The risk approach is aimed at threshold identification, quantification of uncertainties and planning actions to reduce risk. The adaptation framework approach is a combination of the IPCC and human development approaches, and it is basically to evaluate adaptation options. Scenarios have storylines described as a family, they are descriptions of the scenario focused on the features, dynamics and relationships between the driving forces.

Land use legacy plays a very important role in the spatial patterns of future forest cover. The three scenarios - trend, liberalization and self-sufficiency (Price et al., 2017) application in urbanized areas are recommended by Szwagrzyk et al., 2018. The trend scenario employs a linear projection of the land use. This scenario is in concordance with this study's objective to examine trends in population growth and land use. The liberalization scenario assumes a high global economic and population growth, a market-driven economy with or without policy intervention, stronger climate trends, greater greenhouse (GHG) emissions and low support for agriculture. This scenario is typically the context where the population is growing in the urban centre with rapid urbanization and low agricultural ventures. The third scenario of self-sufficiency has the assumptions of regional development with emphasis on self-sufficiency, higher ecological awareness, willingness to pay for conservation and moderate GHG emissions. This scenario is also likely in the setting of this study as be1`swxcause of the effect of floods, people as an adaptation strategy may be willing to pay for conservation.

2.4.2 Land Use Transition and Urban Land Use Theories

Land Use Transition was then defined as any change in the land use system where land cover is changed from one state to another. There are various frameworks on land use change which are classify as actors, drivers, and land change (Hersperger et al., 2010). However, there are no unified theories on Land Use Transitions (LUT) (Long et al., 2021). In the 1990s Mather studied and wrote on forest transitions. Lambin et al., 1999 also followed suit by discussing drivers of change in forest covers. By 2005, Foley discussed five stages of LUT. The LUT has been studied to be non-linear and with various drivers and actors. Drivers of LUT have been classified as historical, social, economic, and of ecological contexts (Lambin & Meyfroidt, 2010; Xu et al., 2008). The increasing interest in LUT has necessitated spatial studies with remote sensing and Geographic Information

Systems (GIS) and other sophisticated systems. Some scholars are therefore proposing the theorization of LUT to fill existing knowledge gaps (Song Li, 2019).

A subset of LUT is the urban land use which has several theories. Urban Land Use Theories (ULUT) were propounded as a result of urbanization where scholars explained how the phenomenon occurred and how land is used in the process of urbanization. The first ULUT by Burgess (1925) propounds that cities grow in a concentric fashion. The nucleus is the central business district from which the city expands in a ring form. Hoyt (1939) however thought it otherwise and believes cities grow in an unconstrained manner. Where there is a nucleus of business districts which result from people of similar social strata associating. This in effect pushes the city further as low-income housing dwellers encroach farther from the central business centres. Harris and Ulman (1945) believe there are multiple nuclei which results in urbanization. They like Hoyt demonstrated their theory but differ by stating how new nuclei emanate as settlements spread to avoid people always obtaining their supplies from the CBD. Therefore, forming newer CBD in places of residence thereby causing urbanization.

Another ULUT is the succession theory. This theory is similar to the gentrification concept by Glass (1964). Old buildings usually owned by older, indigenous yet poorer people are sold to richer people to build apartments or businesses. Gentrification results from economic, physical, socio-cultural and spatial drivers. Some actors in the succession theory are governments, Metropolitan Municipal and District Assemblies (MMDAs), private developers, banks and insurance/investment companies (Anaafo, 2020; Blasius et al., 2016). In GAMA, there is evidence of gentrification per the succession theory (Anaafo, 2020). Whilst some scholars argue for this theory as improving the urban setting by improved amenities, physical appearance, and economic benefits (Subramanian, 2020; Blasius et al., 2016). Others assert that it brings about displacement of original homeowners and causes out-migration. The succession theory has also been assessed as one that brings about much change in land use as the ones who gentrify tend to move away and use resources gathered to resettle (Lim et al., 2013; Sheppard, 2012). And the gentrified communities also experience accelerated land use changes (Mcdonagh, 2007).

Other theories of urban land use are technology, Weber's theory, shopping theory, economic base theory, traffic counts and residential theories (McDonagh. 1997). Technology influences LULC by means such as transportation, industrialization and design of buildings. Due to technological advancements, land may be used judiciously by incorporation into planning and architecture (Mozuriunaite, 2016). Economic theory in LUT is the gravitation of growth a place towards the place where industries are dominant.

Situating these theories in the study, there is evidence of relationships between the LUT and DTT. In the initial stages of the DTT, fertility rates and mortality rates were high coupled with weaker technologies and policies (Lee & Reher, 2011). The DTT plays a secondary but an unstable role in urban transition (Egidi et al., 2021; Briassoulis, 2020). Migration has also been identified as a direct or indirect engine of urban transition (Bocquier & Costa, 2015; Lerch, 2014). At the latter stages of the DTT, technologies are advancing, economic growth is increasing, birth and death rates declining. Excess space coupled with other factors at this stage of the DTT allows for flexibility in land use (Lee & Reher, 2011). A wholistic approach not exclusive to the traditional political-economic approach is needed to study the paradigm of human natural interactions (Bocquier & Costa, 2015).

2.5 Conceptual framework for the study

The combination of the VCM, DTT and land use scenarios resulted in the author's construct in Figure 2. The conceptual framework enables an assessment of population dynamics and changes in LULC and their joint influence on flood risk. It combines the influence of climatic and non-climatic factors as determinants of flood risk. It combines these with socio-demographics and LULC factors to investigate the long-term flood risk in GAMA using LULC and socio-demographic scenarios.

The framework shows that flood risk is directly linked to climatic factors. Climatic factors due to climate change are likely to increase flood risk in frequency and severity of storms in future (Morita, 2014). Flood risk is not solely due to climatic factors. A non-climatic factor such as the elevation (DEM), is significant in exposure to floods and therefore valuable for parameterization of flood risk models (Pa'suya et al., 2019). Non-climatic factors combined with other factors some anthropogenic tend to increase the risk of floods (Kundzewicz et al., 2014). According to Füssel and Klein, (2006), non-climatic factors which are proximate determinants of flood risk are influenced by non-climatic drivers. Thus, for instance, the income of a household head determines the type of settlement, and whether the person can afford a building resistant to flooding in case the location is more exposed to floods. For instance, the occupation of the household head to a large extent determines the place of residence. People have been noted to live closer to their sources of livelihood (Larbi, 2017). Therefore, being at risk of floods may be due to settling close to one's livelihood.

Also, in the conceptual framework (Figure 2), the socio-demographic characteristics of the population influence land use. Land use land cover changes are a function of changing demography (Showqi et al., 2014). The population density, the wealth or economic buoyancy in a district influence changes in LULC. The human interaction with the environment induces dominance of man over the natural causing environmental issues (Petrisor et al, 2016). Where planning is lacking, the urban sprawl will increase fragmentation. Consequentially, a decrease in the quality and quantity of the ecosystem will result (Petrisor et al., 2016). An outcome of decrease in the ecosystem is the upsurge of natural disasters such as floods (UNISDR, 2017) . A vicious cycle may result as occurrences of natural disasters have been linked to environmental degradation

(Kamboj et al., 2020). In order to mitigate, adapt or build resilience, further harm is likely to be caused to the environment as strategies being implemented individually may not be wholistically potent (van Herk et al., 2015;
APFM et al., 2009; WMO et al., 2006).

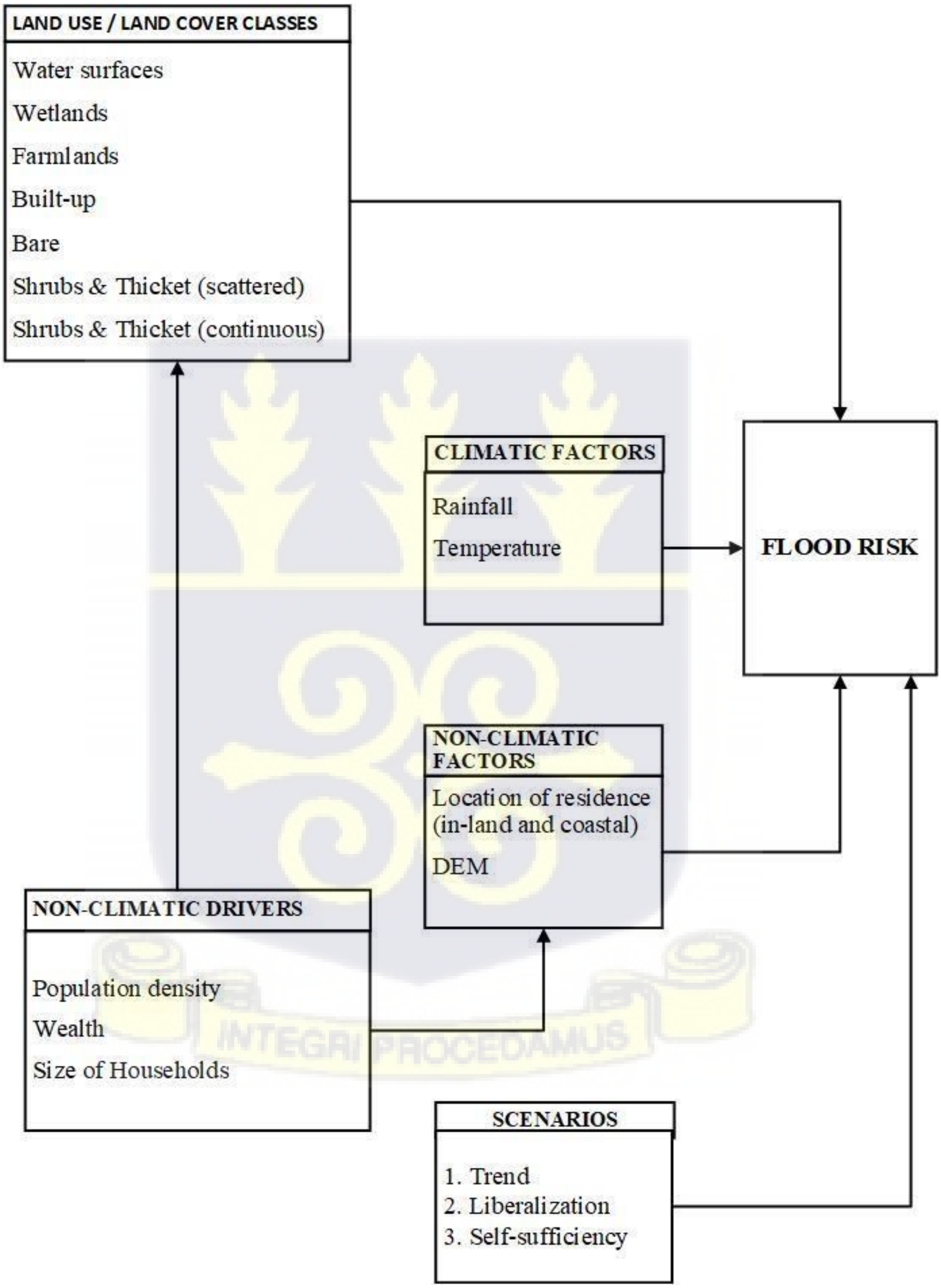


Figure 2: Conceptual Framework (author's construct)

The scenarios used are used to forecast flood risk in GAMA. They are conceptualized using socio-demographic variables (non-climatic drivers), non- climatic factors and LULC characteristics. These combined are directly linked to flood risk. The scenarios – trend, liberalization and self-sufficiency- are built on various assumptions of LULC planning or otherwise and population changes. The variations in the scenarios will inform choices at individual and collective levels. It will drive policies as the risk to floods at future dates will depend on planning otherwise may result in either a vicious or virtuous cycle (Petrisor et al., 2016).

Flood risk is the likelihood of experiencing floods and its associated impacts on lives and properties. In the framework (figure 2), flood risk is categorized into three low, medium and high. Africa is facing increased flood risk as human settlements are increasingly unplanned and intensive (di Baldassarre et al., 2010). Studies assert how coastal areas and flood plains are used for settlements in bid to expand urban areas (IPCC, 2012; Nicholls, 2011). The present and future flood risks are examined using the linkages existing between dynamics of population and LULC. The varied or similar flood risks at the district levels is deduced. Using the built scenarios, flood risk in the future of GAMA is assessed highlighting the districts with higher risks per scenario. Flood risk and its linkages to population and LULC changes after analysis are then discussed viz. the VCM and DTT models.

CHAPTER THREE

METHODS

3.1 Introduction

This chapter describes the study area and design, data - collection, management, and analysis - and the limitations to the study. The chapter details the geographic and demographic features of the study area. It also elaborates on the data collection procedure, describes the data collected, the statistical techniques used in data analyses as well as the tool employed to analyze the data. This chapter also described the philosophical underpinnings to the study and limitations to the study.

3.2 Study Design

This study design is a mixed quantitative method. The study used multiple quantitative datasets including cross-sectional survey, longitudinal and spatial data to examine the relationship of population dynamics, LULC changes and the risk of floods in GAMA. The study used longitudinal population and spatial data to explore the trends in population growth and LULC changes respectively. Using these datasets, the study investigated the predictors of flood risk and forecasted flood risk using three scenarios for three future dates.

3.3 Philosophical underpinning

Research paradigm: A paradigm in research is a philosophical way of thinking which is understood by a set of beliefs that represent a view (Kivunja & Kuyini, 2017). This study of population, LULC and flood risk was done using a positivist approach.

Ontology: Positivism assumes that reality is fixed and measurable. In this research, flood risk is a reality which can be measured by calculating flood hazard and risk. Other variables used as predictors were also measurable.

Epistemology: This paradigm assumes knowledge is quantifiable and objective. Flood risk is quantified and categorized into three (detailed in Chapter Three). Other variables and indicators such as population, LULC classes and other socio-demographic variables were measured and used in analyses.

Methodology: Quantitative methods were used in this study. A survey instrument (questionnaire) was used to interview respondents. Exploratory and analytical models were used to answer the research questions. An Analytical hierarchical Process was used for multicriteria analyses. Ordinary least square models were also used in obtaining the determinants of flood risk.

3.4 Study Area

3.4.1 Overview of Study area

The Greater Accra Region is 3,245km^2, the smallest but the most populous in the country. Due to urbanization, there is a high rate of in-migration (GSS, 2014). As of 2017 when this survey was carried out, the Greater Accra Region had 16 Metropolitan/Municipal/ District Assemblies (MMDAs) but in 2019, it increased to twenty-nine as some were split to aid the agenda of decentralization.

This study area is the Greater Accra Metropolitan Area (GAMA) - an agglomeration of districts. Seven districts were selected, these are Accra Metropolitan Assembly (AMA), Adenta Municipal Assembly (AdMA), Ashaiman Municipal

Assembly (AshMA), Kpone-Katamanso Municipal Assembly (KKDA), La-Dade Kotopon Municipal Assembly (LaDMA), Ledzokuku-Krowor Municipal Assembly (LeKMA) and Tema Metropolitan Assembly (TMA).

Accra lies within the coastal savannah region and is typically low-lying. These areas were mapped as flood-prone at the hazard mapping stage of the survey. In each of these districts, two communities with three Enumeration Areas (EAs) were selected.

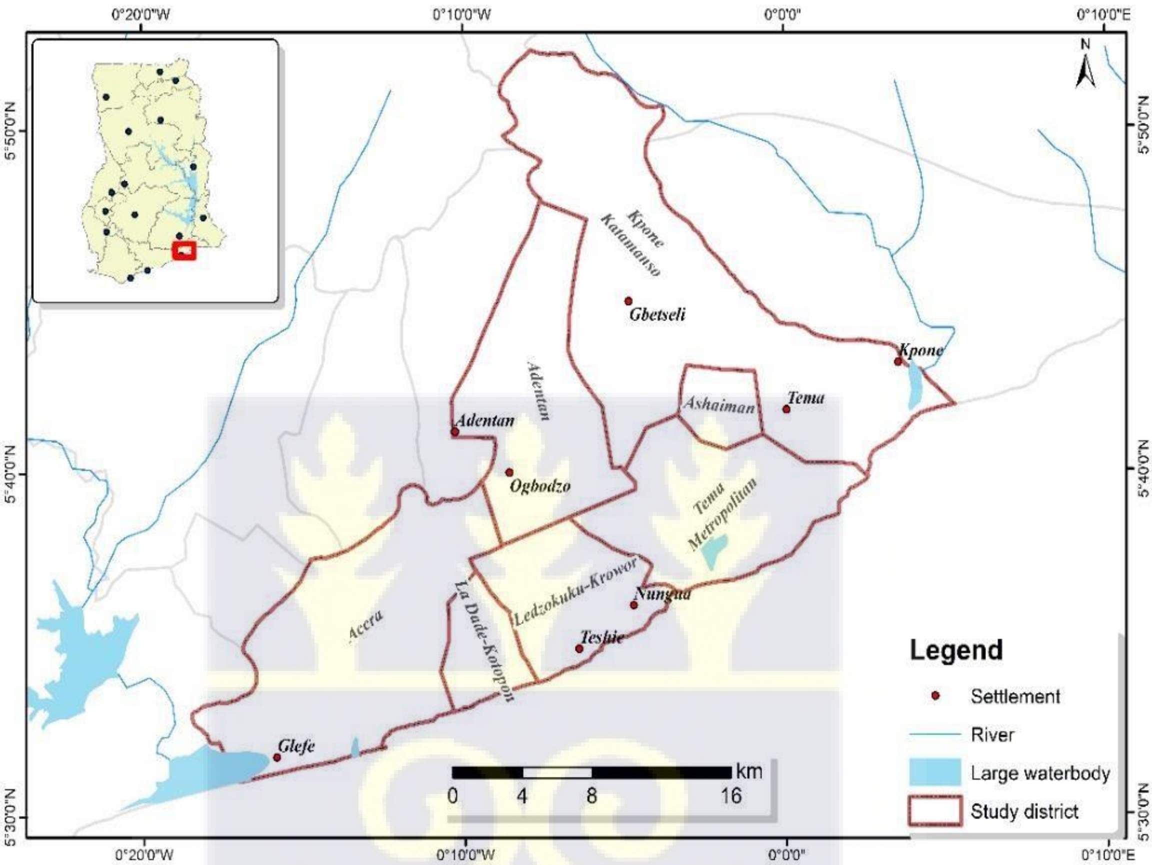


Figure 3: The Greater Accra Metropolitan Area (GAMA).

Source: Author's construct based on ICSFM project

3.4.2 Overview and Topography

Accra Metropolitan Area (AMA)

The Accra Metropolitan area (AMA) is bounded by the Atlantic Ocean, La Dade-Kotokpon Municipal, Ga West Municipal, Ga Central Municipal and Ga South Municipal Assembly (GSS, 2014a). The two communities selected in AMA are Glefe and Alajo, they are largely informal settlements in the heart of the city.

Glefe is heterogeneous, made up of mainly Gas and migrant groups of Ewes, Akans (Amoani et al., 2012). It is at latitude 5º19'5" N and longitude 0º6'0" W. The area, classified as a central geomorphic region consists of soft sandstone layers and the eastern region is made up of hard rocks overlain with soft rocks, which are moderately sensitive to erosion (Appeaning-Addo et al, 2008). Glefe experiences pluvial, fluvial and coastal floods as it is between the sea and two lagoons: Gbugbe and Dzatakpor (Amoani, Appeaning-Addo & Laryea, 2012).

Alajo is about 1km^2 and 6km from the central business district of the city. It is also a low-lying community which is 50 meters below sea level and has two rivers Odaw and Onyansia (Twum & Abubakari, 2019).

Adentan Municipal Area (AdMA)

The Adentan Municipal Area (AdMA) was carved out of TMA and lies 10 kilometres to the Northeast of Accra, which is specifically located on latitude 5.7142° N and longitude 0.1542° W. It is bounded to the South by the La-Nkwantanang Madina Municipal Assembly, to the east by KKDA and TMA, south by LeKMA and west by AMA. The municipality has 18 communities with 12 urban and the rest rural (GSS, 2014b) of which this project concentrated on Adenta East and Ogbojo.

Adenta East is located inland but is a valley to the mountain of Aburi and its environs in the Eastern Region. Adenta East (Commandos) is a levelled ground making it conducive for residential purposes, it hosts various estates and flats (SSNIT). This community has water canals and a relatively good drainage system. Ogbojo is a community in AdMA which has one of the rivers in the Municipality. It also had ponds and dams which became silted due to poor drainage system however, it is reported by residents to fill up during rainy seasons. This community also experienced sand winning activities though a source of informal employment for residents has affected the landform (GSS, 2014b).

Ashaiman Municipal Area (AshMA)

The Ashaiman Municipal Area (AshMA) was carved out of TMA in 2008, it is one of the smallest municipalities which covers $45km^2$ of land. It lies about 30km from Accra and to the north of Tema. The area formed part of the Accra- Togo plains which implies that the land is generally flat with some isolated hills. The nature of land in the district made it possible for various dams to be constructed geared at irrigation projects for vegetable farming.

This settlement is densely populated, rapidly growing and predominantly a migrant settlement of which Ewes form a majority as they were among the earliest migrants (GSS, 2014c). This municipality compared to Tema is poorly planned with a poor drainage system as the main contributor to the rampant experiences of floods. The two communities used as data collection sites in the study were Tulaku and Lebanon. Old Tulaku (Tulaku) was one of the study communities; it is not planned with structures typically wooden shacks and hand-dug drains (Stoler et al., 2014). Lebanon was the initial point of settlement by migrants from Accra (GSS, 2014c) and unlike Tulaku is not typically unplanned but divided into zones from 1 to 5.

Kpone Katamanso District Area (KKDA)

The Kpone Katamanso District Area (KKDA) is in the eastern part of the Greater Accra Region and stretches from the coast to the lower southern slopes of the Akwapim Mountains. This municipality stretches from the coastline inwards sharing boundaries with Shai-Osudoku District on the north and Ningo-Prampram District Assembly on the east, Adentan Municipal to the west, Ashaiman Municipal Assembly, Tema Metropolitan Assembly, and the Gulf of Guinea on the south.

This district was carved out of TMA in 2012. The topography of the district is generally flat and forms part of the coastal plains, ranging from 0m (South) to 35m (North) above sea (GSS, 2014d) level. The varied landform makes it suitable for several uses ranging from farming, animal rearing and fishing. This municipality is large and hosts the biggest solid waste landfill site in the region.

La Dade-Kotopon Municipal Area (LaDMA)

The La Dade-Kotopon Municipal Area (LaDMA) is a coastal municipality bounded to the south by the Gulf of Guinea and covers about 36 square kilometres (GSS, 2014e). It shares boundaries with the AMA and with LeKMA. The land is low-lying approximately 15 metres in elevation. The municipality is home to the Kpeshie Lagoon. However, due to the experiences of sea erosion and floods due to mainly poor drainage, embankments have been constructed which in turn has barred tidal flows to the Lagoon. The two communities selected in this municipality were South La and Labone Apapa.

Ledzokuku-Krowor Municipal Area (LeKMA)

The Ledzokuku-Krowor Municipal Assembly (LeKMA) as previously known was split in 2019 into, Ledzokuku Municipal Assembly and Krowor Municipal Assembly. However, at the time of data collection it was amalgamated by the two Assemblies hence for the purposes of this study it will be treated as LeKMA. It shares a boundary with the Gulf of Guinea, Tema Metropolitan area, Adenta Municipality and La Dade-Kotopon Municipality. This municipality is also located in the flood plain of three streams flowing from the Akawpim Mountains which usually flow to the Mokwe and Songo Lagoons (GSS, 2014f). This municipality is host to the Regional Maritime University and therefore a cosmopolitan society. Nungua and Teshie were the two selected communities. These communities are predominantly resided by Gas. Nungua has more planned areas compared to Teshie, which on the other hand is about 14km from the central business centre and densely populated.

Tema Metropolitan Area (TMA)

The Tema Metropolitan area (TMA) is located approximately 25 kilometres east of Accra, the capital city of Ghana and the second largest district in the Greater Accra Region. It is bounded by Adentan Municipality, Ledzokuku-Krowor Municipality, Kpone Katamanso District, Ashaiman Municipal, Akwapim South District Assembly and Dangme West District Assembly. This district is well planned and stratified popularly known as Communities.

Tema New Town is the largest community in the municipality and hosts a fishing community. In this community, indigenes form the majority of the population. Tema Community 5 on the other hand, is a well-planned residential area in the metropolis. The elevation of the district averages 36m a relatively flat plain (GSS, 2014g). The vegetation cover of the metropolis is primarily shrub and grassland with isolated trees that are only denser towards the northern fringes of the metropolis – the foothills of the Akuapem-Togo mountain range (Mariwah et al., 2017).

3.2.3 Economic Activities

The entire study area can be described as cosmopolitan with people of diverse backgrounds engaging in various economic activities. The sea is a major source of livelihood for residents in communities located in districts which are close to it, particularly: Nungua, Teshie, La, Kpone, Tema and Glefe. Nungua and Teshie are predominantly fishing communities. However, because of the University (Regional Maritime University) in Nungua, residents are involved mostly in service-rendering businesses. The municipality is well-placed between AMA and TMA but is now gradually picking up in relation to diverse economic activities (GSS, 2014f). The Junction mall in Nungua opened in 2014 and has improved the business landscape of the municipality

AMA is the heart of the city and residents are engaged in diverse economic activities. Some residents especially the indigenes of this metropolitan area engage in fishing, fish-mongering and its sale in Agbogloshie, Makola and other markets found in the central business centre. There are various economic enterprises in AMA among which are: manufacturing industries, oil companies, financial institutions, telecommunication, tourism, education and top health institutions – The Greater Accra Regional Hospital (Ridge Hospital), Korle-Bu Teaching Hospital and 37 Military Hospital, Ghana Police Hospital and the University of Ghana Medical Center.

Tema is the industrial hub of Ghana with over 500 industries that produce chemicals, clothing, consumer electronics, electrical equipment, furniture, machinery, refined petroleum products, steel and tools (GSS,2014). This metropolitan area hosts the country's largest port and harbour. It also has a free zones area close to the port to produce goods for both export and local consumption. TMA has one of the biggest markets in Ghana where trade activities are not restricted to special market days.

Residents in Ashaiman engage in varied activities for economic gains. The people of Ashaiman and its environs engage in vegetable farming because of the presence of dams purposefully created for irrigation (Nyantakyi-Frimpong et al., 2016; Mattah et al., 2015; GSS, 2014b) Other economic activities include petty trading, fish smoking and the provision of diverse services. In Ashaiman, residents are mainly employed in the informal private sector, including the agriculture sector (i.e., crop farming, livestock and poultry and fishing), small-scale manufacturing and processing, quarrying and construction (GSS, 2014c)

In Adenta, natural resources are limited, and the area is mainly residential; the majority of residents, therefore, have their livelihoods outside the community (Larbi, 2017). There are few manufacturing industries and several service-providing centres especially hospitality industries (GSS, 2014b). Therefore, apart from petty trading which residents may engage in within and outside the environs, economic activities for many residents are outside the municipality.

The Kpone Katamanso municipality is a hub for many industries as it is close to TMA. Fishing and fish mongering are the main economic activities with factory work, farming and petty trading among the diverse economic activities of residents. Animal rearing and sand winning are other businesses in which members of this municipality are engaged (GSS, 2014d). The first private-owned thermal plant for electricity production in Ghana, Sunon Asogli Thermal Power station is also found in this municipality.

La is a coastal community with an appreciable number of residents engaged in fishing activities. The entire GAMA is cosmopolitan therefore there is a wide range of economic activities in each locality though fishing activities are dominant in especially the communities closer to the sea. Also, there are areas in La where vegetable farming is dominant relying on rainfall, raw wastewater, and streams.

3.5 The Evolution of the Greater Accra Metropolitan Area (GAMA)

The Greater Accra Metropolitan Area (GAMA) is a subset of the Greater Accra Region and is defined in this study according to the administrative demarcations of Metropolitan, Municipal, and District Assemblies (MMDAs)of which it is composed. Data showed that in all the seven districts of focus in this study, the population in GAMA has increased over the years. The increase in population is not only attributable to high fertility but urbanization resulting from rural-urban migration (Teye, 2018).

Ghana after independence conducted censuses in the years 1960, 1970, 1984, 2000, 2010 and 2021. As of the 1970 and 1984 censuses, even though the Greater Accra region had various districts, the GAMA comprised two only metropolitan areas: Accra and Tema. As a result of the increasing population, industrialization and urbanization in general, for an effective administration of GAMA, the AMA and TMA were further re-demarcated and the Ashaiman district was carved out of Tema metropolitan area in 2008. Subsequently, with a growing population and administrative purposes, the AMA was sub-divided into AMA, LaDMA and LeKMA. Whilst TMA had four new districts carved out of it, TMA, AshMA, AdMA and KKDA (Figure 5).

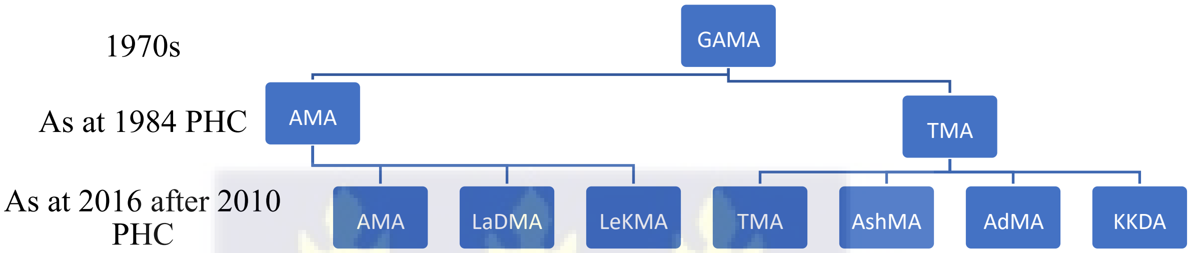


Figure 4: The evolution of GAMA

Source: Author's construct

3.6 Data sources

3.6.1 Quantitative Cross-sectional Survey Data

This primary data was collected under the Integrated Climate-Smart Flood Management (ICSFM) Project hosted by the Regional Institute for Population Studies with funding from the International Development for Research Centre (IDRC), Canada. The survey was carried out in fourteen communities of these seven districts in the Greater Accra Metropolitan Area (GAMA) to explore the nexus of population, LULC and floods. This questionnaire also explored the economic and gender disparities associated with the experience of floods. It mainly provided the socio-demographic data for this study. The instrument also sought to elucidate information on floods dating as far back as seven years which enriches the data.

In addition, data on expert judgement on weighting of flood risk indicators was collected to produce the flood risk model. A panel of six experts sourced from various fields with expertise in climate change-related fields - academia, meteorologists, and other researchers were asked to assign weights to various indicators influencing flood risk using a google form (questionnaire in Appendix C).

3.6.2 Data from Secondary Sources

The secondary data contains population, environmental, land cover and land use changes information. Population data for the study area (census 1981, 2000 and 2010) were obtained from the GSS. Rainfall and temperature data were obtained from GMet whiles data relating to LULC were from LANDSAT and National Aeronautics and Space Administration (NASA). These were used to explore changes in LULC. And together with population data used to calculate flood risk and used in a predictive model.

3.7 ICSFM Project Survey

3.7.1 Sampling Procedure

The survey data was gathered using a multi-stage sampling procedure. In the first stage, seven flood-prone districts were selected from a hazard mapping. These districts served as the first strata which were stratified into communities/localities. In the second stage after stratifying the districts, two communities making fourteen were selected from each district. In the third stage, three Enumeration Areas (EAs) were selected from each of these two communities (Appendix A; Table A2). These EAs are the smallest geographical unit which can be enumerated by one enumerator (GSS, 2019/2021) and in all, forty-two EAs were sampled.

A sampling frame is required to appropriately sample using a probabilistic approach. Therefore, from 23rd to 29th September 2017 a frame was created by listing households in the selected EAs. Thirty households were selected from each EA using a systematic sampling procedure. The interval used for the selection was 3 (i.e. k=3). The sample size before data collection was 1260 households however, with a response rate of 95.56%, the final data obtained was of size 1,204.

3.7.2 The data collection process

The data collection procedure was preceded by training research assistants for three days to undertake the listing of households. This list became the sampling frame used to randomly sample 30 households from each enumeration area for interviews. A one-week training and pre-testing then followed the listing process. Pre-testing was done in the Adentan Municipality specifically at Adenta Commandos. The main purpose of the pre-testing was to identify errors such as grammatical and question construction, enable enumerators effectively translate questions into various local languages. The next step was the household interviews which lasted for approximately four weeks (16th October 2017-18th November 2017).

As part of my PhD training- Experiential Research Learning, I participated in the data collection process of the ICSFM project. I was a field supervisor for both the listing and data collection. There were four enumeration teams made up of five research assistants/enumerators and led by supervisors of which three of us were PhD students. As a supervisor I was responsible for the assignment of households for the interview, proofreading and editing the data before uploading it onto the server.

The instrument for data collection was a questionnaire administered to the household head or an approved delegate of the household by the head in any of these languages, English, Ga, Twi, Ewe, Hausa and Mo. The questionnaire (Appendix) had various questions on household characteristics; age, sex, assets, level of education, sanitation, flood; experience, frequency, adaptation methods and resilience. There was minimal resistance or reluctance in participating in the survey as there were a series of townhouse meetings before the survey.

A google form questionnaire (Appendix C) was used for the weighting process. Experts partook in a twofold exercise. The first part was the assignment of weights to each indicator. The other part is the cumulative weighting; each indicator was weighted such that the total was 100%. This was to obtain the percentage influence each indicator had on flood risk. The mean of weight from the experts was then used in calculating the flood risk.

3.8 Secondary data

The secondary data as mentioned in the previous section were climatic, population and LANDSAT imageries. Climatic and population data were obtained by putting in a formal application for data from GMet and GSS respectively. Rainfall data was obtained with the variable measured in millimetres at designated weather stations and temperature in degrees Celsius. Population data were obtained for existing censuses at the district levels.

3.9 Description of Variables

3.9.1 Dependent Variable

Flood risk is defined as the probability of occurrence of a flood and the aftermath if it occurred (Meyer et al., 2007; UNISDR, 2009). The dependent variable in this study is flood risk. This variable is a model (map) obtained by a multicriteria modelling process. The resultant model is classified by the pixel values of the raster output. The three categories are defined as low, medium, and high risks zones based on pixel values for below 4, 4 to 6, and 7 & above class values, respectively. The process of obtaining the outcome variable is detailed in section 3.5.2.

The risk of flooding is mathematically represented by:

$$R_i = H_i \times P_i \times V_i \qquad \text{...equation 1}$$

R_i is risk, H_i is hazard, P_i is the population, V_i is vulnerability and i is the district.

The flood hazard of the seven districts was predetermined in a hazard mapping by the ICSFM project. Therefore, this function was not explicitly calculated to arrive at flood risk in this study although a variable of hazard that is, rainfall was used in the weighting process. The population variable obtained from the PHC. These variables were used in a raster format to produce a flood risk model (map).

3.9.2 Independent Variables

The main independent variables are population dynamics (growth) and LULC. The population variables are from both the survey and secondary data. The population of the study communities and districts from censuses (1984, 2000 & 2010) were used to project the population for the years 2020, 2030, 2040 and 2050. The survey data was used for descriptive analyses, GPS locations and other relevant variables were superimposed in the rasters for analyses. The detailed description of variables is in Table 2 below.

3.10 Data management

Management of data were in phases. The ICSFM survey data was collected using electronic questionnaires in CsPro application programmed on the tablets assigned to enumerators. Data from these tablets were uploaded onto a server and collated into a Microsoft Excel spreadsheet. The next step was to clean the data for analysis.

The next phase was acquisition and management of the secondary data. The climatic data was obtained in an MS Excel spreadsheet. This was also cleaned for analysis. Remote sensing data obtained from LANDSAT, NASA and Google Earth Engine (GEE). The data, treated with utmost confidentiality, was analyzed using STATA (14), MS Excel for descriptive analysis of the ICSFM survey data, ArcGIS, QGIS and ERDAS for the developing LULC maps, modelling and forecast of flood risk.

Table 1Table 2: Variables and their general descriptions

Land use/ cover category	***General description***
Built-up areas (settlement)	One and compound houses with surroundings, blocks of flats, industrial and commercial buildings with surroundings, other buildings, residential complexes, housing estates, transport/ lorry stations, sport and recreational facilities, parks, public complexes, hospitals, cemeteries, railroads, airports, squares, tarred roads, garbage dumps, other industrial and storage areas
Water bodies	All areas with still, open waters such as ponds or lakes. Channels of moving water include canals, streams and lagoons. Also includes areas where the water table is at, near or above the land surface for prolonged periods of the year. Freshwater marshes with their associated vegetation are classified under this category.
Bare	It encompasses slightly vegetated areas that expose large areas of bare soil.
Vegetative cover, grasslands, farmlands, shrubs and thickets (scattered and continuous)	All areas depict sparsely located trees, shrubs and patches of bare soil. Areas of extensive grass cover and isolated thickets are classified under this category. Lands under annual tillage and lands that have been cleared in preparation for crop cultivation, and lands left untilled such as fallow lands are identified as cropped lands.
Variable	***Description***
Climatic factors Rainfall Temperature	 Rainfall volume and intensity Temperature measured in Degree Celsius

Household characteristics Sex of household head Income Occupation Size of Household Level education of household head Age of household head	 The sex of the head of household measured as male or female The income of the household (this is the monthly disposable income) The occupation of the head of household (the main occupation of the household head) The number of people in the household The highest level of formal education of the household head Age of the household head.
Flood Occurrence and Frequency	 The occurrence and frequency of floods in the study area. (Questions about flood occurrence found in the questionnaire (see Appendix A). Question numbers - FL01, FL04, FL16
Elevation (slope)	The average elevation of land in a district measured in metres.

3.11 Data analyses

The data analysis tools and techniques are discussed in the preceding sections. Techniques are detailed according to the objectives of the study.

3.11.1 Tools

This study analyzed data in two main phases: preliminary and main analyses. The analyses were executed using STATA (14), MS Excel, ArcGIS, QGIS and ERDAS. STATA and MS Excel were used for the descriptive analyses of the survey data from the ICSFM project and the rest of the software used for LULC maps generation, flood risk modelling and forecasting. The use of the various tools is detailed in the techniques section.

3.11.2 Techniques

3.11.2a Objective 1: to investigate the trend of population growth and LULC changes in GAMA: 1990-2000, 2000-2010 & 2010-2020

Investigation of changes in LULC was done by using ERDAS IMAGINE processing and analyze images for the years 1990, 2000, 2010 and 2020. Firstly, in preparation to map the study areas, LANDSAT satellite images with a spatial resolution of 30m×30m. The preference for 30-meter resolution in land cover mapping is driven by its ability to balance detail and practicality (Yu et al., 2014; Chen et al., 2015), improve accuracy and visual representation (Cao et al., 2016; Feng et al., 2018; Xu et al., 2020), ensure compatibility with existing datasets (Cao et al., 2016; Xu et al., 2020), and maintain operational and economic feasibility (Blanchard et al., 2015). This resolution effectively captures significant land cover changes while being manageable for large-scale processing and analysis. The area of study falls within the LANDSAT scene with rows and paths. Images from November to February are comparable as the seasons are the same, images are cloud-free and vegetations are similar. Thus, conventional images from different time periods should consider the season refer to Table 2. For adequate classification of urban landscapes and their associated complexities, high-resolution images must be used to satisfactorily account for pixel heterogeneity (Akubia & Bruns, 2019). Therefore, raster images were imported into the ERDAS software. Homogenous polygons were created and then images were downloaded using the GEE which also served as classification validation maps. The data was then added to the layout and merged to create maps. This step is referred to as image preprocessing which is followed by image classification.

Table 3Table 2: Satellite data sources and years of capture

LANDSAT Image	Path and Row	Date of capture	Download Link
LANDSAT 5 (1990)	193, 056	25/12/1990	earthexplorer.usgs.gov
LANDSAT 7 (2000)	193, 056	04/02/2000	earthexplorer.usgs.gov
LANDSAT 7 (2010)	193, 056	17/01/2010	earthexplorer.usgs.gov
LANDSAT 8 (2020)	193, 056	02/01/2020	earthexplorer.usgs.gov

This research utilized the Gaussian Maximum Likelihood Classifier (GMLC), a recognized technique in remote sensing and pattern recognition, renowned for its efficacy in hyperspectral classification (Wang, 2006). This classifier has a broad range of classification options and produces good results for study areas in this context (Bosompem et al., 2017). The GML classifier distinguishes itself from other machine learning algorithms through its unique approach to parameter estimation and classification accuracy. It models class distributions under the assumption of normality, hence improving accuracy in contexts where this assumption is valid (Ramesh & Gopinath, 1998). GMLC has been employed in many applications, ranging from object classification (Massimo et al., 2008) to soil mapping (Jian, 2005), demonstrating dependable classification efficacy when sample sizes are enough (Psutka & Psutka, 2015). Nonetheless, its precision may be constrained by limited sample sizes or non-Gaussian data (Lee et al., 2004). Although GMLC is extremely effective in spatio-temporal data categorisation (Karaliutė & Dučinskas, 2021), it may exhibit suboptimal performance in complex, non-Gaussian distributions, requiring the implementation of other models (DeLeo & Rosenfeld, 2001; Nayebi & Aref, 1997). This was iterated at *k* algorithms to obtain maps for the entire GAMA and then individual ones for the seven districts. The land use classes used in this study included water bodies, built-up areas, bare land and vegetation (detailed in Table 2; section 3.5.2).

Assessment of accuracy for classification is necessary to ascertain the quality of information obtained from remotely sensed data (Anand, 2017). Another advantage of this method is the additional quantitative metrics used to measure the performance of the products Zhang. The first step is to develop an error matrix. Then calculate errors of omission and commission, user's and producer's accuracy, overall accuracy and Kappa coefficient.

In preparing the error matrix, ground data (known reference data) of GAMA was compared with corresponding results from classification. After building the matrix, the error of omission was calculated. This is done by summing values in the columns excluding the correctly classified value and dividing it by the total numbers of reference pixels. This is the error that results from failure to classify pixels which belong to a certain class. This is also known as the error of exclusion (Anand, 2017). The error of commission or inclusion is classifying pixels into a class they do not belong to. This is obtained by dividing, in exception of the diagonals, the sum of row totals by the total numbers of reference pixels.

$$K = \frac{N\sum_{i=1}^{n} m_{i,i} - \sum_{i=1}^{n}(G_i C_i)}{N^2 - \sum_{i=1}^{n}(G_i C_i)}$$

i is the class number
N is the total number of classified values compared to truth values
$m_{i,i}$ is the number of values belonging to the truth class
i that have also been classified as class i (i.e. values found along the diagonal of the confusion matrix).
G_i is the total number of truth values belonging to class i
C_i is the total number of predicted values belonging to class i

…equation 2

The overall accuracy is the total classification accuracy. This is computed by dividing the total numbers of correctly classified pixels by the total numbers of reference pixels. A disadvantage of this computation is it does not inform on how well individual classes were classified (Chughtai et al., 2021). The producer's accuracy is the probability that a certain feature on the ground is classified as it is in reality. This value can be obtained by dividing the numbers of correctly classified pixels in each category by the sample pixels taken for this category. The user's accuracy is the probability that a pixel labelled as belonging to a class on the map is indeed in that class.

The Kappa coefficient is a discrete multivariate method used in accuracy assessment. A statistical accountability measure is used to explain the role of random chance in the assessment procedure. This coefficient ranges from 0 to 1 and 0 implies no agreement and 1 agreement between the truth and classification values (Chughtai et al., 2021; Kang et al., 2020). This is calculated by

Trend analysis

The trend analyses were executed using LULC and population variables. Change detection of LULC classes was undertaken to obtain data for this analysis. Numerous methods have been developed to undertake change detection but the commonest are image differencing, principal component analysis and post classification comparison (Lu et al., 2003). The post-classification comparison was used in this study for its numerous advantages over pixel-based ones. The former process lessens the salt and pepper effect that is expected in pixel-based methods, moreover, the possible false alarms generated by area transitions and object nonalignment in the traditional object-based methods are minimized (Bosompem et al., 2017; Pabi et al., 2021; Wan et al., 2019). Post-Classification Comparison Change Detection is used to classify the rectified images separately from two periods of time, giving appropriate marks to different particles on the surface of the ground (Huang & Hsiao, 2009). A comparison and analysis of classified images from two time periods i.e., 1990 and 2000 were done. This enabled the change-detecting matrix to be constructed and then the change map.

The area change, percentage conversions and rate of change were calculated as part of the change detection process. The trend analyses for population and LULC were analyzed at an aggregate level of municipalities (metropolitan): 1991-2000, 2001-2010 and 2011-2020. Trend graphs were constructed for the percentage of land classes and population of the census year for each district at the above-mentioned times. This dataset was also used to undertake a test of association between population and the percentage of land cover (LC) types.

$$\%\ \text{area of LULC type} = \frac{\text{total area of LULC type } (y)}{\text{total area of district}} \times 100$$

...equation 3

Hence, for water surface land cover type (in say 1990) for AshMA,

It will be calculated by;

$$\%\ \text{area of LULC type in AshMA in 1990} = \frac{\text{total area of LULC type } (1990)}{\text{total area of AshMA}} \times 100$$

...equation 4

To calculate the population of a district for a given year,

$$\%\ \text{population of district } (y) = \left(\frac{\text{population of district } (y)}{\text{total population of GAMA } (y)} \right) \times 100$$

…equation 5

Thus, for example, to calculate the percentage population in say 1990 in AshMA,

$$\%\ \text{population of AshMA } (1990) = \left(\frac{\text{population of AshMA } (1990)}{\text{total population of GAMA } (1990)} \right) \times 100$$

…equation 6

Population, population growth and projection

The population data for 1984, 2000, 2010 and 2020 (projected) were extracted Ghana Statistical Service (GSS) population census data at District/Municipal levels. Population data were interpolated in MS Excel for the year 1990 to coincide with LANDSAT data for the LULC characteristics. This, however, could be achieved for AMA and TMA as they were the only districts with data available.

$$P_t - P_1 = \left(\frac{P_2 - P_1}{(x_2 - x_1)}\right)(x_t - x_1)$$

$$P_t == \left(\frac{P_2 - P_1}{(x_2 - x_1)}\right)(x_t - x_1) + P_1$$

...equation 7

P_t is the population at the time t

P_1 is the population at the initial census

P_2 is the population at the final census

x_t is the year for which the population is being interpolated

x_1 is the year of the initial census

x_2 is the year of the final census

Population growth was calculated by assuming an exponential growth rate given by;

$$r = \left(\frac{1}{t\ln\left(\frac{P_2}{P_1}\right)}\right)$$ ...equation 8

where
r is the exponential growth rate
t is the time frame i.e. difference in the base year and projection year
$P_{t=1,2}$ population in respective years. In this case, 2010 and 2020

The Warring-Lagrange procedure was used to then project the population for 2030. This method was selected because of the format the population was available. In order to use the Spectrum software for instance, population data should ideally be captured by age. Some advantages of this method are that it is convenient to use for unevenly spaced arguments and higher derivatives improve the accuracy of results thereby decreasing the error.

Given

$$P_3 = \left[P_1 \left(\frac{Y_3 - Y_2}{Y_1 - Y_2} \right) \right] + \left[P_2 \left(\frac{Y_3 - Y_1}{Y_2 - Y_1} \right) \right] \qquad \text{...equation 9}$$

To project for 2030;

$$P_{2030} = \left[P_{2010} \left(\frac{2030 - 2020}{2010 - 2020} \right) \right] + \left[P_{2020} \left(\frac{2030 - 2010}{2020 - 2010} \right) \right] \qquad \text{...equation 10}$$

Where $P_{t=1,2,3}$ is the population in 2010, 2020 and 2030 and Y is the year of census.

Univariate Analyses

This was the first phase of the analysis which was exploratory, at this stage, variables were described using frequencies and percentages for nominal variables. The results of these analyses were presented either graphically or in tables.

Bivariate Analyses

In this second phase, exploratory analyses between the dependent and independent variables are carried out. These tests are necessary to further describe the data and the relationships between variables. The test of association was executed to explore the association between place of residence and a household's experience of floods.

Correlation analysis

A Pearson correlation analysis is conducted between LULC types and population at the time points (2010 and 2020) and was done to explore the relationship that exists between them. This is a measure of linear relationship between two continuous variables (Schober et al., 2018). The correlation coefficient (*r*) is dimensionless and ranges from -1 to +1.

The correlation coefficient is interpreted differently as statisticians belong to different schools of thought. Cutoff points are arbitrary and inconsistent across (Chowdhury & Turin, 2020; Schober et al., 2018; Boslaugh, 2012). The guiding principle however is that the closer the correlation to the -1, the weaker the association between the variables.

Strong association of variables are *r* values closer to +1. Descriptors such as "weak", "moderate" and "strong" are used to describe the relationship between variables (Schober et al., 2018). Table 3 is the adopted interpretation of correlation between the LULC classes and population in this study.

Table 4Table 3: Correlation coefficient categorizations and interpretations

Adapted from (Chowdhury & Turin, 2020)

Correlation coefficient	Interpretation
0.00-0.10	Negligible correlation
0.10-0.39	Weak correlation
0.40- 0.69	Moderate correlation
0.70-0.89	Strong correlation
0.9- 1.00	Very strong correlation

3.11.2b Objective 2: Examine the predictors of flood risk in GAMA

Multicriteria analysis

Multi-criteria analysis modelling approach, specifically using the Analytical hierarchical process (AHP) embedded in the weighted overlay analysis tool in the ERSI ArcGIS software, was used for these analyses. In the first step of this process to obtain the outcome variable - flood risk, ten experts from various fields of climatology, education, disaster management, meteorology, and policy weighted variables of multiple criteria. The variables used included age, rainfall, slope or topography (DEM), impervious surface, human base settlement areas, population, income, LULC, and motorable roads (Table 1).

Experts were engaged to score the interrelationship and interrelationship of the various criteria based on their level of influence on flood risk. Each variable was scored individually depending on the likelihood of influencing flood risk and as part of the entire criteria, their overall percentage influence on flood risk.

The evaluation criteria were accessed with a focus on factors that may be represented geographically. The criteria rated in these analyses are summarized in Table 1. The next step was to synthesize the results of the experts' judgment weighting by checking for congruence of ratings and then average the weights. In the next step, the relative weights of the elements of each criterion were calculated and weights were assigned to the various rasters for a suitability analysis process using the software.

Initially, the experts' weightings result was assessed based on logical consistency, for instance, if a particular area is known to be flood prone but the expert weighting shows the area to be the reverse, that weight is set aside. None of the experts' weightings met the logical consistency assessment standard, hence the research resulted in using the minimum and maximum representing all the experts' weights as a threshold and adjusted the results until they were logically consistent with places with known flood risk status. The resulting rasters were reclassified into three classes using a common scale.

Based on the functional relationship (i.e., whether negative or positive) literature on flood risk with each variable, the variable was configured accordingly (Table 4). Thus, in locations with a higher number of people aged 65 and above, flood risk is configured as higher. Therefore, the locations with higher proportions of the population aged 65 and above years are classified as class 1, and the next dense areas are class 2 and follow in that order. On the other hand, the higher the amount of dispensable income, the higher the likelihood for those people to rebound after a disaster, hence the assumption of their risk being lesser than those that cannot recover easily after a flood incident. Hence the classification for this variable and flood risk is also done where those with lower dispensable income were classified as 1 and so forth.

The raster layers were overlaid to estimate the flood risk model. The suitability value was derived by multiplying each raster cell's suitability value by its layer weight. These values were then written in an output layer. One advantage of this method regarding the forecast of flood risk in the succeeding years was the ability to control the influence of different criteria in the suitability model.

The final model of the flood risk was then categorized as low, medium and high risk based on a scale of 3-9 because there were no pixels found at values less than 3 or above 9 though the actual scale was between 0-10. Where pixel with values

$0.0 \leq y_i < 4.0$ low flood risk

$4.0 \leq y_i < 6.0$ medium flood risk

$6.0 \leq y_i < 9.0$ high flood risk

Table 5Table 4: Variables rated by experts for flood disaster risk

Parameter	Spatial Data	Data source	Resolution
Precipitation	Precipitation 20%	IMERGE Final (NASA)	GMeT
Terrain/slope	Slope 15%	DEM (https://dwtkns.com/srtm30m/)	30m x 30m
Percentage Imperviousness	Impermeable Surface 10%	NASA- SEDAC (https://sedac.ciesin.columbia.edu/mapping/gmis-hbase/downloadview/#)	30m x 30m
Standard Error of percent impervious	Standard Error of percent impervious 5%	NASA- SEDAC (https://sedac.ciesin.columbia.edu/mapping/gmis-hbase/downloadview/#)	30m x 30m
livelihood, species or ecosystem	Homebase human built up and settlement 12%	NASA- SEDAC (https://sedac.ciesin.columbia.edu/mapping/gmis-hbase/downloadview/#)	30m x 30m
Probability of HBASE	Probability of HBASE 10%	(https://sedac.ciesin.columbia.edu/data/sets/browse)	30m x 30m
social/cultural asset	Home base human built up and settlement		30m x 30m
Population Age 0-14yrs Age 15-65yrs Age 65 above	Basic Demographic Characteristics	NASA-SEDAC (https://sedac.ciesin.columbia.edu/data/set/gpw-v4-basic-demographiccharacteristics-rev11/datadownload)	Census
Income	Household dispensable income	NASA-SEDAC (https://sedac.ciesin.columbia.edu/data/set/gpw-v4-basic-demographiccharacteristics-rev11/datadownload)	ICSFM survey
Location of Dams	GAMA Water Bodies	Department of Geography and Resource Development	ICSFM survey

Roads	GAMA Water Bodies	Department of Geography and Resource Development	ICSFM survey

Statistical analyses in ArcGIS

There exist various statistical modelling techniques in ArcGIS needed to comprehensively understand the data distribution, trends and whether features form spatial patterns which are not conspicuous in maps. There are statistical analysis tools in this software like in other statistical software for summary/descriptive statistics and inferential statistics. The summary statistics has tools for summary - minimum, maximum, mean, standard deviation and variance and frequency - sum and count.

Inferential statistics comprises spatial statistics and raster statistics. The spatial statistics consists of geographic distribution measurements, geographic pattern analysis, geographic cluster analysis and regression analysis. The raster statistics include cell statistics, focal statistics, point statistics, line statistics and zonal statistics.

Models for modelling spatial relationships included in ArcGIS are the ordinary least square (OLS), geographically weighted regression, gaussian, logistic and poison to name a few. In this work, the ordinary least square approach was used to obtain the factors influencing flood risk in GAMA. In the regression analysis, there are diagnostics used to obtain the best-suited model. The model diagnostics undertaken to choose the OLS as the best-suited model for the data.

Ordinary Least Square Regression (OLS) Modelling

This regression was used to identify the significant predictors of flood risk. The ordinary least square regression is a type of regression that minimizes the sum of squared residuals for the coefficients. Variables can be selected for regression analysis by backward elimination, forward selection, stepwise selection and hierarchical method. In the backward selection, all the independent variables are included in the initial model and dropped until a significant model is attained. This is done considering parsimony and other assumptions of the model (Chowdhury & Turin, 2020). This technique allows the least predictive variable to be eliminated. In the forward selection, the model is built by adding variables one after the other. This is the reverse of the backward elimination method. The forward selection starts with a smaller model. Both methods are easy to conduct (Chowdhury & Turin, 2020). One disadvantage of both methods is that all the possible combinations of variables cannot be explored (Rencher & Schaalje, 2008). This is because, once a variable is dropped (backward) or added (forward), the model-building must continue.

A stepwise selection combines the forward and backward selection. It starts with the backward elimination technique and deletes variables but can add back if they are significant in the presence of other variables. In this study, however, a hierarchical approach was used which is similar to the stepwise approach. However, the advantage of the hierarchical model over the stepwise method is variables are selected based on theory or literature and this drives the selection of the final model (Grekousis, 2020; Lewis, 2007). The general form of the model is in equation 8 and the specific model is in equation 9.

$$R_i = \beta_0 + \beta_1 x_1 + \ldots + \beta_i x_i + \varepsilon \qquad \text{...equation 11}$$

R_i is the risk of flooding
β_0 is the intercept when the coefficient
$\beta_1, \ldots, \beta_i$ are the coefficients
$x_1, \ldots, x_i$ are the independent variables say, rainfall,

$$\begin{aligned} \text{flood risk} &= \beta_0 + \beta_1(\text{population}) + \beta_2(\text{slope}) + \beta_3(\text{rainfall}) \\ &+ \beta_4(\text{built up area}) + \beta_5(\text{impervious surface}) + \beta_6(\text{level of education}) \quad \text{....equation 12} \\ &+ \beta_7(\text{distance from water body}) + \varepsilon \end{aligned}$$

OLS model assumptions and diagnostics

Best-fitting regression models are selected based on tests of assumptions and diagnostic outputs. Some OLS model diagnostics in ArcGIS include p-value, Variance Inflation Factor (VIF), Koenker statistic, R-squared, Wald test and the Akaike's Information Criterion (AIC). In the regression output, asterisks are used to indicate a statistically significant p-value ($p < 0.01$). The coefficients represent the strength and type of relationship (positive or negative) between each explanatory variable and the dependent variable. Multicollinearity between the independent variables was tested using the VIFs. Large Variance Inflation Factor (VIF) value (> 7.5) indicated redundancy among explanatory variables.

Also, the R-Squared and AIC measure model performance. The Joint F and Wald Statistics indicates overall model significance ($p < 0.01$). If the Koenker (BP) Statistic is statistically significant, use the Wald Statistic to determine overall model significance. When this test is statistically significant ($p < 0.01$) for Koenker (BP) Statistic, the relationships modelled are not consistent (either due to non-stationarity or heteroskedasticity). Instead, the Robust Probabilities (Robust_Pr) should be used to determine coefficient significance. Jarque-Bera Statistic when statistically significant ($p < 0.01$) shows the model predictions are biased (the residuals are not normally distributed). However, the use of social variables such as population, wealth, among others may violate some of these assumptions.

3.11.2c Objective 3: Forecast of flood risk in GAMA (2030) using population and LULC scenarios

The flood risk prediction for GAMA was conducted for the years 2030, 2040 and 2050 using data mainly from projected population, projected LULC from the years 1990, 2000, 2010, and 2020 and weights obtained from the expert judgment. These variables were adjusted based on the scenario to obtain a final flood risk model in the form of a map which has risk categorized as low, medium, or high risk. CA-Artificial Neural Network (ANN) a machine learning algorithm within the MOLUSCE (Modules for Land Use Change Simulations) plugin in QGIS was used for projection of LULC changes. The MOLUSCE is a spatial analysis tool in QGIS. It is used for LULC change evaluation and forecast of changes in LULC. The tool analyzes the spatiotemporal land changing patterns and the simulation of future scenarios offering a complete view of current and future developments (Muhammad et al., 2022; Ramdani et al., 2021; Guidigan et al., 2019). This makes it suitable to be used forecasted LULC changes for various analyses. In applying this tool, all the input data were converted into rasters with 30m spatial resolution to ensure good alignment of all input features. The rasters must be of the same size, and this can be achieved using the "Align" feature. The models are obtained by comparing the Before data with the After data for instance between the years 1990 to 2000, the initial year is set as 1990 and the final date as 2000.

Flood risk forecast was done using MOLUSCE; a plugin that allows the usage of LULC data and rasters of other explanatory variables. The primary data was used to project variables; income, population for 2030, 2040, 2050. The results for projected data were interpolated using the Inverse Distance Weighted (IDW) algorithm to form a raster. The combination of these datasets was trained to forecast LULC changes. A validation process was performed to determine the association between previous maps example, 2020's predicted map and 2020 's real (actual) map. LULC maps for future maps, say 2030 (one of the forecast years) was performed using previous maps example, 2010 and 2020 were used. Simulation process proceeds by obtaining ANN model parameters which were used weighted overlay in ArcGIS to forecast LULC maps for 2030, 2040 and 2050.

Trend

The trend scenario is based mainly on observed trends in LULC and population growth. It assumes that the rate of population growth in the years ahead to 2030 mimics the past events where total fertility rates and mortality rates may not decline drastically. And LULC changes will continue in similar fashion based on the trend. Also, there is the assumption that economic growth is not markedly notable and therefore the consciousness of the environment and its sustenance is not prominent. This scenario can also be referred to as business-as-usual scenario. In modelling for this scenario therefore, a multiplicative weight is assigned to the population, economic and LULC rasters to model the flood risk.

Liberalization

This scenario adapted from Price et al., (2017), assumes laxity on policies regarding LULC especially. In this scenario, there is high economic growth, high population growth, indiscriminate land use with no constraints on new settlements and `conversion of other land cover types. This scenario depicts a liberal society where there are no policies on environmental sustainability and agricultural support is low. Flood risk is modelled under this scenario by suppressing weights of LULC variables whilst weighting population and economic variables higher.

Self-sufficiency

The self-sufficiency scenario assumes the society that prioritizes sustainability. The population growth rate is moderate and economic growth is high. There are policies that focus on the environment and people are also willing to preserve the environment by using land properly, conservation of some land cover types such as wetlands and water bodies and investing in technologies especially in the fields of agriculture.

Table 6Table 5: Summary of scenarios used in flood risk forecasting

Trend	Liberalization	Self-Sufficiency
Business-as-usual (little or no change) • . Population is the same • Economic growth is the same • LULC is same	Everything is liberal/ chaotic • High economic growth • High population growth • No policy intervention on LULC (indiscriminate land use)	Ecological awareness/ sustainability • Population growth • High economic growth with people ready to invest in the environment • Good policies on LULC therefore there is a sustainable use

The entire workflow of the analyses is shown in Figure 4 below. The first part of this chart (top left) shows the objective one. It gives a summary of how LULC change detection was done and the trend analyses of changes in population and LULC. The next section of the flowchart, coloured light blue, shows the process of obtaining the predictors of flood risk. In the last section on the right (light brown) is the chart for objective three. In this final section, the forecast of flood risk is shown. It also shows how results from the trend analyses and OLS are combined using three LULC scenarios to forecast flood risk.

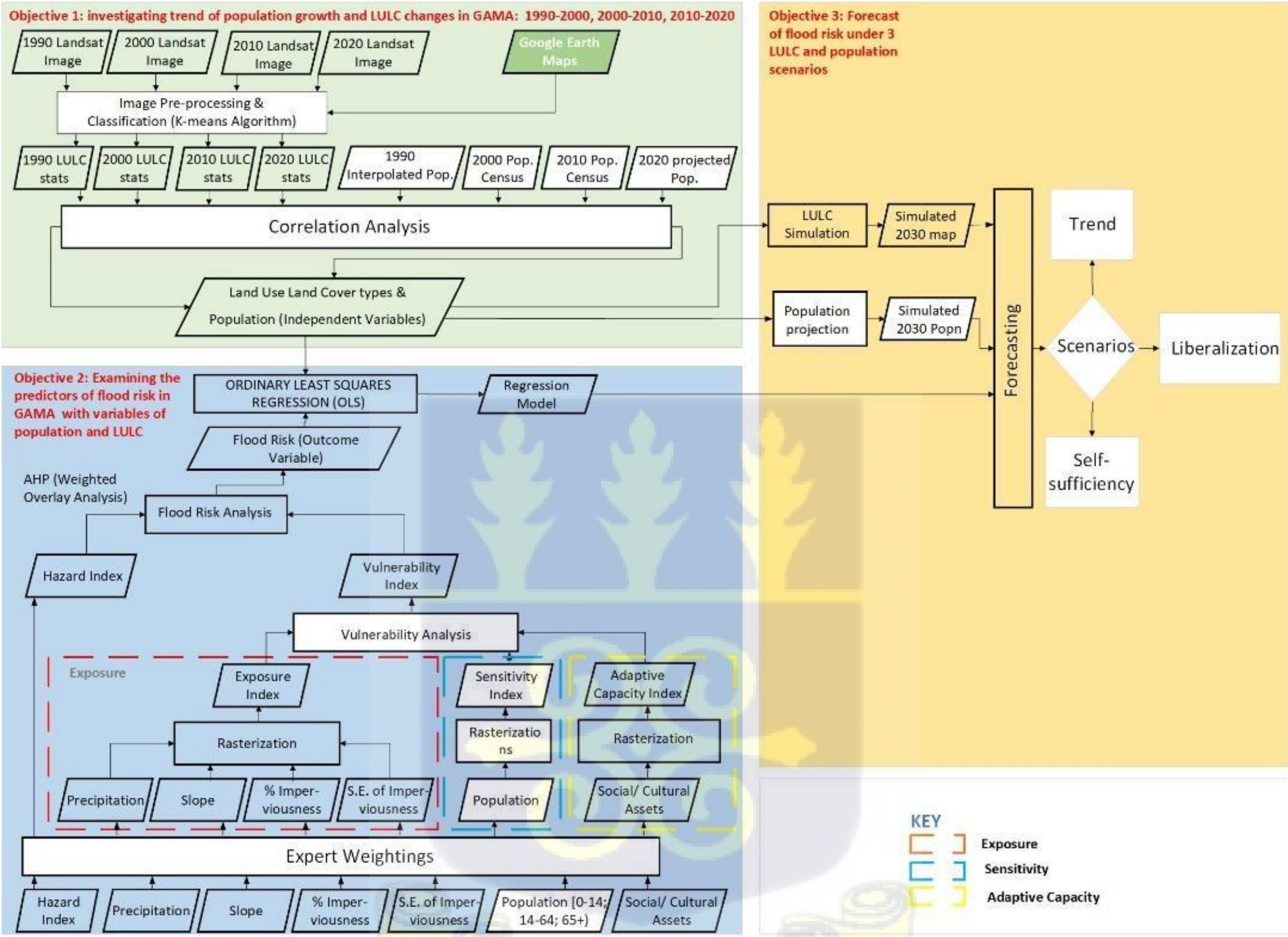


Figure 5: Flowchart for data processing and analyses

3.12 Limitation to the study

The main limitation to this work is related to the population data. The changes in demarcation of districts made obtaining data for past censuses cumbersome. The TMA, AdMA, AshMA and KKDA as of 1984 were one district known as TMA. AdMA and AshMA were carved out of TMA in 2008, whilst KKDA became a district in 2012. In 2018, AMA birthed six municipalities namely, Ablekuma West, Ablekuma East, Ayawaso East, Ayawaso North, Ayawaso West and Okaikwei. These new districts were formed to expediate development as well as decentralize the government.

Again, on 19th February 2019, six new districts were created in Greater Accra Region. The assemblies created which affected this study included Ablekuma Central, Ayawaso Central and Korle Klottey all from AMA (AMA, 2019), Tema West Municipal Assembly from TMA and Krowor Municipal Assembly from LeKMA. However, the survey which was carried out in 2017 has AMA, LeKMA and TMA and has therefore been maintained in this thesis.

CHAPTER FOUR

DESCRIPTIVE STATISTICS AND POPULATION OF GAMA

In this chapter, descriptive results of the study are presented. These results mainly provide a general description of the survey data by summarizing the attributes of household heads (age, sex, occupation), the experience of floods and association with place of residence.

The chapter further discusses the population of GAMA, offering insights into the past and projects into the future. The evolution process of the metropolitan area is described and discussed with data. In concluding this chapter, a population projection is also presented as GAMA is the most urbanized settlement in Ghana. This depiction of the future offers the platform for projections of flood risk in the subsequent chapter seven.

4.1 Descriptive results of survey data

In Table 5, is a description of selected features of the household and household heads of the ICSFM survey. Most households in the GAMA are comprised of one to six members. The majority of households were headed by males and female-headed households formed about 30%. Although Africa has a low prevalence of female-headed households globally (Bai et al., 2015), Ghana is ranked as a country with one of the highest (34%) in Africa (Sawe, 2018) which is in congruence with this study.

The educational level for household heads was categorized from no formal education to tertiary education. More than half of the household heads had completed their basic education. Occupations of respondents were grouped as unemployed, professional/technical/managerial, sales, agriculture, services and skilled/unskilled manual workers. About 32% of respondents are engaged in skilled/unskilled manual work and about one in five household heads were unemployed at the time of the survey.

On average, household heads were aged between 30 to 49 years. About half of household heads are aged between 19-39 years and about one in five (175; 14.5%) were 60 years or older.

Table 7Table 6 Characteristics of households and household heads

Variable	Frequency	Percentage
Sex of Household Head		
Female	357	29.7
Male	847	70.3
Household size		
1-3	564	46.8
4-6	549	45.5
7 and above	91	7.7
Level of formal education of household head		
None	113	9.4
Primary/JHS (Basic)	673	55.9
Secondary	271	22.5
Tertiary	147	12.2
Occupation of household head		
Unemployed	216	18
Professional/Technical/Managerial	113	9.4
Sales	296	24.6
Agriculture	32	2.7
Services	162	13.5
Skilled/Unskilled manual	385	32.0
Age of household head (years)		
19-39	551	45.7
40-59	478	39.8
60 and above	175	14.5

A description of the experience of floods by households in the study area is presented in Table 6. Most households are reported by their heads to experience floods at least once a year (55.6%). The main effect reported caused by floods is the destruction of household assets (21.2%) though other effects of the destruction of the structure, outbreak of diseases and loss of income were mentioned. One major effect of floods in GAMA found by previous studies was the negative impact on livelihoods (Larbi, 2017). One out of ten households reported they were not physically affected by floods though they experienced floods. Drinking water was reported to be the least affected by floods by the households affected by floods. This finding is consistent with earlier studies (Echendu, 2020; Mensah & Ahadzie, 2020; Afriyie et al., 2017) which showed that housing, savings, and livelihoods were vulnerable to flood disasters in Africa. This is a result of poverty, poor planning of spaces (Cissé & Sèye, 2015) and low insurance (Ouikotan et al., 2017; OECD, 2016).

Table 8Table 7: Household's experience of floods and their effect.

Variable	Number	Percentage
Experience of flood		
Yes	669	55.6
No	535	44.4
Frequency of floods		
Yearly	333	49.8
Every two years	29	4.3
Seasonally	307	45.9
Effect of floods on household		
Destruction of house	96	8.0
Polluted drinking water	7	0.6
Disease(s)	78	6.5
Loss of livestock	10	0.8
Loss of household assts	255	21.2
Loss of income	27	2.2
Other	76	6.3
Unaffected	120	10.0

A Chi-square test of association was conducted to verify if the location of residence and the experience of floods were independent. The results of the test between the location of residence (coastal and inland) and the household's experience of floods (Table 7) are significant at α equal to 0.05 with a p-value from the test less than 0.001. Households' location, therefore, is associated with their experience of floods. This means households closer to major water bodies particularly the sea and rivers were more likely to experience floods compared to those farther from such water bodies.

Similarly, Table 8 shows results for the tests association between place of residence and frequency of floods. This test is also statistically significant and means that the experience of floods and the frequency of it is linked to where one lived. The proximity to the sea and other water bodies which is closely related to land elevations determined how often a household experienced a flood. Similar studies (UNDESA, 2013; Nicholls, 2011) have shown how coastal areas are more prone to floods and these experiences are exacerbated by urbanization and infrastructural developments (Bai et al, 2015). This was evident in this study because the study area is coastal, has various water bodies in the districts of which some flow into the sea. The study area is also among the most urbanized in Ghana and the amalgamation of these factors agrees with previous studies.

Table 9Table 8:Tests of association between the locations of homes and the experience of floods

	Yes	No	Total
Coastal	432	263	700
(Expected values)	*(64.57)*	*(49.81)*	*(58.14)*
Inland	237	265	504
(Expected values)	*(35.43)*	*(50.19)*	*(41.86)*

Pearson chi-square (2) =26.93 P-value < 0.001 (α= 0.05)

Table 10Table 9:Test of association between the location of homes and household's frequency of experience of floods

	Yearly	Every two years	Seasonally	No experience	Total
Coastal	208	25	199	268	700
(Expected value)	*(62.46)*	*(86.21)*	*(64.82)*	*(50.09)*	*(58.14)*
Inland	125	4	108	267	504
(Expected value)	*(37.54)*	*(13.79)*	*(35.54)*	*(49.91)*	*(41.86)*

Pearson chi-square (3) = 31.8063 p-value < 0.001 (α= 0.05)

The size of GAMA is 74,026 hectares. The largest district is AdMA which occupies about 24% of the GAMA lands. The second and third largest districts were

KKDA and AMA respectively. The La Dade-Kotopon district was the smallest and occupied 4% of GAMA.

Table 11Table 10: The seven districts of GAMA and their land sizes

District	Area (ha)
Accra (AMA)	14,620
Adenta (AdMA)	17,997
Ashaiman (AshMA)	8,053
Kpone Katamanso (KKDA)	15,524
La Dade-Kotopon (LaDMA)	2,970
Ledzokuku- Krowor (LeKMA)	4,890
Tema (TMA)	9,972

The total populations of GAMA at the 1970 and 1984 censuses were 738,498 and 1,160,112 respectively (GSS, 1984). In 1984, the population increased by 36.3% (1,160,112). In the next census in 2000, the population of GAMA increased to 2,315, 649 which was a 49.9% increase of the previous census. The population in GAMA during the 2010 population and Housing Census (PHC) was 2,748,370 which was a 15.7% increase from the 2000 population.

These findings are consistent with the study by (Vimard & Fassassi, 2012) which demonstrated Africa has a higher population growth rate of 2.59% compared to 1.82% of other developing countries. The dynamics of the population especially growth in sub-Saharan Africa has been of interest to many researchers as results usually indicate high fertility, high mortality and migration both internally and internationally (Mbacké, 2017; Ekane, 2013; Caldwell et al., 1982; Caldwell, 1977). The changes in population, especially in urban centres have dire implications on the resources available to these locations.

Table 12Table 11: Population of GAMA from 1970-2020 and their percentage increment

	1970	1984	2000	2010	2020
Population	738498	1,160,112	2,315,649	2,748,370	3,464,926
Percentage increase (%)	N/A	36.3	49.9	15.7	20.7

Ghana since 2010 had more than half of its population living in urban centres (Anarfi et al., 2020) thus the population growth rate in these areas remains higher than the national average. Africa is projected to be home to 1.3 billion people living in urban areas by the year 2050 with uncertainties about its urbanization patterns (Cobbinah & Erdiaw-Kwasie, 2018). In the Greater Accra region, in 2010 there were 16 Metropolitan, Municipal and District Assemblies (MMDAs) but as of 2020, this has increased to thirty-three (GSS, 2014a). Urbanization is a multi-faceted phenomenon with demographic, economic, sociological and ecological roots (Cobbinah et al., 2015). In the GAMA, there is increase in not only the population but economic growth and various social transformations (Yankson & Bertrand, 2012). Meanwhile, 60% of urban dwellers were studied to be living in areas of high risk of exposure to at least one form of natural disaster (Heilig, 2012). Hence, the necessity of implementing strategies to address not only the increase in population but environmental, health, poverty and other related issues that arise from rapid urbanization.

4.3 Population projections

The population data for the seven districts are presented in Table 9. The population data were not available for the districts marked with "*" This was because those districts were not created at the time of these censuses. The population of AMA at the various dates remained the highest. The population of AMA constituted between 60% - 70% of the seven districts combined at the various censuses. TMA is the next populous district of the seven districts. It formed about 15% - 20% of the population of GAMA from the years 1990- 2020. LeKMA is the third most populous district and formed between 7%-8% of the population of GAMA. AdMA is the least populated district of the seven districts.

The population is projected for the year 2030 using the 2010 census values and projected 2020 values from the GSS and the Warring-Lagrange two-point approach due to the data available. These projected figures (Table 9) were used in conjunction with experts' weights for flood prediction in the three scenarios. The population in AMA remained the highest of the projected populations for the year 2030. Though the differences in projected populations for 2020 and 2030 are slight, TMA, LeKMA and AshMA remain among the highly populated districts in that order. AdMA remained the district with the least projected population forming about 3% of the population.

Table 13Table 12: Population and projected population values by districts

District	Population in 2010	Projected population in 2020***	Projected population in 2030	Projected population in 2040	Projected population in 2050
AMA	1,665,086	2,099,174	2,349,734	2,967,350	3,401,438
AdMA	78,215	98,682	119,149	119,149	160,083
AshMA	190,972	240,841	290,710	290,710	390,448
KKDA	109,864	138,529	167,194	167,194	224,524
LaDMA	183,528	231,306	279,084	279,084	374,640
LeKMA	227,932	287,334	346,736	346,736	465,540
TMA	292,773	369,060	335,483	335,483	597,921

*Source: Ghana Statistical Services (1984, 2000, 2010, 2020), "***" projected values by Ghana Statistical Services*

The population growth rate was calculated using the exponential growth method; the results are shown in Table 12. TMA has the highest growth rate of about 0.8 which is higher than the national growth rate of 0.23 (Population Reference Bureau [PRB], 2020). The growth rate in the seven districts was higher than the national growth rate. Though

LeKMA was the third most populous district, it had the lowest growth rate. KKDA is the second growing district with a rate of about 0.7. Between 2020 and 2050, West Africa is expected to experience a rapid population growth rate. The expected growth rate in the subregion will be as high as 174% with Ghana's growth rate at 85% (Population Reference Bureau [PRB], 2020).

Table 14Table 13: Population growth rate of the seven districts

District	Growth rate (r)
AMA	0.53
AdMA	0.46
AshMA	0.56
KKDA	0.68
LaDMA	0.38
LeKMA	0.37
TMA	0.81

The population change in GAMA particularly growth is notable in this study. Linking these results to the DTT, like other studies, transitions are not strictly homogenous in sub-Saharan Africa where the effects of socio-politics - colonization, re-demarcations of boundaries - are grave (Leshabari, 2021). Colonization has affected each African country differently regarding population dynamics. The introduction of formal education and healthcare has transformed the landscape of procreation. More women obtaining formal education meant fewer children in households as births are averted by time spent in school, the use of modern contraception and the choice of quality life for the children born (Ahmed Shallo, 2020; Bongaarts, 1978; Stover, 1998). In some countries, cultural and religious affiliations have proven to shape fertility transition (Turner, 2021; Ekane, 2013).

Also, the demand for more children and pronatalism in the subregion was due to a variety of factors from cultural, social, availability of healthcare, livelihood practices and

politics. For instance, due to high infant and child mortality, parents had a greater number of children as insurance against child mortality. In Ghana and most
SSA countries, agrarian households tend to be larger as children were a source of labour (Bryceson, 2018; Owusu & Kwarteye, 2008). All of these are embedded in a cultural belief of children being blessings and legacy of parents hence the high birth rates in SSA. In Africa, where the rate of medical advancement is slower, diseases such as Ebola and HIV/AIDS had severe impacts on the population (Leshabari, 2021). Altogether, GAMA which is an urbanized centre of Ghana is experiencing rapid population growth.

4.4 Chapter Summary

This chapter described some household and household heads' characteristics. The majority of households were headed by males. The proportion of female-headed households from the survey showed how Ghana relative to other countries especially in the subregion had a higher proportion of females as heads of households. Half of the household heads were between the ages of 19-39 years and a majority of these household heads were employed.

The tests of association were all statistically significant as it tested the relationships between the location of the household's residence and the experience and frequency of floods. Both tests demonstrated how floods were related to the household's proximity to a major water body. Households closer to water bodies tend to experience floods with a higher frequency. Households' assets were the most damaged in GAMA whenever floods occurred.

The population of GAMA has clearly evolved where the metropolis has grown from two districts to seven at the time of the survey, whilst the entire region had 16 districts. The growth of GAMA will affect the natural resources, especially land in the metropolis. The manner in which these resources are used will affect the human population.

CHAPTER FIVE

POPULATION DYNAMICS AND CHANGES IN LAND USE AND LAND COVER (LULC)

5.1 Introduction

In the previous chapter, the change in population is expounded. In this chapter, LULC changes are discussed. Land use, land cover is classified in an unsupervised classification technique using ArcGIS into the following classes, water bodies (water surfaces, wetlands), vegetation (scattered shrubs and thickets, farmlands, continuous shrubs and thickets), bare and built-up areas. The areas covered by each of these classes and how they have changed from 1991 to 2020 are presented in this chapter.

Also, the relationship between population growth and LULC changes is presented. The positive or negative relationship that exists between the various LULC is explained. The linkages are discussed at the aggregate level of districts to unearth the intricacies of the relationships between population and LULC.

5.2 Changes in Land Use and Land Cover (LULC)

The percentage covered by the various LULC classes in 1990, 2000, 2010, and 2020 in Ashaiman is represented in Figure 5. Table B1 (Appendix B), Figure 5 and Figure 6 summarize the major LULC conversion that occurred within the AshMA between 1990 and 2020. In 1990, the vegetative cover class constituted the major type of LULC, it covered 66% of the total area, built-up area followed closely covering about 32% of the total area and water bodies 2%. During the 30-year time frame, that is from 1990 to 2020, vegetative cover in AshMA declined by 526 ha, viz. 31% of the initial area. The area covered by bare lands increased in the year 2000 to 8.9% (152.56ha) but decreased in 2010 to 1.6% (27.92ha). This could be due to commencement of developmental projects such as buildings and roads which necessitated clearing of large parcels of land at that time. In 2020, bare lands increased by 5.1% in the municipality.

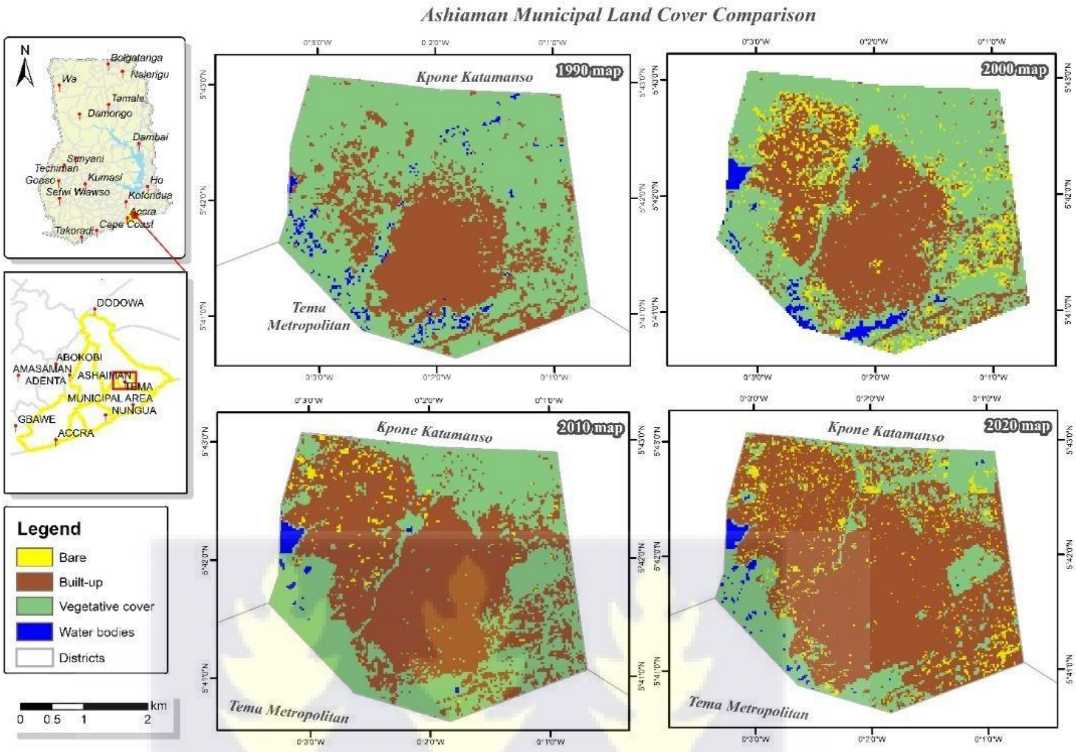


Figure 5: Classified maps for AshMA (1990-2020)

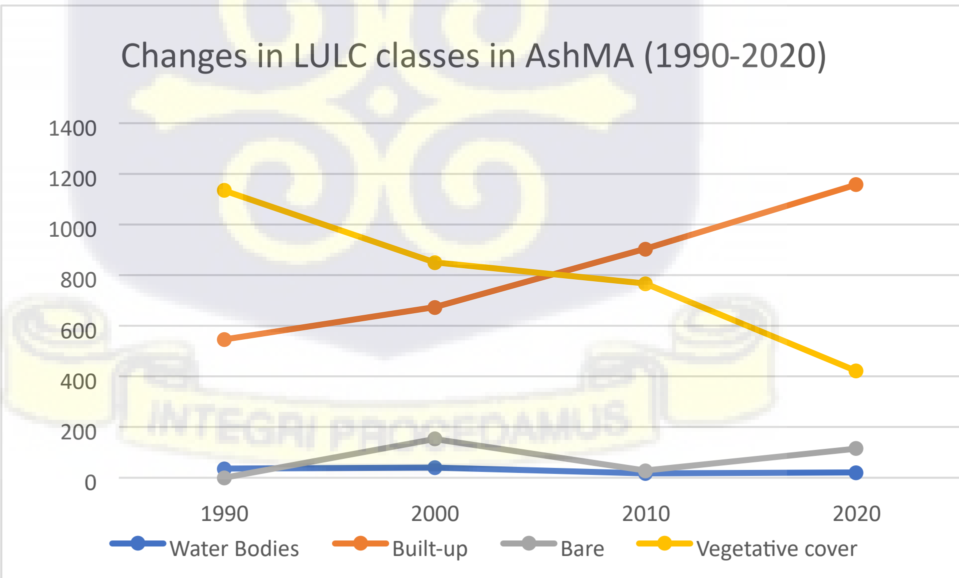
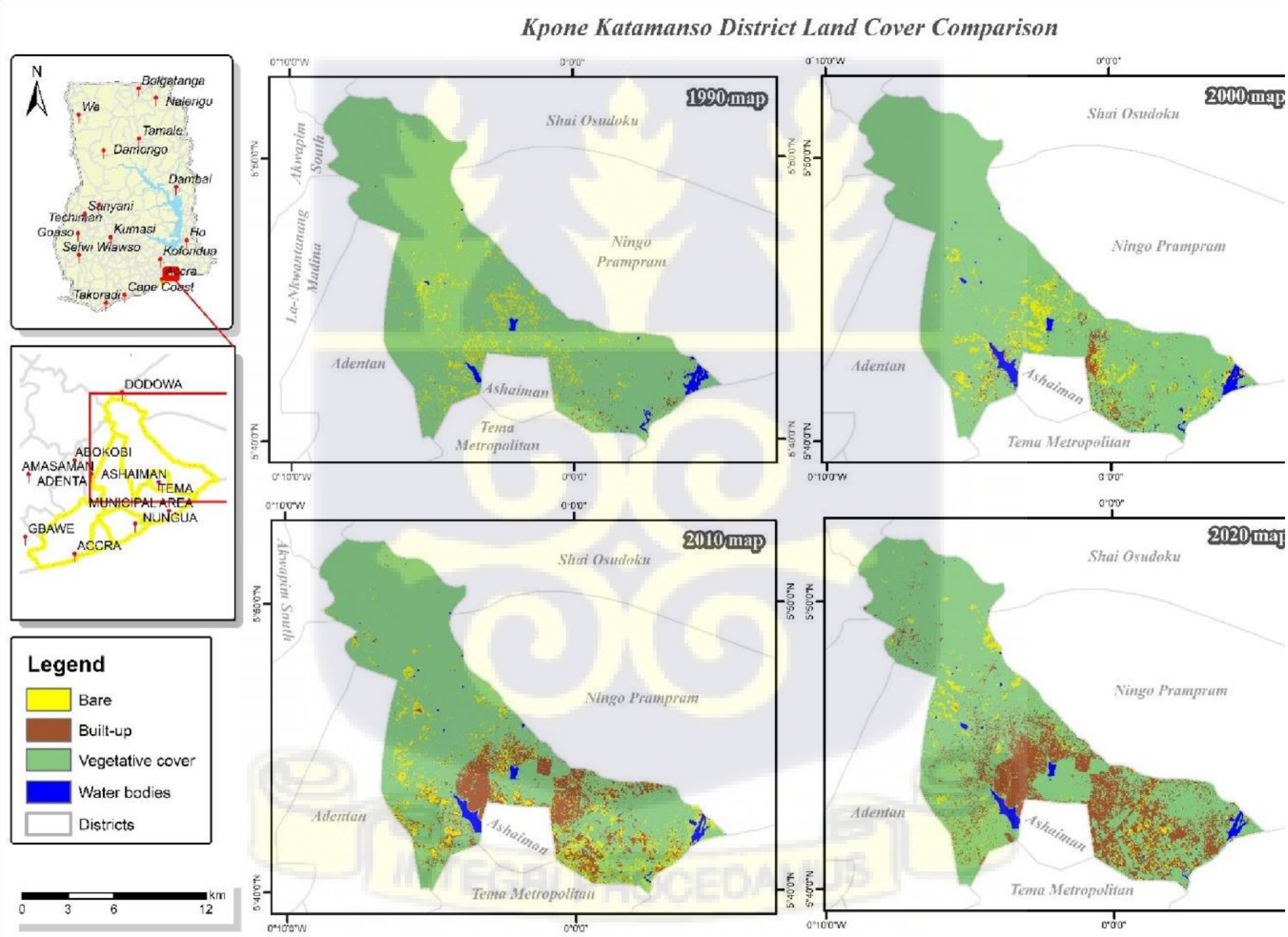


Figure 6: Changes in LULC classes in AshMA (1990-2020)

In KKDA, Figure 7, 8 and Table B2 (Appendix B), the vegetative class occupied the largest area – 20,058 ha (94%) - of the municipality in 1990. Though this land class remained the dominant land class until the year 2020, there was an appreciable decline in the area it covered in the district. Water bodies class constituted the least land cover type in 1990 at 290.7 ha (1%). However, in 2020, built-up area coverage had increased and occupied almost one-fifth of the land (4187.4 ha: 19.5%). The largest LULC in 1990, was reduced by some 3,888.73 ha over the 30 years. Though generally, water bodies were not prominent in KKDA, due to farming activities, construction of dams increased which also serve as reservoirs for domestic use (GSS, 2014), hence water bodies by the year



2020, covered about 2% (323.9 ha) of the area.

Figure 7: Classified maps for KKDA for 1990, 2000,2010 & 2020

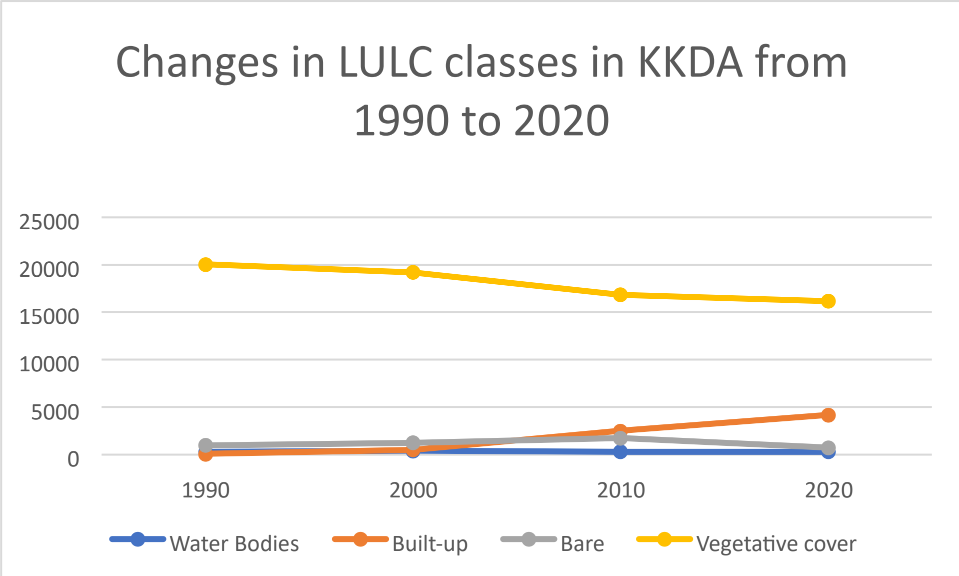


Figure 8: Changes in LULC classes in KKDA (1990-2020)

In 1990, the vegetative cover like in KKDA was the largest LULC class (Table B3, Appendix B) in the Adenta Municipality (Figures 9 & 10), it covered 92% (9057.8 ha). In the year 2020, about 49% of vegetative cover was converted to other land cover types in the municipality. Built-up areas became the largest LULC class in 2010 (4018.11 ha; 40.7%) and 2020 (4970.8 ha; 50.4%) in the municipality. Water surface remained a small part of AdMA but increased from (44.12 ha; 0.45%) in 1990 to (115.76 ha; 1.2%) in 2020. Bare lands in the municipality increased throughout the period, from occupying 0.05% (4.67ha) of the municipality to 5.4% (530.98ha) in 2020.

This land cover type increased by about 530.31ha (5.35%).

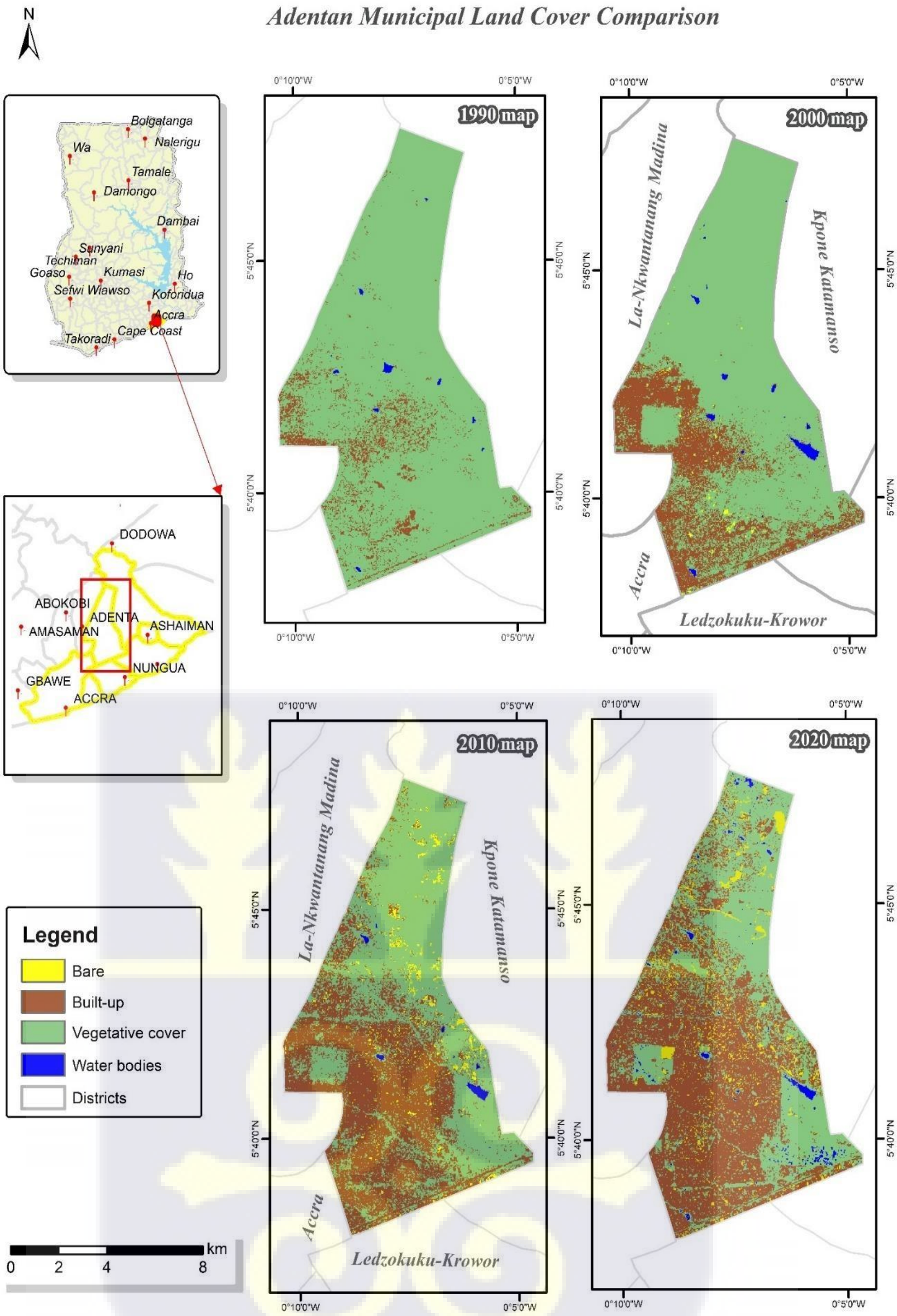


Figure 9: Classified maps for AdMA (1990-2020)

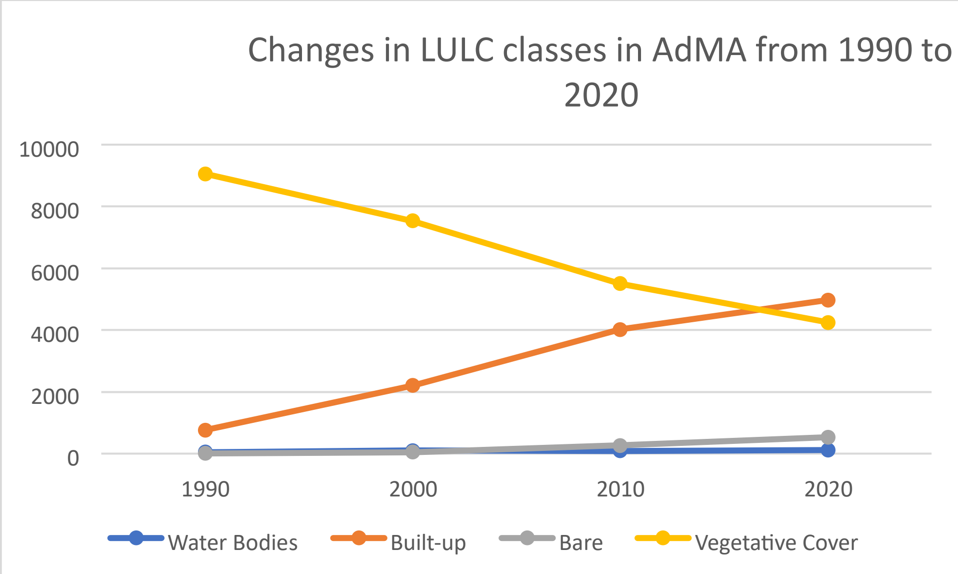


Figure 10: Changes in LULC classes in AdMA (1990-2020)

The built-up land class from 1990 to 2020 has remained the largest LULC type in AMA (Table B4; Appendix B). Initially, (refer to Figure 11 & 12), built-up areas constituted 48.7%, in 2010, it constituted 71.6% (10, 319.1 ha) of the total area of AMA. By 2020, though built-up spaces reduced in the metropolis it was still the largest land cover type in AMA. This reduction can be attributed to demolishing exercises which are rampant in the metropolitan area to remove illegal structures and unplanned settlements. Vegetation was the second largest cover from 1990 to 2020. The vegetative land cover was 37% (5313.2 ha) in 1990 and reduced to 27% and 22% in 2000 and 2010 respectively. There was an increase in this class of LULC in 2020. This can be a result of policies and projects on the greening of the capital city. Water bodies decreased in the metropolis from 902.5 ha (6%) to 340.6 ha (2%) from 1990 to 2020.

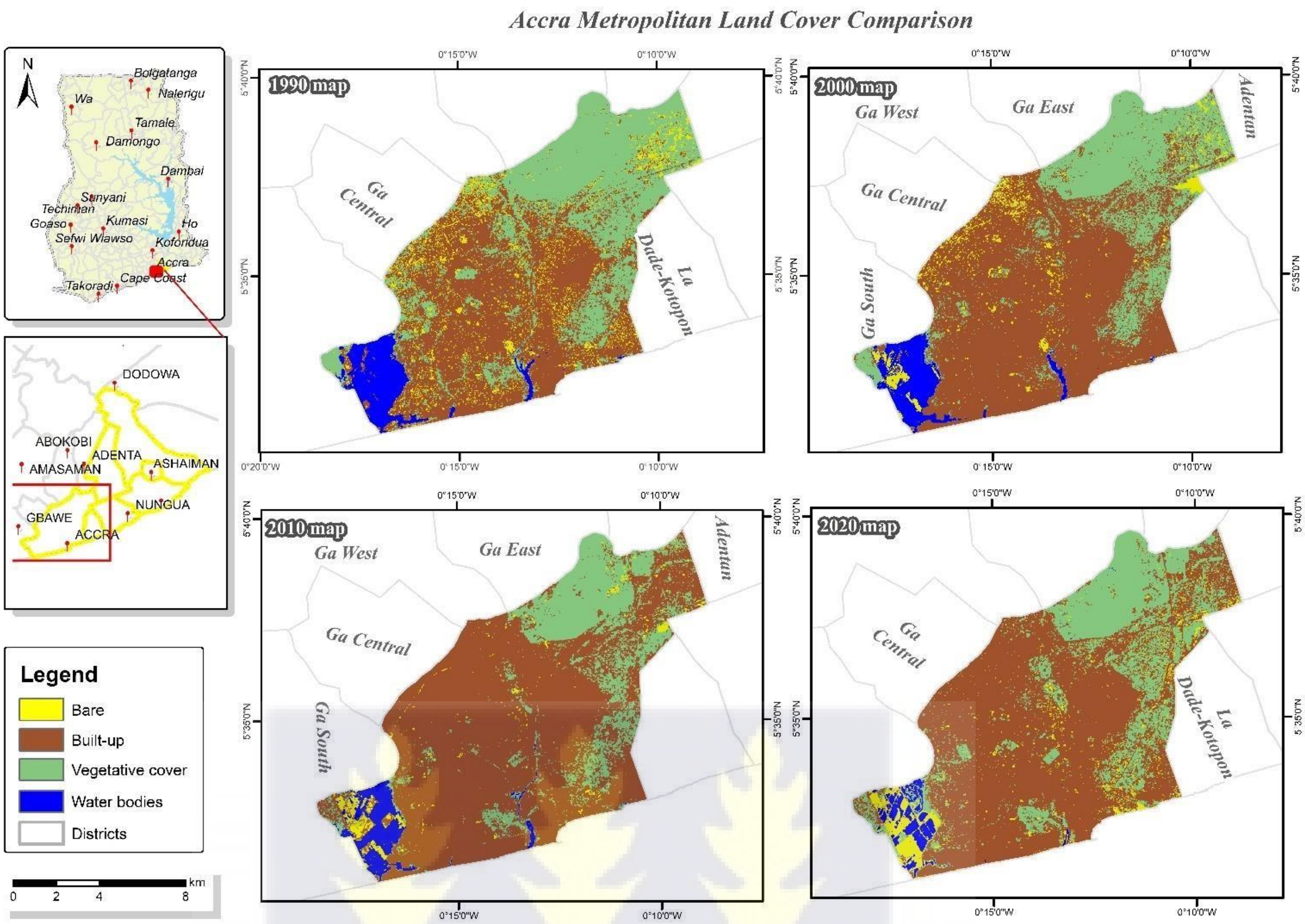


Figure 11: Classified maps for AMA (1990-2020)

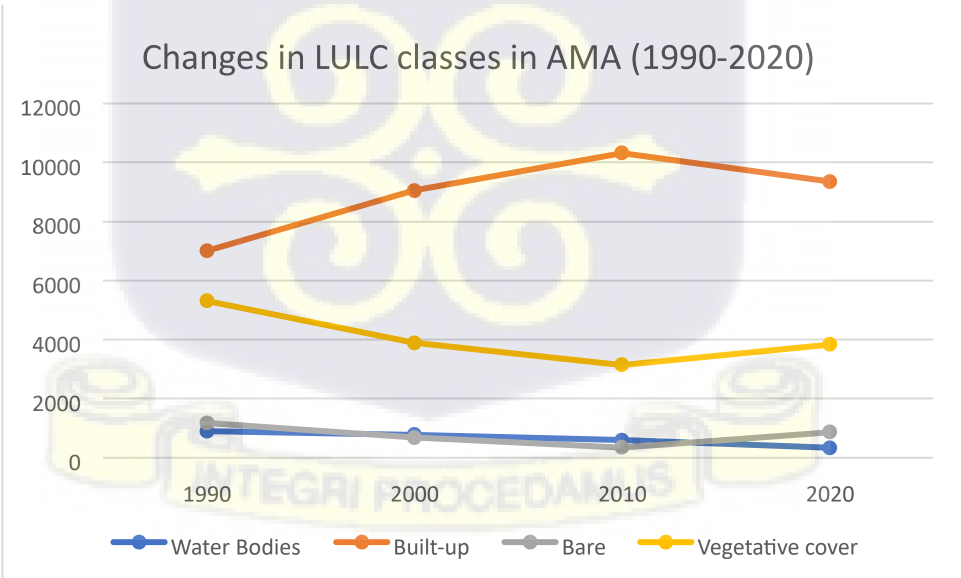


Figure 12: Changes in LULC classes in AMA (1990-2020)

In Tema, shown in Figures 13 and 14, the largest LULC in the year 2020 was built-up areas occupying 67.5% of the total area of the metropolis. This land cover class in the year 1990 occupied about a quarter (2186.51 ha: 25%) of the total area (Table B5, Appendix B). Vegetative cover occupied more than half (5828.07ha - 67%) of the land in 1990 in the Tema Metropolis. Built-up areas increased by some 3005.75 ha from 1990 to 2020. In 1990, built-up spaces in TMA occupied 2186.51ha (25%) but increased to 2186.51ha (25%) in 2020. Built-up areas were the largest land cover type in 2020, followed by vegetation, and water bodies remained the least landcover type throughout the 30 years.

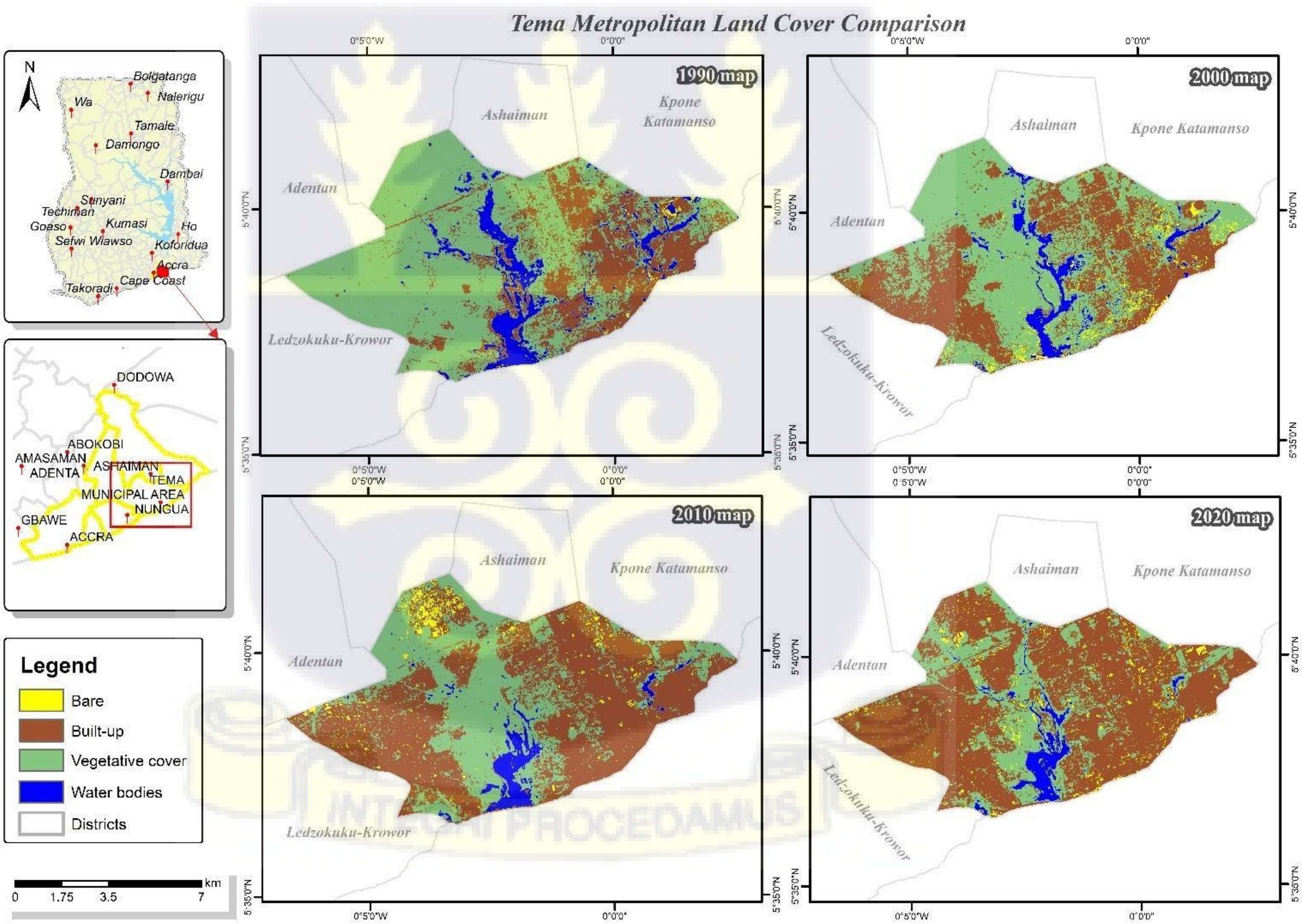


Figure 13: Classified maps for TMA (1990-2020)

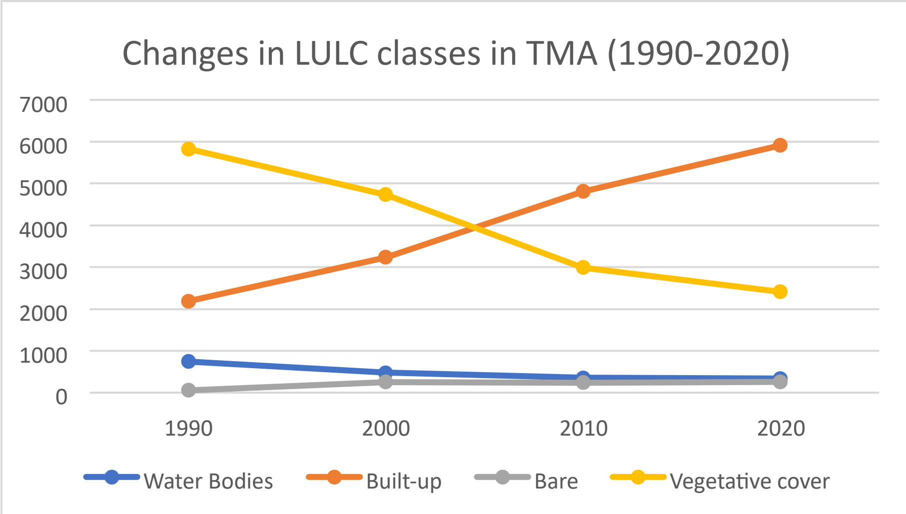


Figure 14: Changes in LULC classes in TMA (1990-2020)

In Table B6 (Appendix B) all shows the changes in LULC for LaDMA from 1990 to 2020. Vegetation (1457.95 ha, 60%) and built-up (797.38 ha, 32.8%) were the two largest LULC types in the year 1990 in the municipality. Water surface has remained the least LULC over the three decades. Built-up areas (1395.22 ha; 57.3%) in 2020, were the largest LULC type in LaDMA whilst vegetation reduced by 26% from 1990 to 2020. The built-up spaces from the year 2000 became the largest LULC type (1145.77 ha; 47.1%) and 2010 (1211.98 ha; 49.8%) after being the second largest in 1990 in this municipality. These trends are shown in Figures 15 and 16.

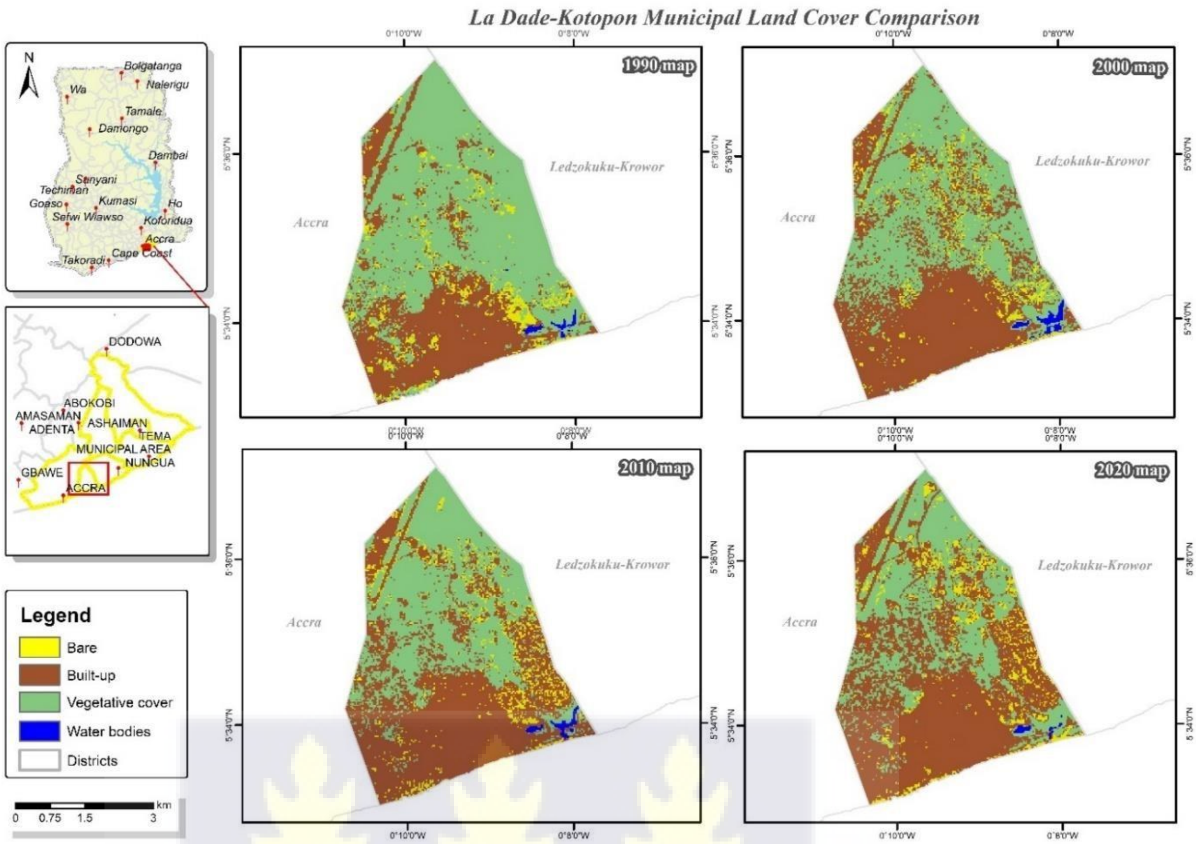


Figure 15: Classified maps for LaDMA (1990-2020)

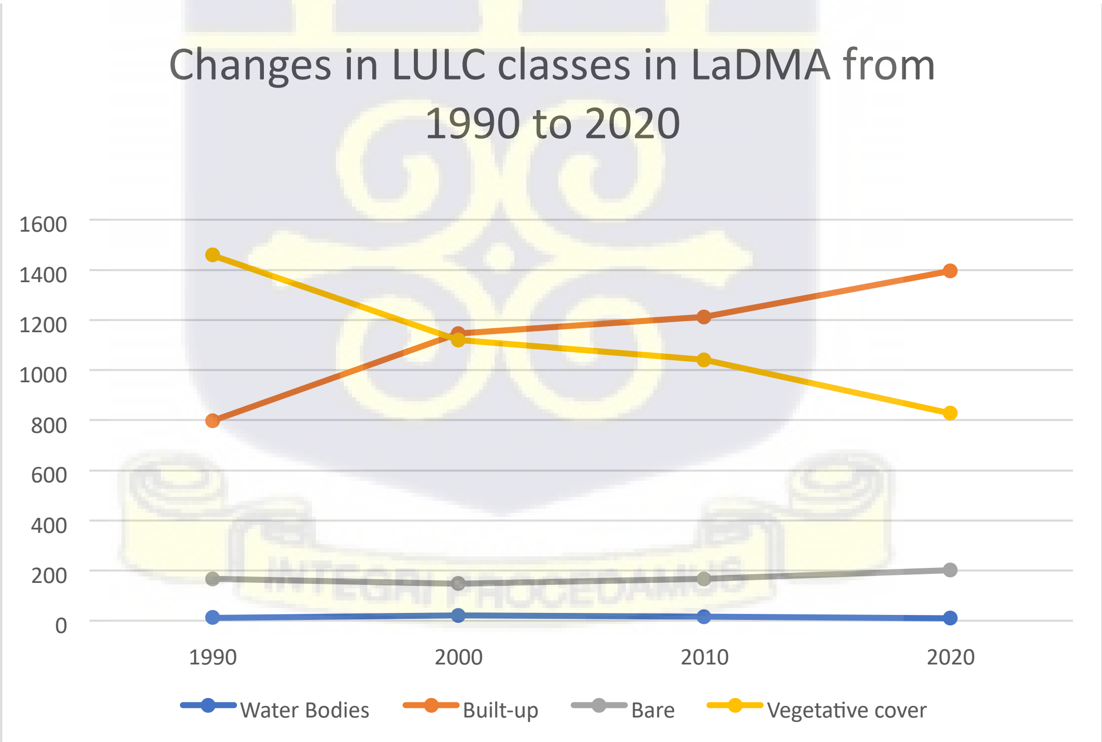


Figure 16: Changes in LULC classes in LaDMA (1990-2020)

The first largest and smallest land cover classes in 1990 in LeKMA (Table B7; Appendix B) were vegetation (4273.55ha; 76%) and water bodies (16.59 ha; 0.3%). In 2000 (2787.59ha; 49.5%) and 2010 (4243.36ha; 75.3%) built-up class constituted the largest LULC class. This means the municipality which is highly residential with various estates such as Devtraco, Manet, EMEFS, Teshie-Nungua estates among others, experienced massive developments during these times. LeKMA in 2020 has 70.3% of its land composed of built-up areas. Bare land class however in 2020 increased by 456.91 ha from 80.19 ha in 1990. Wetlands remain among the least land class in the municipality Figures 17 and 18.

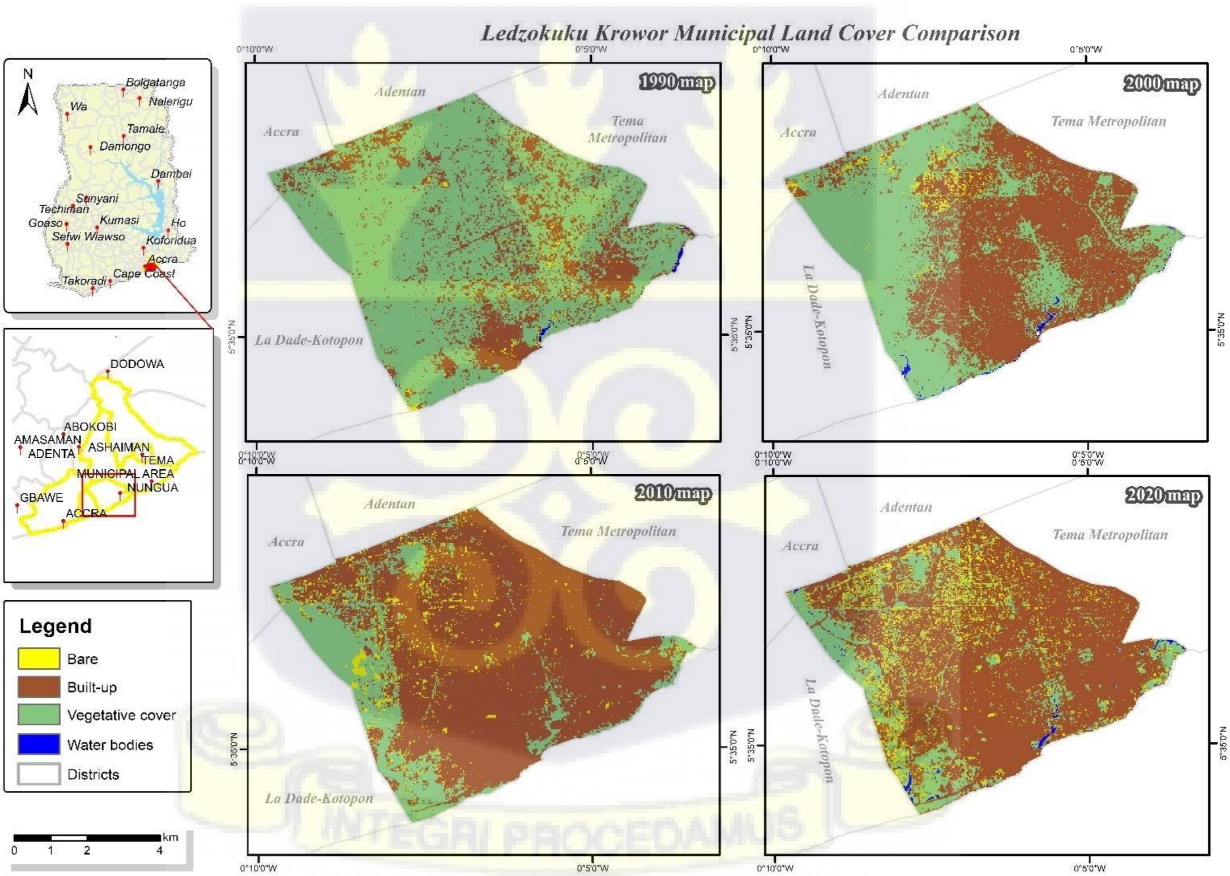


Figure 17: Classified maps for LeKMA (1990-2020)

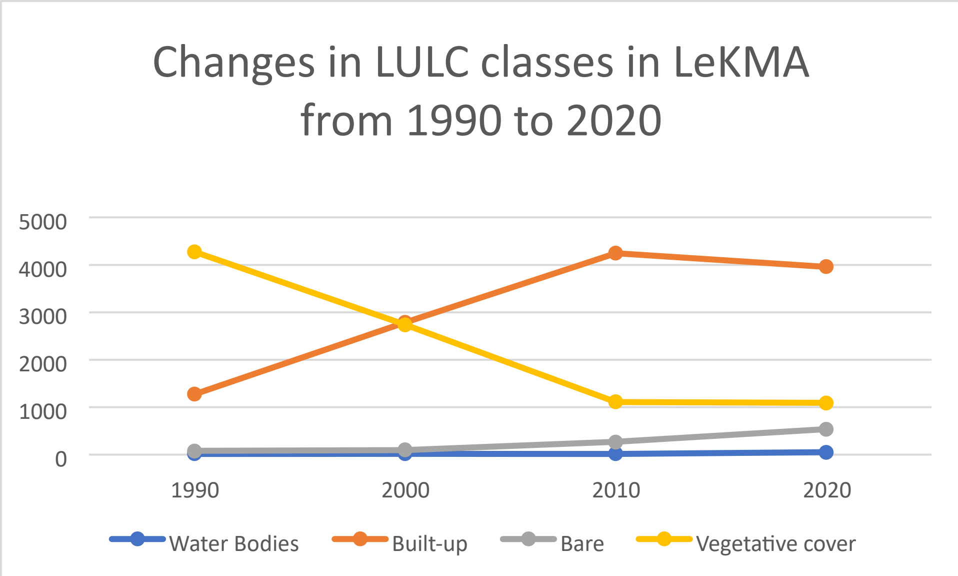


Figure 18: Changes in LULC classes in LeKMA (1990-2020)

In the GAMA, there is evidence of changes in LULC and the majority of land cover changes is the conversion of other classes to built-up. (Addae & Oppelt, 2019a). There are projections of continuous increase in coverage of built-up spaces in the light of urbanization of GAMA (Ackom et al., 2020; Akubia et al., 2020; Yeboah & Shaw, 2013). There is also evidence that the periphery of the metropolis is expanding especially towards the eastern and western directions (Akubia & Bruns, 2019). Danquah, 2013).

Again, contextually, the Ghanaian housing arena is not typically dominated by high-rise buildings (Asante & Ehwi, 2022) hence the increasing demand for land for accommodation purposes. Most housing units are not high rises hence they take more space consequently causing more use of land to accommodate the growing population. And in a bid to have a well-managed compound, paving of compounds surrounding homes becomes a norm. Meanwhile, increasing imperviousness increases the risk of floods (Szwagrzyk et. al., 2018). The acquisition of land and use is to a large extent unregulated as zoning and land use are not clearly defined in many parts of the country.

Individuals can acquire lands by buying directly from families or through inheritance or gifting. The decision on land use, therefore, becomes the individual's prerogative leading to noncompliance with planning regulations by the District Assemblies and Local Government. The weak inclusion of traditional authorities in land use planning makes land resource management quite a herculean task for the state in achieving the objective of an orderly physical development (Anane, 2021). Local actors are recommended to be integrated into urban flood management strategies (Abeka et al., 2020).

5.3 Classification Assessment Accuracy

The results of the confusion matrix for an unsupervised classification for the years 1990 to 2020 are presented in tables 14 and 15. The assessment accuracy metrics for the classification of LULC in this study from 1990-2020 are generally good. Kappa coefficients 0.92(1990), 0.89(2000), 0.87(2010) and 0.84(2020). These coefficients showed perfect agreement between the classified LULC types from the study and the ground true values. The overall accuracy was 95%, 92%, 91% and 89% (1990-2020) respectively. The overall accuracy metrics were all greater than 85% the acceptable level and standard of digital image classification (Ismail et al., 2009) . The user's and producer's accuracies were good. For water bodies for instance, both accuracies ranged between 88% to 100%. Which indicates a good classification though unsupervised. The accuracies however decreased for the latter years. The errors associated with the assessment were generally low. The highest error of commission 23% (2010 & 2020) but generally, errors of inclusion and exclusion were low.

Table 15Table 14: Accuracy metrics of LULC maps (1990 & 2000)

Accuracy metrics of the 1990 Landcover map

	Water bodies	Builtup	Bare	Vegetation	Total	Error of Commission	User's Accuracy
Water bodies	60	0	0	0	60	0%	100%
Built-up	0	30	7	1	38	21%	79%
Bare	0	0	20	0	20	0%	100%
Vegetation	1	0	2	89	92	3%	97%
Total	61	30	29	90	210		
Error of Omission	2%	0%	31%	1%			
Producer's Accuracy	98%	100%	69%	99%			
Overall Accuracy	95%						
Overall Kappa statistics	0.92						

Accuracy metrics of the 2000 Landcover map

	Water bodies	Built-up	Bare	Vegetation	Total	Error of Commission	User's Accuracy
Water bodies	56	0	0	1	57	2%	98%
Built-up	0	30	3	3	36	17%	83%
Bare	1	1	25	3	30	17%	83%
Vegetation	4	0	0	83	87	5%	95%
Total	61	31	28	90	210		
Error of Omission	8%	3%	11%	8%			
Producer's Accuracy	92%	97%	89%	92%			
Overall Accuracy	92%						
Overall Kappa statistics	0.89						

Table 16Table 15: Accuracy metrics of LULC maps (2010 & 2020)

Accuracy metrics of the 2010 Landcover map

	Water bodies	Builtup	Bare	Vegetation	Total	Error of Commission	User's Accuracy
Water bodies	50	0	1	0	51	2%	98%
Built-up	0	30	4	5	39	23%	77%
Bare	1	1	27	0	29	7%	93%
Vegetation	6	1	0	84	91	8%	92%
Total	57	32	32	89	210		
Error of Omission	12%	6%	16%	6%			
Producer's Accuracy	88%	94%	84%	94%			
Overall Accuracy	91%						
Overall Kappa statistics	0.87						

Accuracy metrics of the 2020 Landcover map

	Water bodies	Built-up	Bare	Vegetation	Total	Error of Commission	User's Accuracy
Water							
Built-up	2	30	2	5	39	23%	77%
Bare	1	0	26	0	27	4%	96%
Vegetation	11	0	2	83	96	14%	86%
Total	62	30	30	88	210		
Error of Omission	23%	0%	13%	6%			
Producer's Accuracy	77%	100%	87%	94%			
Overall Accuracy	89%						
Overall Kappa statistics	0.84						
bodies	48	0	0	0	48	0%	100%

A noticeable trend in the seven districts of GAMA was the decline in vegetative covers and increase in built-up spaces. Over the 30 years, population change caused GAMA to urbanize therefore demand for land for other uses caused observable changes in the various land cover types, particularly vegetations. In some districts such as LeKMA, AdMA and TMA where large parcels of land are used for residential purposes, particularly flats and estates, a decline in vegetation is observed after the 30-year period. Also, in AMA, LadMA and AshMA, where business activities are high, the presence of unskilled migrants is high (GSS, 2014). And this will cause the springing up of many informal settlements in the metropolis as most migrants are of lower socioeconomic statuses. These settlements, since they are informal may be in waterways, unplanned and are at the risk total or partial demolitions.

5.4 Population and Land Use Land Cover in GAMA

Population densities and different population growth rates produce different land use patterns and changes over time (Genet, 2020). There are rapid changes in LULC when the growth rate is high. Greater Accra according to the 2010 Population and Housing Census (PHC) recorded the highest growth rate of 3.1 % which was greater than the national annual intercensal growth rate of 2.5% (GSS, 2012). In Table 11 is displayed the population figures for the seven districts for the 2000 and 2010 PHC. However, projected 2020 figures are included. The population figures show that the population in all the districts show continuous growth.

Table 17Table 16: Population figures by districts for PHC in 2000 & 2010 and projected values for 2020 census

Districts	Population in 2000	Population in 2010	Population in 2020 (projected)***
AMA	1,658,937	1,665,086	2,099,174
AdMA	*	78,215	98,682
AshMA	150,312	190,972	240,841
KKDA	*	109,864	138,529
LaDMA	*	183,528	231,306
LeKMA	*	227,932	287,334
TMA	506,400	292,773	369,060

Source: 2000 and 2010 population censuses of Ghana by the Ghana Statistical Service.
***Projected figures for 2020 by Ghana Statistical service
*Unavailable population figures as those districts were not created at that time

A Pearson correlation analysis of LULC types and population at the time points (2010 and 2020) was done to explore the relationship that exists between them. The nexus between population and LULC cannot be overemphasized as there exists a relationship demonstrated statistically. The correlations generally were statistically insignificant. There was however a positive correlation between water bodies and population for both census figures. Some studies however have explored the relationship between population and water extensively beyond simple correlations. Some relationships investigated included proximity of human settlements to major rivers (Fang & Jawitz, 2019), population and water pollution (Chen et al., 2022; Kurochkina, 2020; Liyanage & Yamada, 2017), increasing population and water shortage (Boretti & Rosa, 2019) and depletion of surface water resources (Nayan et al., 2020; Tikader & Biswas, 2013). In all these studies, results showed that population growth which induces urbanization tends to increase the tendency of human settlements to move closer to water bodies in the urban centres, increasing pollution, reducing water quality and causing scarcity in clean water.

Table 18Table 17:A correlation between population and the LULC types in the GAMA, 2010 and 2020

LULC class	Correlation coefficient (r)	
	2010	2020
Water bodies	0.62	0.36
Vegetative cover	-0.18	-0.09
Built-up areas	0.86*	0.74
Bare	-0.15	0.57

*Correlation is significant at 0.05 (2-tailed test)

The vegetative cover and population though not statistically significant had negative relationships of -0.18 (2010) and -0.09 (2020). The increasing population connotes a decrease in vegetation in GAMA. This is in concordance with other studies that showed diminished vegetation with an increasing population (Zemba et al., 2013). However, this negative relationship between population and the vegetative cover was found to be not significant in other studies and was concluded as a localized occurrence (Cusicanqui et al., 2013). In a study to probe causality, vegetation cover changes due to population growth have proven to impact the population in the future time (Li et al., 2015).

Population had a strong positive correlation with built-up areas which was statistically significant for 2010 (0.86) at α of 0.05. The correlation though strongly positive was not significant for 2020 (0.74). Accommodation, roads, schools, hospitals and other infrastructural needs arise as the population increases, thus the increase in the area of built-up spaces. This relationship though may seem linear has complexities which according to Ehrlich et al., 2018 are two societal variables that need in-depth investigation in addressing climate hazard impact.

There existed a weak inverse relationship between population and bare lands in 2010 (-0.15) but a moderately positive relationship in 2020 (0.57). Bare lands in earlier years seemed to decrease with the increasing population. However, in 2020, bare lands seem to increase with the increasing population. This can be a result of clearing more parcels of land to make way for anthropogenic features and appeared as bare lands at the time of remote sensing data capture.

Human populations influence changes in LULC and can exacerbate degradation and natural disasters (Ansah et al., 2020). This happens as a result of humans settling in places not conducive to supporting human activities. The impacts of disasters are also great when the adaptive capacity and resilience of the population are weak. Population evolution effects are coupled with present ongoing activities to either increase or magnify the impacts of these natural disasters.

CHAPTER SIX

PREDICTORS OF FLOOD RISK

6.1 Introduction

This chapter explored the nexus of population dynamics, LULC changes and flood risk. The chapter commences with the description and presentation of the results of the expert judgment weighting which was part of the AHP and was used to develop the flood risk map and run the OLS regression.

Subsequently, the predictors of demographic and LULC which predict flood risk are presented and discussed. The relationships whether positive or negative associations with the outcome variable – flood risk in the multiple regression model are explained.

6.2 Expert Weighting

The Analytical Hierarchical Process is a multi-criteria decision-making technique applied in various fields. The measurement of flood risk in this study is obtained using this method. An expert judgement was used to obtain weights for variables for modelling flood risk in GAMA. The questionnaire (Appendix C; Table 1 & Table 2) yielded the following results: Table 16 and Table 17. In Table 10, experts were required to weight variables (indicators) giving weights between 1 and 10.

In Table 16, two experts weighted rainfall, slope, impervious surfaces and percentage of impervious surfaces 10. Expert 6 weighted all variables (indicators) below 5 whilst Expert 5 assigned weights between 8-10 to almost all variables (indicators) except for the population (0-14 years) and motorable roads.

Table 19Table 18: Experts weighting variables on a scale of one to ten

Variable	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
Rainfall	10	7	7	9	8	3
Slope	9	7	10	7	10	2
Impervious surfaces	5	7	10	7	10	2
Impervious surfaces (%)	5	6	10	8	10	2
Homebase human built up areas	5	6	8	8	9	3
Probability of HBASE	2	7	2	5	2	3
Population aged 0-14 year	8	7	8	4	10	3
Population aged 15-64 years	2	8	6	5	10	3
Population aged 65+ years	7	6	7	2	10	3
Male population	3	7	9	3	10	3
Population of females	8	8	3	8	9	2
Distance from water bodies	6	5	10	6	4	2
Roads	10	7	7	9	8	3

In Table 17, rainfall was rated as the most influential variable on flood risk by Expert 6 (60%) and Expert 4 (30%). Four out of six experts alluded 10% influence of distance of water bodies to flood risk. Expert 6 assigned no influence (0%) by the probability of human settlement, population (0-14, 15-64 and 65+) and motorable roads on flood risk. The population of people aged 65+ was generally rated with a low percentage influence on flood risk by all six experts. Meanwhile, studies have indicated that older people are more vulnerable to floods (S. Lee & Vink, 2015). In events of floods or other natural disasters, older people are more prone to injuries, death, post traumatic stress disorder, depression, those with disabilities are more exposed and the disruption of ongoing therapies (Bukvic et al., 2018; Greiner et al., 2016; Tomata et al., 2015; Aboagye, 2012).

Table 20Table 19: Experts rating of the percentage influence of variables on flood risk

Variable	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
Rainfall	9	13	4	30	10	60
Slope	10	5	7	10	8	5
Impervious surfaces	8	5	8	8	10	10
Impervious surfaces (%)	8	8	9	9	10	5
Homebase human built up areas	9	10	12	8	20	10
Probability of HBASE	7	5	7	5	5	0
Population aged 0-14 year	4	10	8	5	2	0
Population aged 15-64 years	10	10	9	2	5	0
Population aged 65+ years	4	4	4	5	5	0
Male population	8	10	8	1	5	0
Population of females	5	5	7	2	5	0
Distance from water bodies	8	10	7	10	10	10
Roads	10	5	10	5	5	0

6.3 Flood Risk

The flood risk map was obtained by weighting results from the experts' weighting (Table 15 & Table 16). These weights were used to calculate the relative weights of the elements of the criterion, and weights assigned to the various rasters in a suitability analysis in the software. Then, using a common scale, values in the raster were reclassified and overlaid to obtain the flood risk model. This step of the analysis and resultant models were executed for the year 2020. Flood risk was categorized as low, middle or high on a scale of 0 to 10. Where 0 implied the least flood risk and 10 the highest.

In Figure 7, showing the flood risk model for GAMA, most of the areas showed high flood risk. At the aggregate level of analyses, shown in Figures D1 and D2 (Appendix D). In Table 12, results showed that out of 64243.11ha, about 45 % of the land of GAMA (7 districts) is at medium risk of floods. Cumulatively, 87% of land in GAMA is faced with medium to high risk. The flood risk in GAMA is presented in Figure 7 and Table 18. GAMA showed a medium to high risk with 45.5% of the total area belonging to the medium flood risk category. This result indicates the flood risk in GAMA as of the year

2020. Most parts of the metropolis were at medium to high risk of floods and predictors of this risk are discussed in the ensuing section.

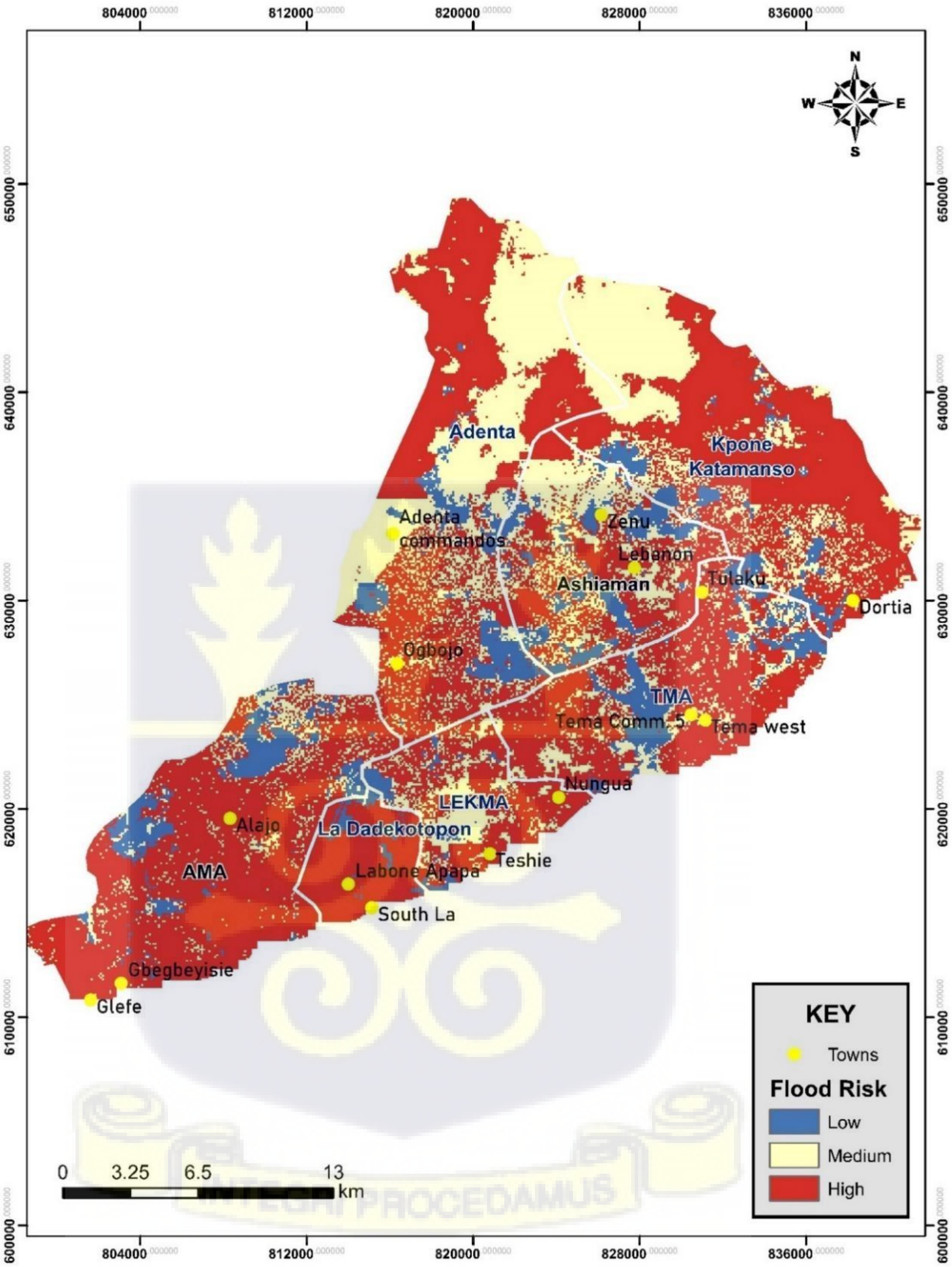


Figure 19: Flood risk map for GAMA (2020)

Table 21Table 20: Flood risk distribution in GAMA

Classification	Category	Area (ha)	% Area
0.00-4.00	Low risk	8594.55	12.3
4.10-6.00	Medium risk	31655.56	45.2
6.1-10.00	High risk	29774.88	42.5
TOTAL		70024.99	

In West Africa according to Ouikotan et al., (2017), flood events in most coastal cities are riverine, surges in the seas due to storms and high-water tables causing groundwater floods. Most urbanized cities in Africa have been classified as flood disaster risk hotspots (Baker, 2012). The risk of Africa to natural disasters particularly floods is being exacerbated by the vulnerability of the population; where there are higher proportions of poor people (Lucas, 2020). Poor planning of urban spaces, improper waste management and poorly constructed and maintained drainage systems (Dovie, 2020; Loudyi & Kantoush, 2020; Amoako & Inkoom, 2017; Danumah et al., 2016) which can be classified under LULC have also contributed to flooding risk in Africa.

The illustration (Figure 7) showed how GAMA like other coastal cities is at risk of floods. Flood risk management strategies in the subregion have been diverse and contextual. Interventions for flood risk management in can be grouped as structural, ecosystem-based, floodproofing, early warning systems and regulations on land use (Lucas, 2020; Twerefou et al., 2019; Ouikotan et al., 2017). The use of structures to manage flood risk includes embarkment, dikes, and improved and well-constructed drainage systems. Planting mangroves, zoning and maintenance of vegetation in floodprone areas especially are some ecosystem-based interventions. Building new structures on stilts to raise them above the heights of floods is referred to as floodproofing.

Early warning systems have been developed in some communities globally to reduce the impact of floods. These systems are diverse and come in forms such as the creation of apps, automated phone calls, text messaging and indigenous knowledge (Cools et al., 2016). Flood early warning systems have proved useful to communities at risk but with challenges regarding their efficiencies especially in resource Participation of community members to develop systems from local technologies and history are recommended to improve the efficiency (Abudu Kasei et al., 2019; Cools et al., 2016). Other studies found gaps in the implementation and monitoring of flood early warning systems in the sub-region (Almoradie et al., 2020) where most of these strategies are considered by the populace to be governmental responsibilities (Seifert Dähnn, 2018).

Flood risk management is multi-faceted, it requires expertise, knowledge, funds, implementation and monitoring. Research outputs are a necessity for a successful outcome of mitigation of flood risk in GAMA. However, a well communicated finding coupled with good institutional structures is important for good outcomes (Dovie, 2017). Other necessary strategies include early warning system creation including community members (Kasei et al., 2019), improvement of infrastructure (Ouikotan et al., 2017), awareness creation on flood risk and implementation of certain policies to prevent human activities in some parts of GAMA (Wagner et al., 2021).

6.4 Ordinary Least Square (OLS) Regression Model

An Ordinary Least Square Regression (OLS) model was constructed aimed at identifying the predictors of flood risk in GAMA. The multiple OLS regression model yielded the following results Table 18 and Equation 12. In forward-step regression analyses, all variables in the final iteration of the model were significant.

Model diagnostics

Statistically significant p-values are indicated by an asterisk next to the number. The VIFs (Table D1-Appendix D) were less than 7.5 and therefore multicollinearity is not present in the final model. The explanatory variables explain about 49% of flood risk in GAMA based on the adjusted R squared value.

OLS Model

There exists an inverse relationship between flood risk and the slope/elevation, level of education, and distance from water bodies. This means that, as these variables decrease, the risk of flood increases. Population, built-up areas, rainfall and impervious surfaces have direct relationships with flood risk. As these variables increase, the risk of floods will increase.

A unit increase in population means that flood risk will increase by 7.8×10^{-5}. Results also show that, when rainfall increases by 1mm, built-up area by 30m*30m and impervious surfaces by 30m*30m, then flood risk is increased by 7.03, 0.10 and 1.7×10^{-3} respectively. Similarly, variables with inverse relationship slope/elevation (metres), education and distance from water bodies (metres) whilst decreasing by 0.05, 0.40 and 41.13 respectively, increase flood risk in the GAMA.

Table 22 Table 21: The OLS regression of flood risk in GAMA,

Variable	Coefficient	Std Error	t-statistic	Probability	Robust _SE	Robust _t	RobustPr	VIF
Intercept	-17.06	1.72	-9.93	< 0.001*	1.90	-8.97	< 0.001*	
Population	7.8*10^-5	0.00	33.35	< 0.001*	0.00	38.66	< 0.001*	1.34
Slope	-0.05	0.00	-43.06	< 0.001*	0.00	-27.70	< 0.001*	1.13
Rainfall	7.03	0.16	43.97	< 0.001*	0.17	40.10	< 0.001*	1.66
Built-up	0.10	0.01	11.30	< 0.001*	0.00	10.21	<0.001*	2.76
Impervious surfaces	1.7*10^-3	0.00	26.03	< 0.001*	0.00	22.81	<0.001*	2.54
Income	-0.40	0.02	-18.61	< 0.001*	0.02	-16.62	<0.001*	2.03
water body (proximity)	-41.13	0.37	-111.72	<0.001*	0.47	-86.63	<0.001*	1.09

$$flood\ risk = \beta_o + (\beta_1)population + (\beta_2)slope + (\beta_3)rainfall + (\beta_4)builtup + (\beta_5)impervious\_surface + (\beta_6)education + (\beta_7)distwaterbody + \varepsilon$$

$$flood\ risk = \beta_o + (7.8 \times 10^{-5})\ population - (0.05)\ slope + (7.03)\ rainfall + (0.10)\ builtup + (1.7 \times 10^{-3})\ impervious\_surface - (0.40)\ education - (41.13)\ distwaterbody + \varepsilon$$

... Equation 13

6.5 Nexus of population dynamics, LULC and Flood Risk

The resultant model is in concordance with literature on flood risk. Population growth is a driving force of urbanization and land use (Cirella et al., 2019) and is associated with floods. The growth of population affects land use such that there is an increase in demand for amenities (housing, schools, hospitals, roads, etc.), which causes changes in LULC. As discussed in the conceptual framework, non-climatic drivers influence non-climatic factors to affect flood risk. Clearly, the population was a positive predictor of flood risk in GAMA. Human settlements (built-up) and their proximity to water sources have been found to predict the risk of floods. This is in concordance with

Füssel & Klein, (2006) assertion that non-climatic factors are driven by human factors to predict floods.

Vulnerability to flood risk is a combination of several factors of which the majority are attributes of the population under study. In this study, the population was categorized into three main groups: 0 to 14 years, 15 to 64 years and 65 years and above. However, due to multicollinearity, these variables were combined as one. Studies have shown age differentials and vulnerability to floods; those populations less than 15 years and older than 65 years were the most vulnerable to floods (Al-Rousan et al., 2015; de Sherbinin & Bardy, 2015). Also, poverty has been shown to worsen one's vulnerability and recovery from floods. Poverty is a barrier to development, magnifies vulnerability and serves as a non-discriminatory agent with respect to floods (Rentschler & Salhab, 2020; Erman et al., 2019; Dube et al., 2018). Poorer households tend to lose assets they are unable to replace quickly due to their financial circumstances.

Another factor associated positively to flood risk is poor planning of urban spaces in general (Rogger et al., 2017). In most developing countries, LULC changes are uncontrolled due to factors such as population growth (Addae & Oppelt, 2019b; Petrisor, 2016), poor planning of cities and lack of and poor drainage systems (Addae & Oppelt, 2019b). Attributes of poor planning of urban spaces include indiscriminate built-up spaces. These built-up spaces are fraught with several issues such as excessive paving of surroundings, structures being haphazard and not allowing for drains and encroachment on wetlands or green spaces. All these factors from the model (Table 19) are associated with flood risk and are similar to other studies (Koranteng et al., 2020)

Other determinants of floods include climatic occurrences of which intense rainfall has been studied to directly affect floods in most parts of Africa (Panthou et al., 2014; Tschakert et al., 2010). There are studies showing changes in rainfall patterns over the years globally. Rainfalls causing floods have either been shorter days heavy downpours or cumulative downpours over several days (Ansah et al., 2020) and in other places heavy cumulative rainfalls (Brown et al., 2020). The predictability of the weather has lessened, and rains have become heavier and more uncertain (Olorunfemi, 2011). All these have been reported to be associated with floods combined with other anthropogenic factors.

Most coastal cities have rivers and water bodies as these feed into the sea. And because GAMA is growing at a fast rate, people tend to live closer to some of these water bodies. This tends to increase the risk of flooding as these water bodies overflow their banks. Intricately linked to the variable proximity to water bodies is the elevation of land (slope). Most districts studied are low-lying as well as have several water bodies. AdMA for example lies in the valley of Aburi (a town in the mountains) with about three major rivers. Run-offs are therefore common and affect most households thereby contributing to flood hazards in the area.

Referring to the theory of the vicious cycle by Petrişor et al., (2016), GAMA will require rigorous enforcement of policies on land use especially to effectively manage flood risk in the metropolis. It is evident in this work that a vicious cycle is in motion as population increase is propelling an increase in land use and land cover alterations which is increasing the risk of floods in the metropolis. Population, geographical constraints, developmental urbanization, and governance have been identified as crucial determinants which influence land use and subsequent flood risk (Ahamed & Anilkumar, 2022). Hence, a holistic approach to flood risk management is required in Ghana using an integrated approach. Effective flood risk management involves incorporating both **structural** and **non-structural measures** (Lucas, 2020). Structural measures include building physical infrastructure to control floods and reduce their impact. Non-structural measures focus on reducing population vulnerability through poverty alleviation, implementing land use and land cover (LULC) policies, and providing early warning systems. For these efforts to succeed, strategic plans by governments and city authorities must be robust, supported by rigorous research, public dialogue, and education. Continuous evaluation of these action plans is essential to ensure their effectiveness and adaptability. (Egbinola et al., 2017). Policies on the insurance of properties against flood risk can also be used as a measure to reduce its impact on the population and their resources (Sarmiento & Miller, 2006; Seifert-Dähnn, 2018; Surminski & Thieken, 2017). Regulations on land use have been developed in some countries to curb the indiscriminate use of land. In Ghana, a Land ACT (2020) has been developed to improve LULC challenges of the past and future. Rain et al., 2011 also developed a GIS-based flood management approach, where flood risk is determined for properties using satellite data and flood return data.

CHAPTER SEVEN

FLOOD RISK FORECASTING IN GAMA

7.1 Introduction

In the concluding part of this study, chapter seven is the final analytical chapter. Based on the significant predictors, flood risk is forecasted for GAMA. The flood risk forecasts were executed under three scenarios - trend, liberalization, and self-sufficiency for the years: 2030, 2040 and 2050.

Comparisons for the forecasts at GAMA and the district levels reveal the similarities and differences under each scenario for the respective years.

7.2 Flood Risk Forecasting

Flood risk is predicted for the year 2030 in the GAMA categorized as low, medium or high risk under three main scenarios. The trend (business-as-usual), liberalization and self-sufficiency scenarios were created using the projected population, LULC and weights from the expert judgment. The resulting models (maps) are shown in Figures 8, 9 and 10.

7.3 Flood risk forecast in GAMA

In the next three sections, results for flood disaster risk for GAMA under the three scenarios- trend, liberalization and self-sufficiency are presented and discussed. The similarities and differences in risk for the years 2030, 2040 and 2050 in the seven districts of GAMA are analyzed.

7.3.1 Flood risk forecast in GAMA for the trend scenario

In Figure 8 below, showing the flood risk map for GAMA in 2030 under the trend scenario, it is notable that, the majority of the areas have medium to high risk. The fringes of AdMA and KKDA will have a high flood risk. In Table 20, it is notable that, about 73% of GAMA lands were within the medium flood risk category under the trend scenario in 2030. KKDA and AdMA were the districts with most areas within the high flood risk category. Only 11% of GAMA is likely to experience low flood risk in 2030 under this scenario.

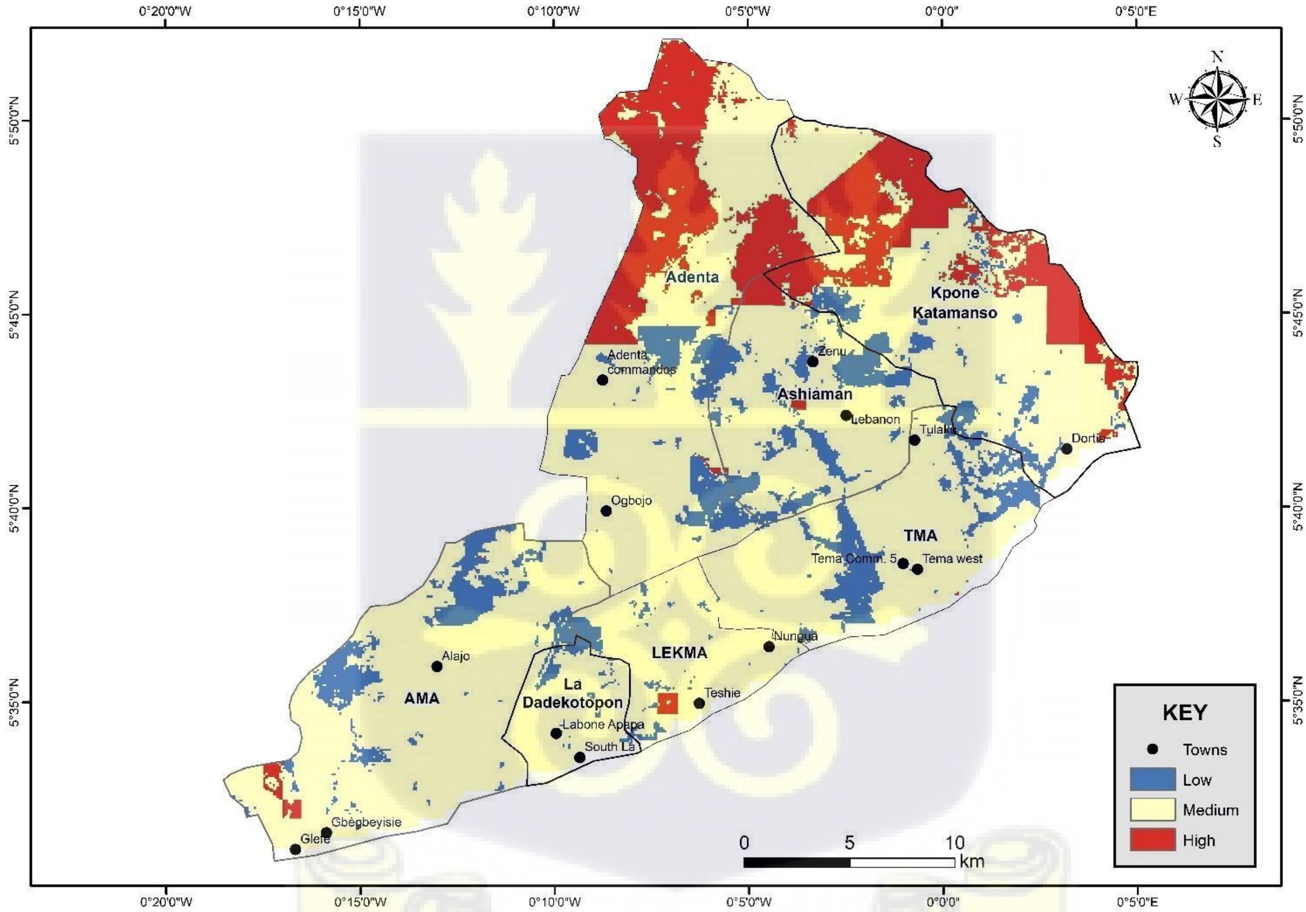


Figure 20: A model of flood risk in 2030 of GAMA under the trend scenario

The risk of flood in 2040 under the trend scenario is generally medium to high risk. Most areas under this scenario are at risk of medium to high risk. Compared to the high risk of 2030, the area of high risk in 2040 reduced to 31%. However, medium flood risk is the most likely to be experienced in GAMA as it covers more than half the area.

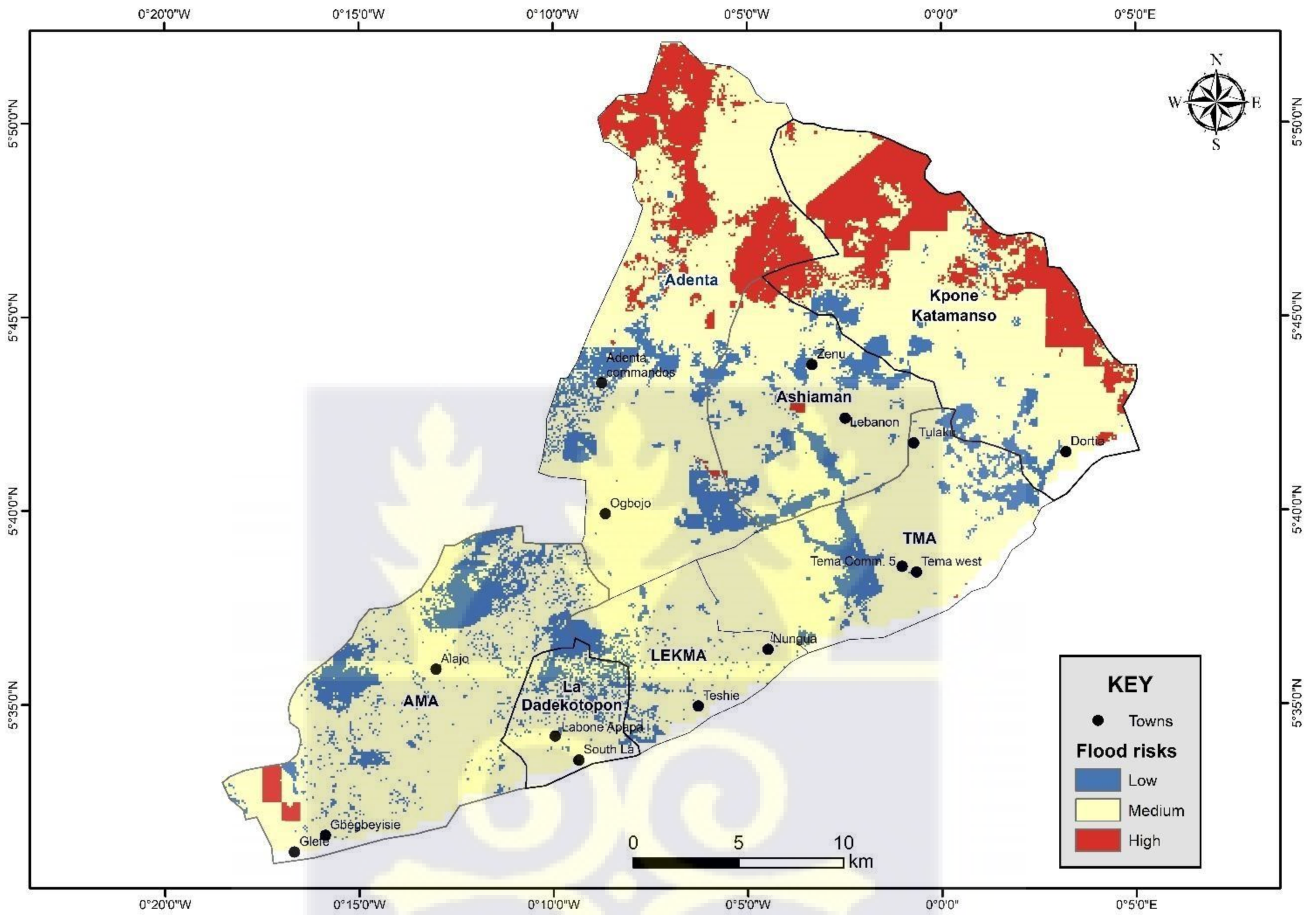


Figure 21: A model of flood risk in 2040 of GAMA under the trend scenario

Similarly in 2050, like the previous years, medium to high flood risk is widespread. Only 12% (Table 22) of the land area will experience a low risk in 2050. Cumulatively, 88% of GAMA is prone to medium to high flood risk in 2050. These categories of risks are not localized but widespread throughout the metropolitan area

(Figure 22).

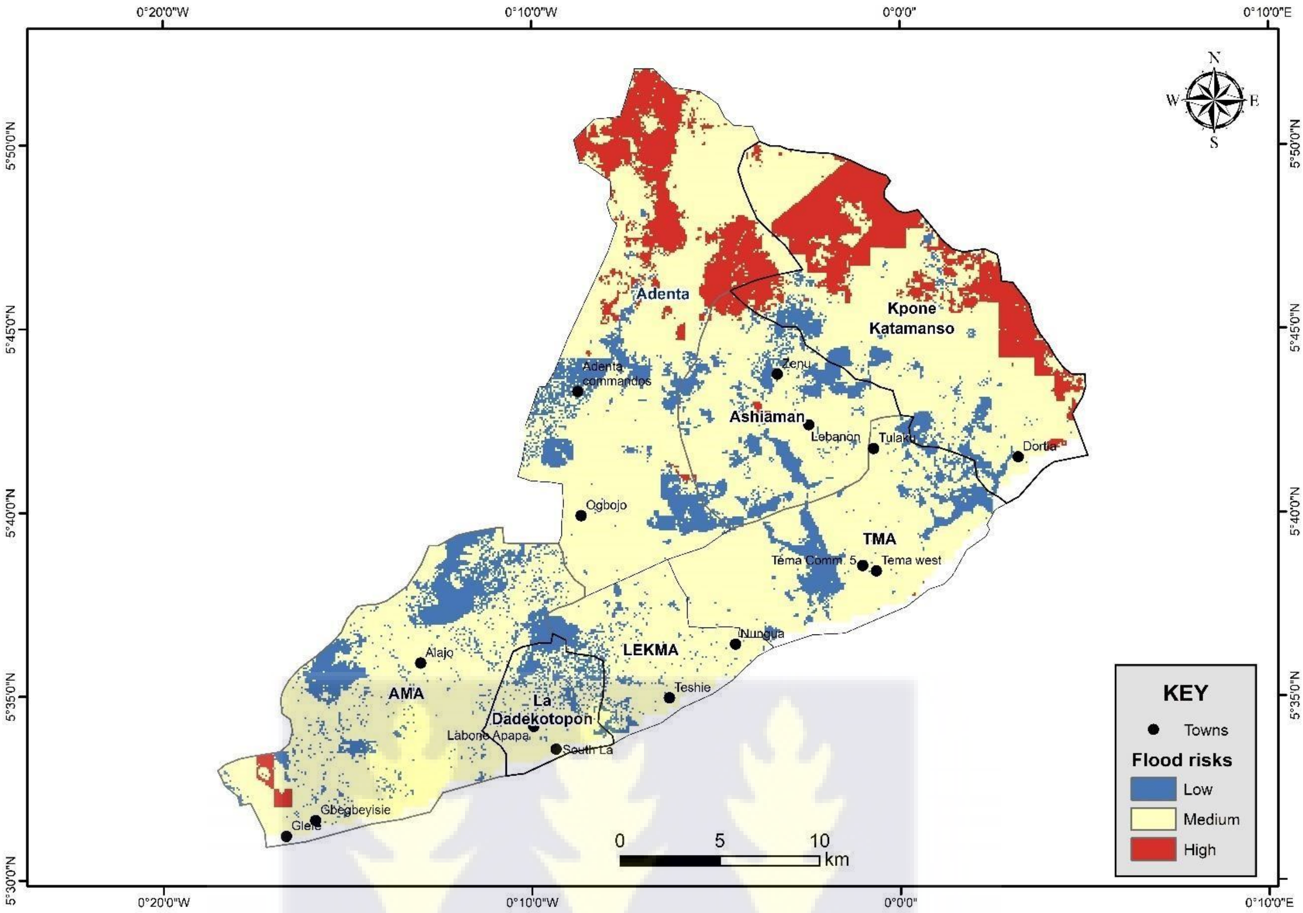


Figure 22: A model of flood risk in 2050 of GAMA under the trend scenario

Table 20 shows the area in hectares and percentage of flood risk categories under the trend scenario for the years 2030, 2040 & 2050. This table quantifies the visuals of the figures (Figures 8-10) above. The results for this scenario for the three time points indicated that flood risk will generally be medium to high. More than half of the GAMA lands in 2030, 2040 and 2050 will be prone to medium flood risk.

Table 23Table 22: Areas in hectares and percentage of flood risk categories under the trend scenario for the years 2030, 2040 & 2050

Classification	Category	Area in hectares (2030)	%	Area in hectares (2040)	%	Area in hectares (2050)	%
0.00-4.00	Low	8531.73	11	7238.16	9	8929.44	12
4.10-6.00	Medium	53312.58	73	45236.07	59	44748.45	63
6.1-10.00	High	10368.81	16	23826.96	31	17802.18	25

7.3.2 Flood risk forecast in GAMA for the liberalization scenario

Under this scenario, with its assumptions (Table 4), the medium flood risk is pervasive in GAMA (Figure 11). In Figure 11, high flood risk regions were mainly found closer to the boundaries of AMA, TMA, KKDA and AdMA. In Table 21, about 79%of the total area in hectares is likely to experience medium flood risk in GAMA, the low flood risk areas formed 9% under the liberalization scenario forecasted for 2030. In 2030 from figure 23, low to medium flood risk is likely along the coast of GAMA.

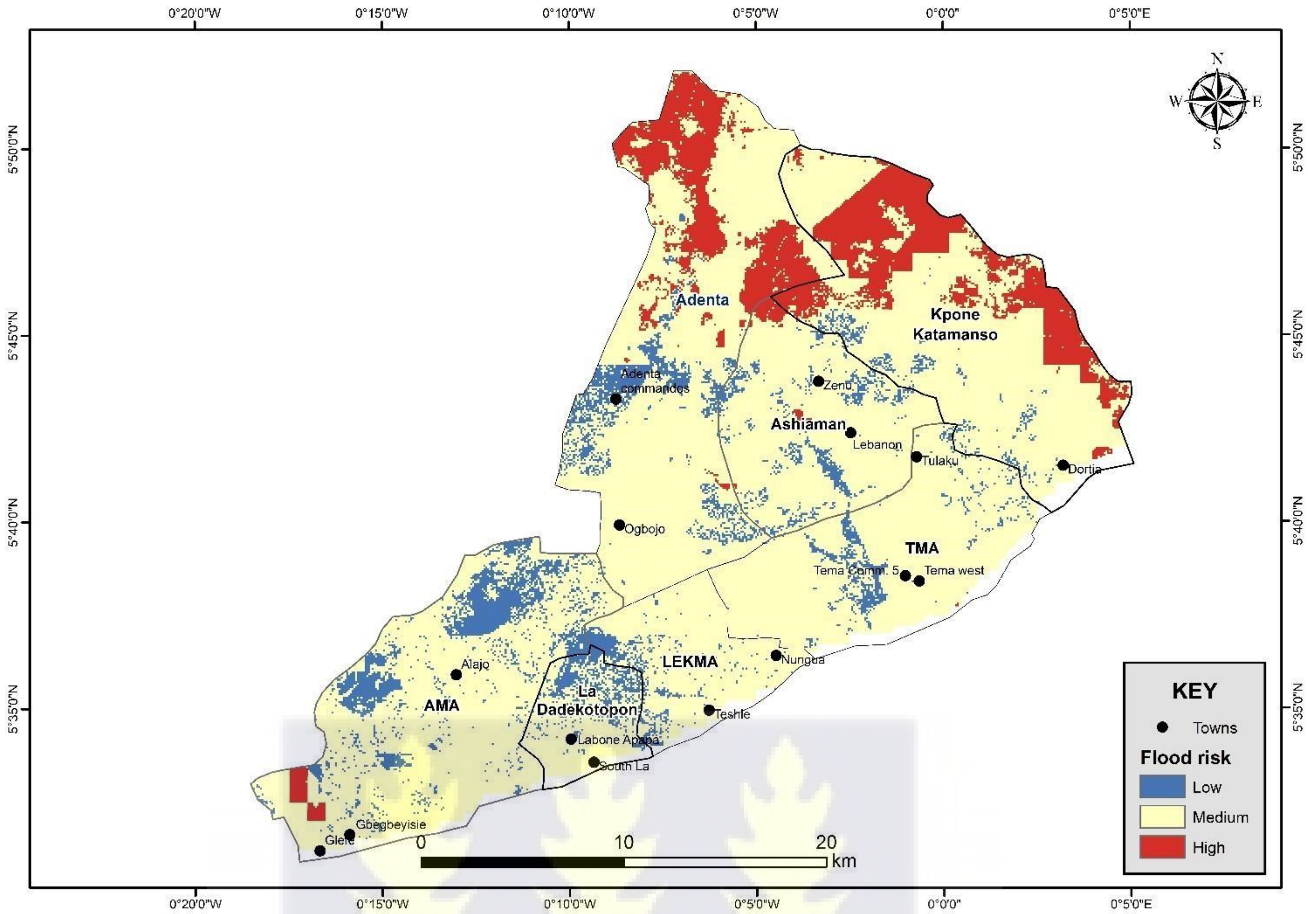


Figure 23: A model of flood risk in 2030 of GAMA under the liberalization scenario

In Figure 12 and Figure 13, the model showed under the both the liberalization and self-sufficiency scenarios pervasive medium to high flood risk in GAMA. Under the liberalization scenario both low and high flood risk are likely to cover some 15% each of GAMA in 2040. In figure 24, the boundaries of AdMA and KKDA are more likely to experience high flood risk under this scenario in 2040.

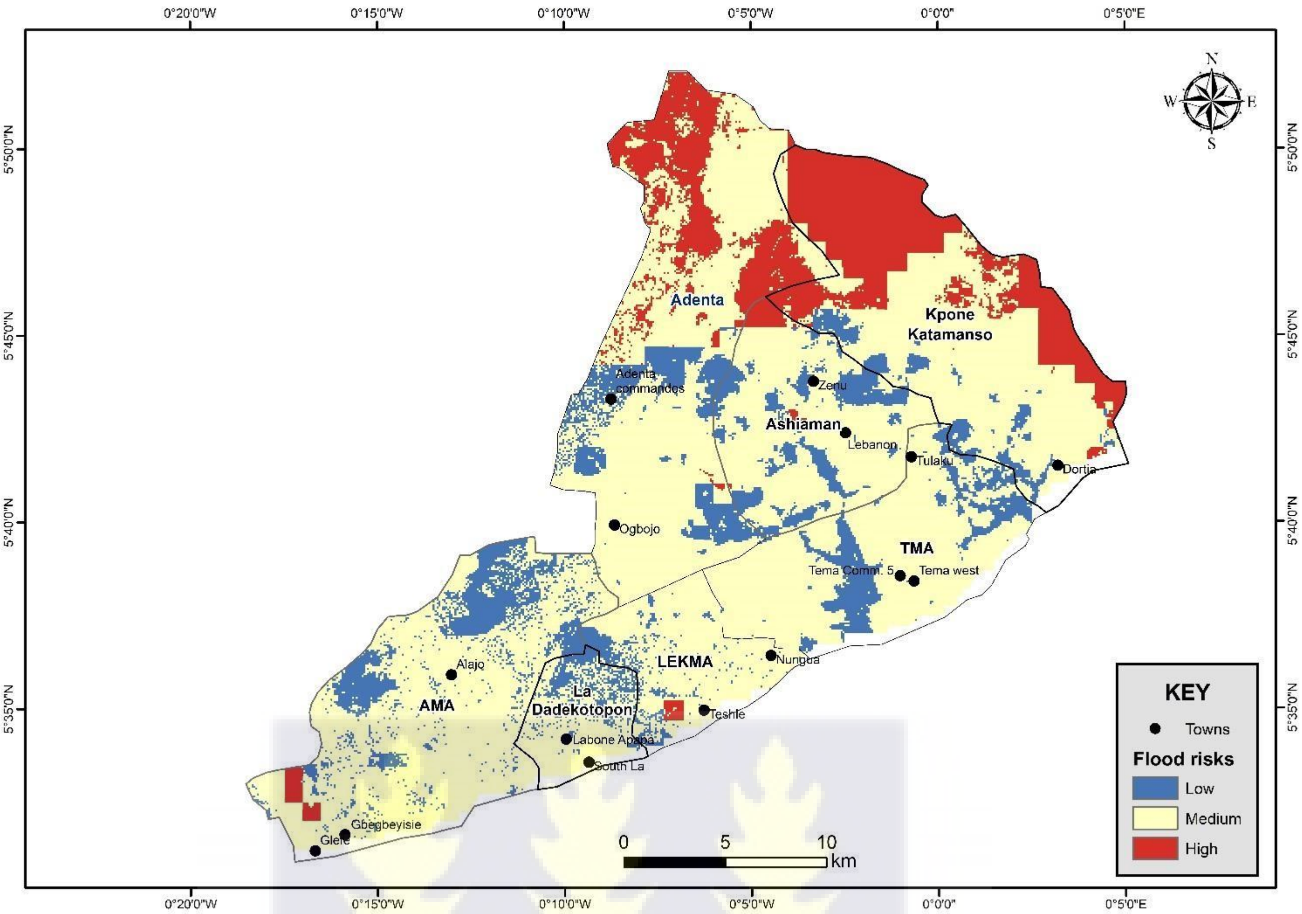


Figure 24: Flood risk model in 2040 of GAMA under the liberalization scenario

In 2050 under the liberalization scenario, many districts will experience medium flood risk. The relatively new settlement districts, which is AdMA and KKDA, however, show high flood risk. The risk of floods projected for this year however is low for older settlements such as LeKMA, AMA and LaDMA. There will be low to medium flood risk generally in AshMA and TMA. However, for the three years of forecast (2030, 2040, 2050), 2050 has the highest likelihood of a medium flood risk. There is also the equal likelihood of both low and high flood risk in this year for this scenario.

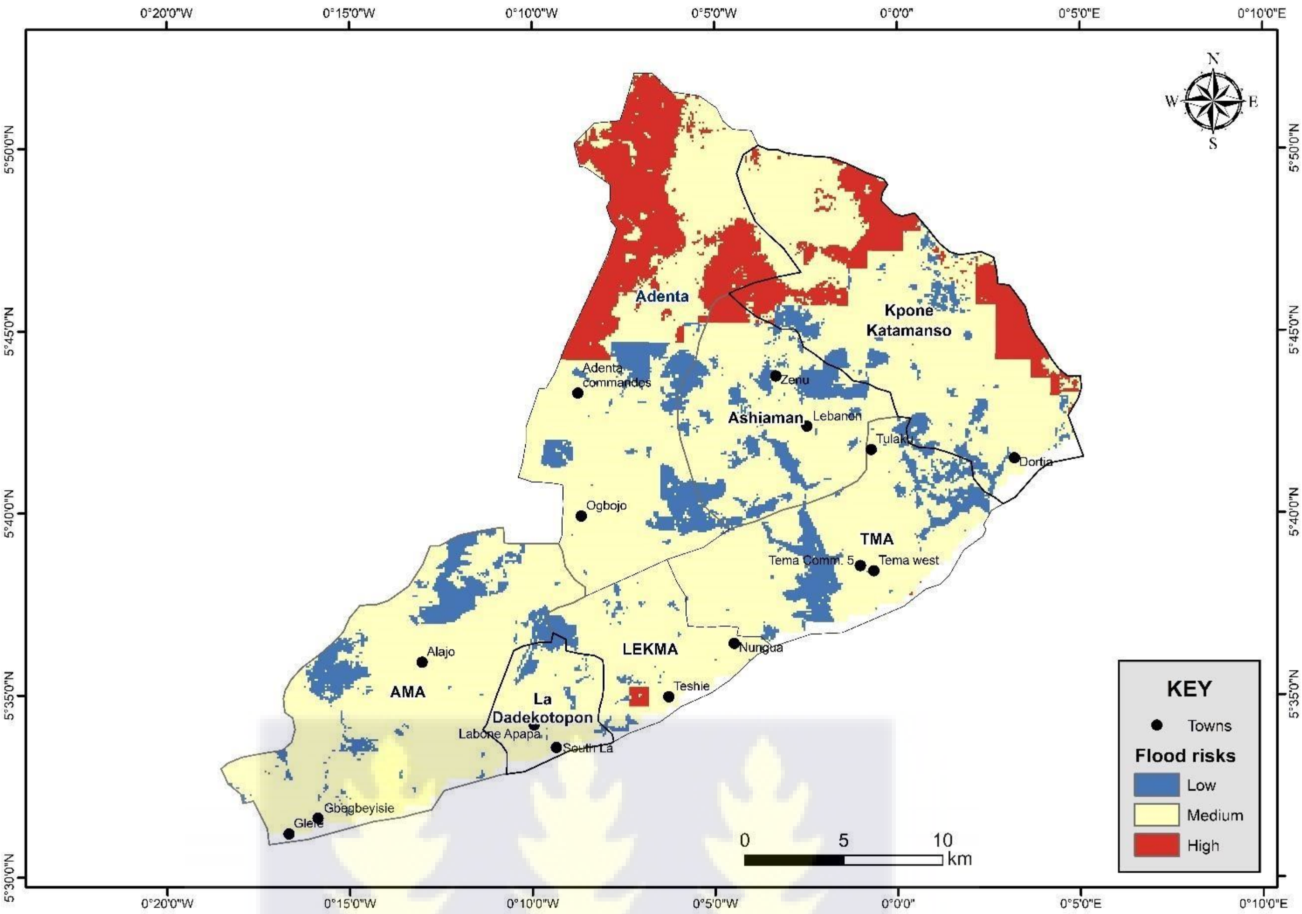


Figure 25: Flood risk model in 2050 of GAMA under the liberalization scenario

Table 24Table 23: Areas in hectares of flood risk categories under the liberalization scenario for the years 2030, 2040 & 2050

Classification	Category	Area in hectares (2030)	%	Area in hectares (2040)	%	Area in hectares (2050)	%
0.00-4.00	Low	6872.04	9	10721.97	15	8739.09	12
4.10-6.00	Medium	56996.46	79	50929.56	70	55030.59	76
6.1-10.00	High	8344.62	12	10561.59	15	8443.44	12

7.3.3 Flood risk forecast in GAMA for the self-sufficiency scenario

Figure 14 shows the model of flood risk under the third scenario. This model showed that in 2030 under the self-sufficiency scenario, low to medium flood risk is likely. Most areas in AMA, AdMA, AshMA and KKDA have a widespread low flood risk. The medium risk was mainly found in TMA whilst medium to high flood risk is pervasive in LaDMA, LeKMA and KKDA.

In Table 24, cumulatively, a majority (78.3%) of the GAMA will experience low to medium flood risk. Though the medium flood risk under this scenario had the highest area coverage (27040.9 ha; 42.1%), the area covered by low risk (23275.07 ha; 36.2%) is comparatively high. In figure 26, high flood risk appears to be spread across other districts aside KKDA and AdMA.

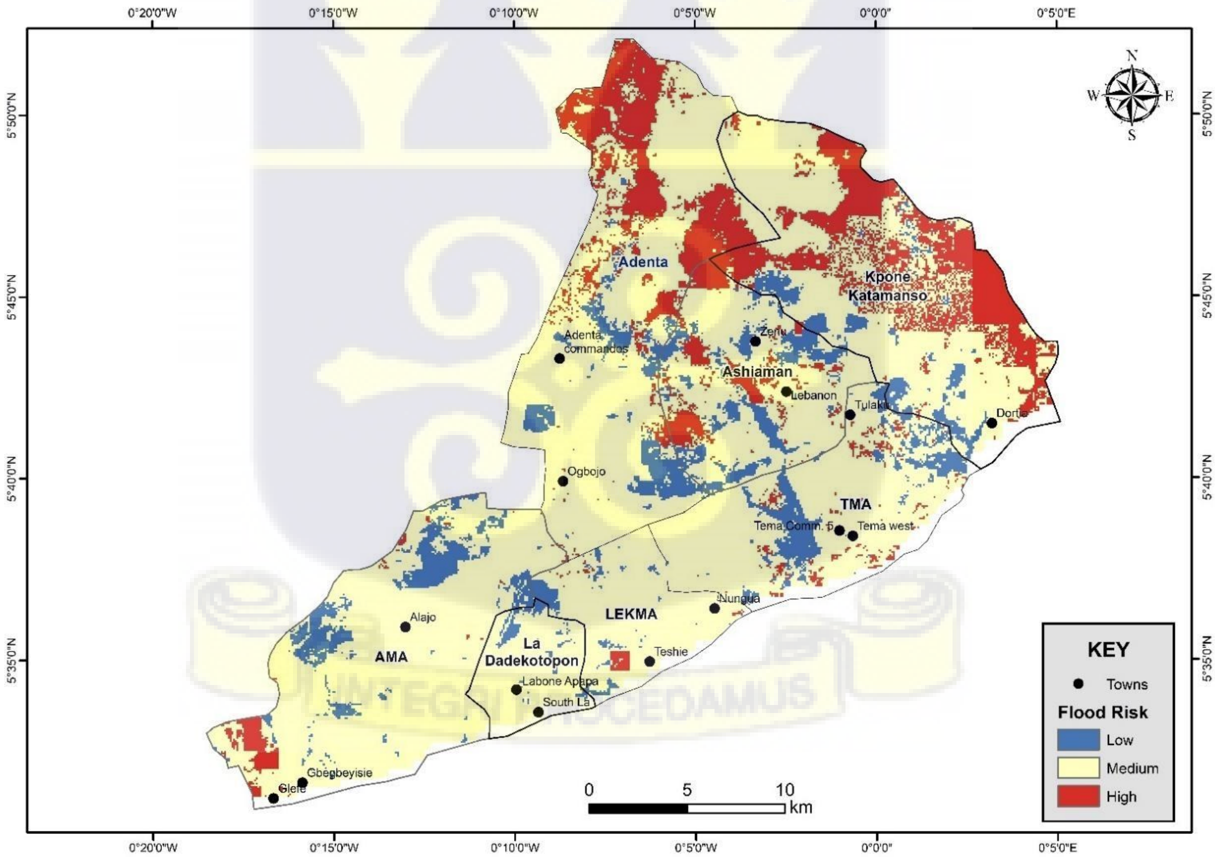


Figure 26: A model of flood risk in 2030 of GAMA under the self-sufficiency scenario

In figure 27, high flood risk on the border of AdMA is towards the part of Eastern Region of Ghana which is recognized for its high mountains. The table 24 indicates that in 2040, medium flood risk has the highest likelihood in GAMA under this scenario. Though some other parts of the metropolis are prone to high flood risk (figure 27), it is a predominantly likely in Adenta and Kpone Katamanso districts.

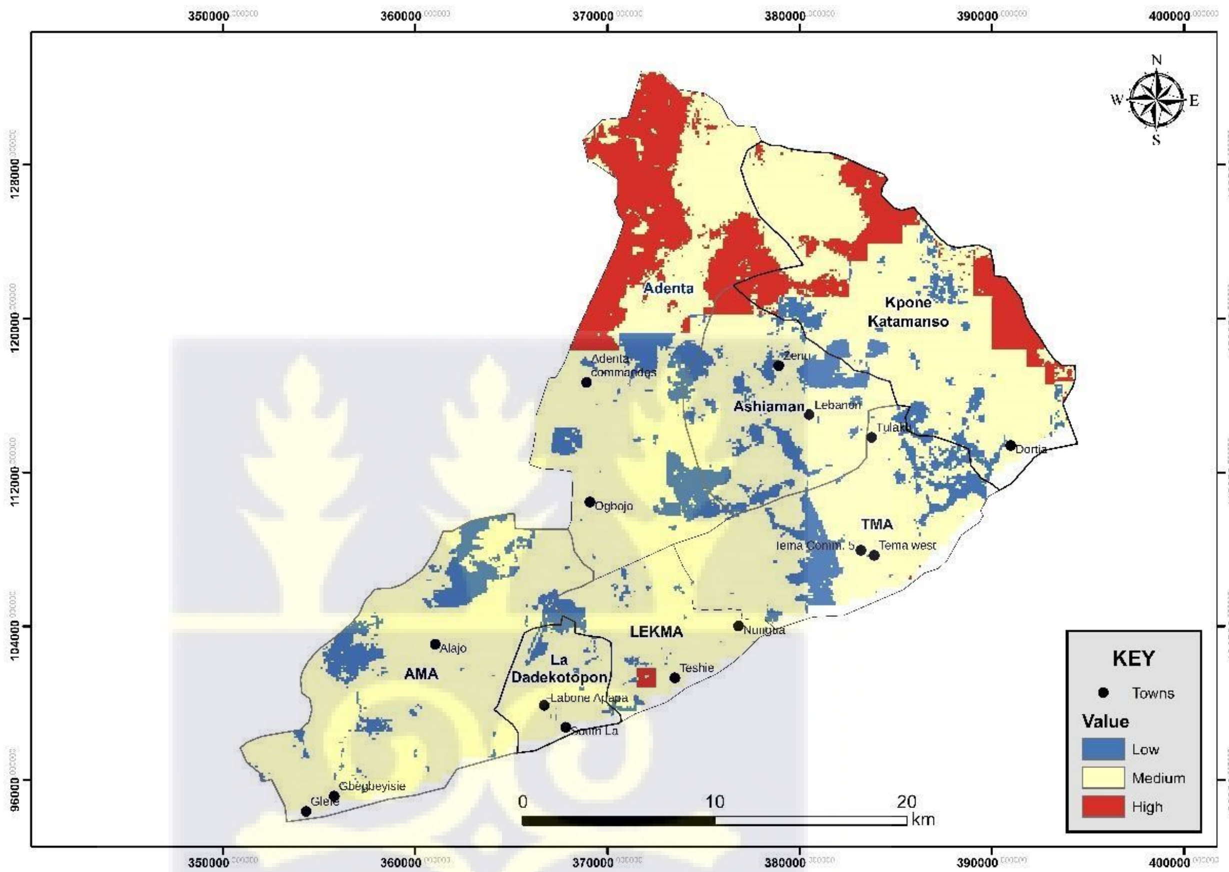


Figure 27: Flood risk model in 2040 of GAMA under the self-sufficiency scenario Low flood risk is the second most likely level of flood risk under this scenario in 2050. In figure 28, low flood risk is observed along the coastal belt of GAMA. The medium flood risk however remained the category with the highest value - 45% - (table 24). Medium to high flood risk under this scenario which is cumulatively will cover

69% of GAMA is found mostly in the inlands of the metropolis (figure 28).

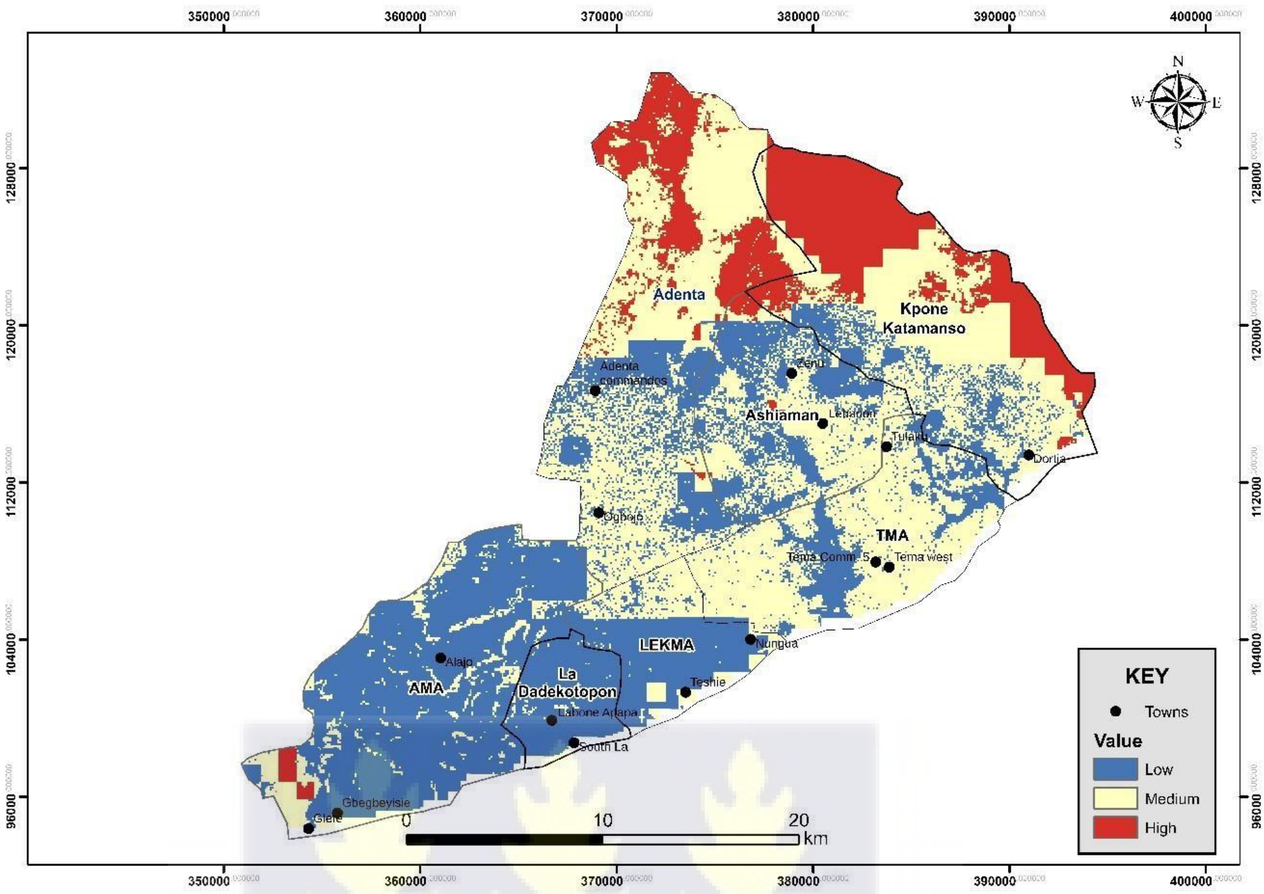


Figure 28: A model of flood risk in 2050 of GAMA under the self-sufficiency scenario

Table 25Table 24: Areas in hectares of flood risk categories under the self-sufficiency scenario for the years 2030, 2040 & 2050

Classification	Category	Area in hectares (2030)	%	Area in hectares (2040)	%	Area in hectares (2050)	%
0.00-4.00	Low	7302.96	10	8739.09	12	29811.24	41
4.10-6.00	Medium	53418.69	74	55030.59	76	32310.90	45
6.1-10.00	High	11324.61	16	8443.44	12	10090.98	14

7.3.4 Comparison of future flood risks with current flood risk

In this section, the three flood risk scenarios are compared to the flood risk model of 2020. Figure 29 is a line graph comparing flood risk categories under the three scenarios of 2030 and flood risk of 2020. Apart from the medium flood risk of 2030 for all scenarios which is higher in value, flood risk values in 2020 were generally higher in the other two categories. The highest likelihood of the liberalization scenario is the medium flood risk in 2030. And the low flood risk has the likelihood of 9% coverage of GAMA in 2030. The trend and self-sufficiency scenarios coincide and showed that high flood risk is likely to reduce by some 27% from 43% in 2020. The medium flood risk category, however, almost doubled under all the scenarios of 2030 forecast. Like 2020 flood risk, medium flood risk has the highest likelihood in all the scenarios for 2030.

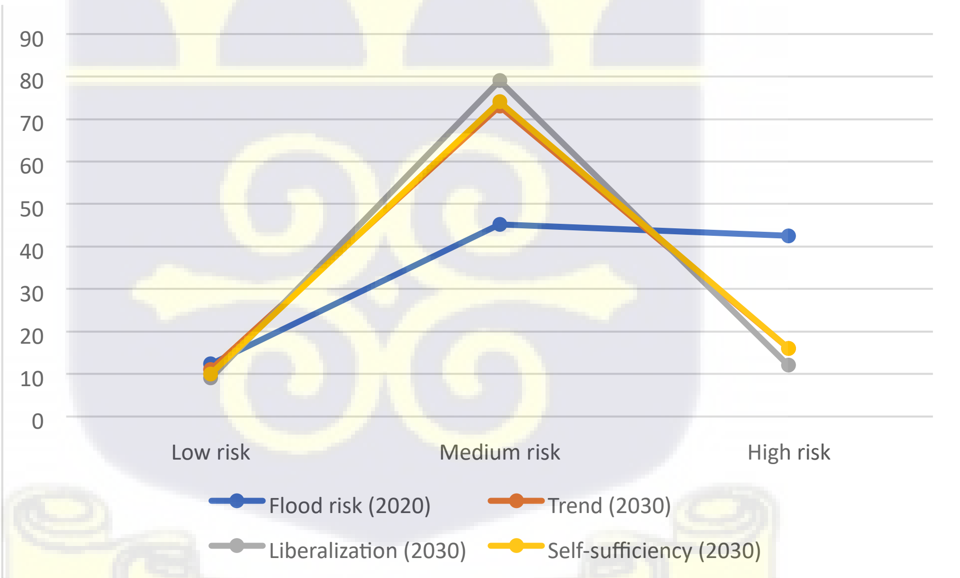


Figure 29: Comparison of flood risk for 2020 & 2030

Flood risk in 2040 is generally higher than in 2020, however, in all the scenarios, the high flood risk likely to be experienced is lower than in 2020 (figure 30). Low flood risk in both years coincide for the self-sufficiency scenario. The results of the under scenarios for low flood risk are however similar to that of 2020. In all the scenarios for 2040, medium flood risk is more likely to be higher than in 2020 but less for high flood risk.

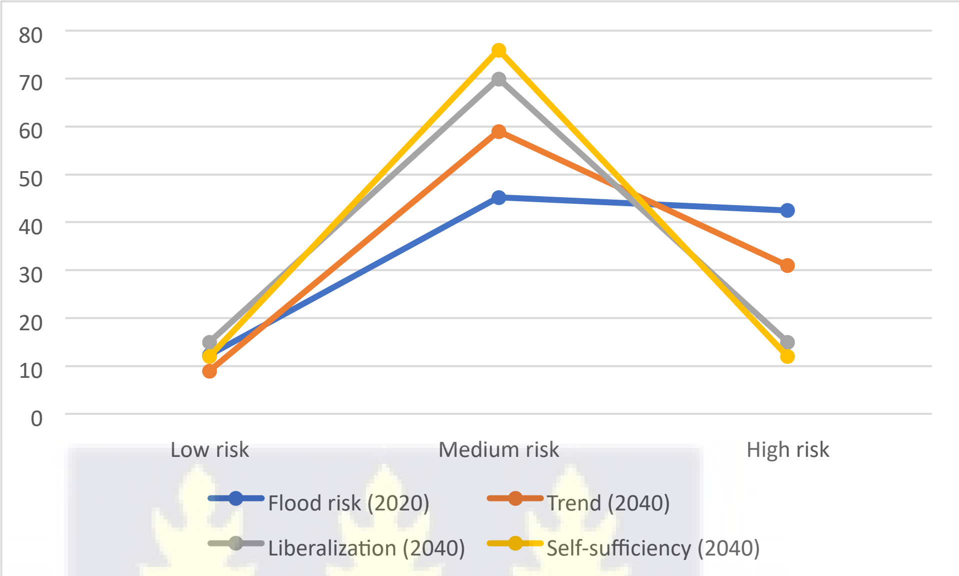


Figure 30: Comparison of flood risk for 2020 & 2040

In figure 31 which is a comparison of 2020 and 2050 flood risks, it is notable that medium flood risk is the most likely under the liberalization scenario. Medium flood risk coincides under the self-sufficiency scenario of 2050 and 2020. However, liberalization has the lowest likelihood of high flood risk compared with 2020, flood risk and all the scenarios in 2050. Under the self-sufficiency scenario, in 2050, low flood risk is very likely as it had the highest value (41%) of all the other scenarios.

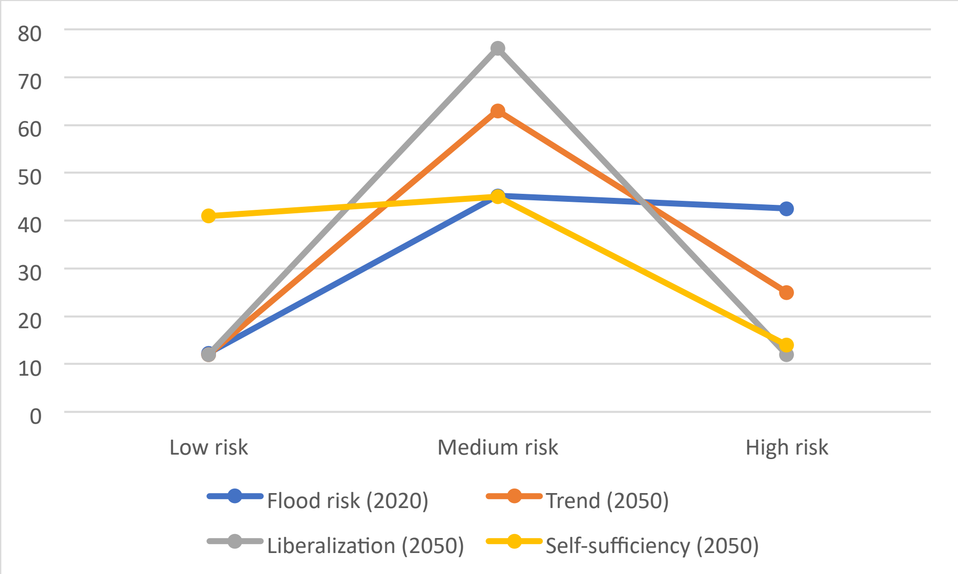


Figure 31: Comparison of flood risk for 2020 & 2050

7.4 Flood risk forecast in the seven districts

The results of forecasted flood risk are presented and discussed at the district level in the preceding sections. These sections are discussed in reference to the years not the scenarios as in the previous sections in order to unearth the nuances of the problem.

The flood risk forecast at district levels for the year 2030 is presented in Appendix E in the form of maps (Figures E1-E21) and tables (Tables E1-E3). In 2030, flood risk under each scenario for each district, the population will be prone largely to medium flood risk. As a majority of areas in these districts fall in this category.

The area coverage for high flood risk in AdMA shown in Figure E1 and Table E1 is relatively large under the three scenarios. Medium flood risk will cover a range of 62% to 73% under these scenarios for medium flood risk. Compared with the other districts, about 29% (5303.88ha) of this district will experience higher risks of floods in 2030 under all the scenarios. Figures E11 and E18 show the periphery of AdMA being susceptible to high flood risk, this may be a result of new poorly settlements (Njomaba et al., 2021). It may also be a result of the nature of the land and the presence of numerous water bodies. Hence the closer built-up areas get to these water bodies, the higher the risk of experiencing a flood event.

In AMA, for the year 2030, 85% of the district lands are prone to medium flood risk under the trend and self-sufficiency scenario. The high flood risk categories under these scenarios however will cover about 2% (165.24ha) and 3% (464.94ha) respectively. Flood risk under the scenarios will largely be from minimum to medium for the year 2040 (Figures E9 & Table E2). Though the majority of the land and people will be prone to medium flood risk, relatively a smaller proportion (Table E1: Trend; 2%; Liberalization, 2% and self-sufficiency, <1%) will be predisposed to high flood risk. The three scenarios in 2050 will be similar to 2040 (Figures E16 & Table E3) for this metropolis. The risk of floods will be high in about 0 to 2 per cent of the area. Meanwhile, the majority of AMA land will be disposed to the minimum flood risk in the near future.

AshMA is one of the smallest districts in GAMA, yet experiences flood attributable to poor planning and the presence of water bodies. This district in 2030 and the years after up to 2050 is susceptible to medium risk of floods. The risk of floods in AshMA in 2040 will have a majority of areas will have more than half of their land and population prone to low to medium flood risk. In 2050, 14% (1135.62ha) of the AshMA will be prone to the high risk of floods. The poor layout of this district especially will lead to various forms of disasters including floods (Ocran, 2015).

In KKDA, similar to AdMA, the risk of floods will be relatively high as the district is newer and has more vegetative cover which will be cleared for human settlements. The flood risk maps for 2030 (Figure E4) for KKDA indicated generally a medium to high flood risk under all the scenarios investigated. About one-third of the district will face high flood risk in the future. The boundary of this district showed high flood risk colour codes under all three scenarios. This, like AdMA, may be a result of new settlements. Developments over the years precede planning, it is evident in the forecast of flood risk for this study. KKDA is adjacent to AdMA, and both lie in the valley of Aburi and its environs. The rapid development of these mountainous regions also has an adverse impact on floods in these districts.

LaDMA is the smallest district of the seven studied and will in 2030 mostly be predisposed to medium flood risk for all the scenarios. In Figure E5 and Table E1, 91% of LaDMA will be predisposed to medium flood risk under the trend and self-sufficiency scenarios. In 2040 however, LaDMA is likely to have larger areas (Table E2: 26% for scenarios 1 & 2) prone to low flood risk for the three scenarios compared with the 2030 figures. There will per the model be no high flood risk in GAMA in 2040 under all the scenarios. In 2050 as in 2040, LaDMA will not be prone to high flood risk, but a majority will be predisposed to medium flood risk for the trend and liberalization scenario Table E2 and Figure E12. In the self-sufficiency scenario, low flood risk will be the majority of 97% (2655.18 ha) (Table E3).

The LeKMA, which is an adjoining district to LADMA and will have quite similar experiences to future flood risk as they have similarities especially in land features, such as proximity to the sea and low-lying. About 90% of LeKMA will be susceptible to medium flood risk in 2030 shown in Figure E6 and Table E1. In 2040 for LeKMA, though there is no high flood risk likely under the trend scenario, there will be at most 2% (Table E2) in the district. High flood risk will cover not more than 2% of LEKMA in 2050 under all the scenarios. Under the trend scenario in 2050, the low flood risk In LeKMA (Table E3 & Figure E20) will be 13% (599.4 ha), 7% (325.62ha) for liberalization and a majority of 69% (3171.96ha) for the self-sufficiency scenario.

The TMA is like AMA the oldest metropolis in GAMA. This district is more planned, with many industries and the harbour of Ghana. The near future of 2030 presents TMA with a low to medium flood risk. The situation will be similar in 2040 compared with 2030. About 20% - (Table E2) of the TMA will be susceptible to medium flood risk. In 2050, a minimum value (Table E3 and Figure E21) of 7% (622.08ha) under the liberalization scenario and the highest coverage of medium flood risk of 93% (8728.56ha) for the same scenario.

7.5 Future flood risk in GAMA

This study considered population growth, changes in LULC and future flood risk in GAMA. The results are similar to existing studies which demonstrated how proneness to floods depended on the nature of land: low-lying, flat, and sited in valleys (Szwagrzyk et al., 2018). Though GAMA generally is low-lying, AdMA and KKDA are the two districts in GAMA which lie directly in the valley of Aburi and its environs. The entire GAMA is low-lying thus other anthropogenic factors of land use and population density will negatively influence future floods and associated risks. The population which influences land use and cover change through urbanization which may be either appropriate or otherwise tends to impact the environment. A negative impact on the environment will in turn affect the population which may respond negatively to further depletion of their resources resulting in a vicious cycle (Petrişor et al., 2016).

Results from the forecast for flood risk for 2030, 2040 & 2050 under the trend, liberalization and self-sufficiency indicate GAMA is prone to flood risk with some level of variations. Flood risk in GAMA will be influenced by changes in the population and land use. These two variables are crucial in forecasting flood risk as Ehrlich et al., (2018) have described them as variables vital in addressing climate hazard impacts. The achievement of some of the Sustainable Development Goals (SDGs), especially the climate action in 2030 will also be hinged on the monitoring of these variables. In this study as a means of surveillance, flood risk was forecasted in GAMA with population and LULC as some of the main factors.

The assumptions of population and LULC used in the scenarios showed their impacts on the future risk of floods in GAMA. Firstly, the trend scenario made assumptions about population growth, economic growth and changes in LULC following a similar trend using 2020 as a baseline. The population will be increasing, LULC changes will be unregulated, and the economy does not grow at a fast rate compared with economic growth under the other scenarios. The outcome for forecast under this scenario for the three time points (2030, 2040 and 2050) indicates that a business-as-usual in GAMA will lead to a majority of the population being exposed to the medium to high flood risk.

The AdMA and KKDA districts clearly showed how flood risk will in future have their boundaries experiencing high flood risks in the future. These areas close to the boundaries of the two districts (Figures B3 & B2 respectively) were previously full of vegetation. These two districts are in the valley and share boundaries with some districts in the Eastern Region which are mountainous. The rate of developmental urbanization in these districts has been rapid. AdMA and KKDA are districts with rapid structural developments, and urbanization is driven by economic activities which are high in these districts. In KKDA for instance are many emerging factories and industries. The main driver of urbanization is the population which tends to interact with the environment through its activities. The risk of floods therefore in these districts under this scenario is relatively high compared with the other five districts.

Flood risk will be medium to high in the coming years under the liberalization scenario. With the assumptions of high growth in population, indiscriminate land use and economic growth, flood risk compared with the other two scenarios will be predominantly medium. This is because even though population growth is increasing and LULC is altering at a fast rate, because of the good economy, people will have the capacity to adapt and be relatively resilient. Studies have shown how wealth is positively related to flood management (Erman et al., 2019; Sayers et al., 2015; Adeloye & Rustum, 2011). The ability to adapt to floods is based on several factors broadly grouped as physical and social capitals (Lucas, 2020). Therefore, the possession of these capitals as individuals or collectively can aid in the management of flood risk under this scenario.

In LeKMA and TMA under the liberalization scenario, the results of areas affected by medium flood risk are the largest. These districts are unique because of the large residential areas and presence of industries. Thus, corroborating the findings on how high economic growth will influence flood risk in the future. The high economic growth will imply the construction of structures that will be able to withstand floods. Also, other studies explained how wealthier households tend to be less vulnerable as they have better coping mechanisms (Adeloye et al., 2015). Based on income levels, residents can cope differently regarding relocation as a coping strategy. Low-income residents tend to move just a little outside the flood zone, middle- income residents tend to either move a little out of the zone or remain in the community. High-income residents only move when floods reach more than 2m and they move to places of higher elevation (Felsenstein & Lichter, 2014). Though other studies in parts of Ghana showed income levels did not predict relocation as an adaptive strategy (Babanawo et al., 2022). Wealthier people tend to have various flood protections in place; the ability to build floodproof structures, the ability to construct drains, buy sandbags and insure their properties (Aboagye et al., 2018; Felsenstein & Lichter, 2014).

The effect of time, population growth and economic growth is evident in the flood risk forecasts for GAMA. The risk of flood becomes lower in 2050 under the self-sufficiency scenario, this may be a result of time (long-term effect). The assumption of the scenario is that economic growth and investment into sustainability make time an asset for the population to become less vulnerable to floods. This is because, with economic growth, adaptive capacities and thus resilience of the populace are built over time and improved (Kyere, 2018; Bowen et al., 2012; Brooks & Adger, 2005). The ability to improve adaptive capacity which is contextual and progressive (Adger & Agnew, 2004) requires both the individual (household) and/or collective effort. The population in 2050 under this scenario is therefore most likely to be prone to lower flood risk.

The self-sufficiency scenario in this study showed districts will be prone to generally low to medium risk. Communities such as the AMA, LadMA and LeKMA under this scenario showed most of its parts prone to lower flood risk. In AMA, which is the business hub of GAMA, it is no doubt that an increase in economic growth through economic activities will place residents and businesses in a better position to manage floods. Also, in these districts because of the presence of a lot of businesses and with the assumption of increased interest in sustainability, these businesses wanting to thrive will be willing to invest in flood management by mitigating, adaptation and resilience-building strategies. The susceptibility to low flood risk under this scenario will be a combination of strategies and population attributes which marks this scenario as the best compared with the others.

Also, to manage flood risk, studies have shown how flood insurance is a means of anticipatory management strategy (Surminski & Thieken, 2017). In this strategy, risk reduction is categorized into the provision of knowledge, sharing of knowledge, prevention through the planning of land use and building codes, adaptation, protection of large-scale structural flood infrastructure, emergency measures, monitoring and early warning (Seifert-Dähnn, 2018). Also, regulations of floodplain management in these Western countries include mandatory elevation of residences above the base flood elevation and non-residences floodproofed to the base elevation (Sarmiento & Miller, 2006). Other studies also recommend the consideration of the range of flood hazard intensities including rare and extreme events (Pabi et al., 2021). Though other studies found low patronage of flood insurance, its implementation as a policy at the national level was not an impossibility (Aliagha et al., 2014). Therefore, with time, people in GAMA are more likely to insure their homes and other properties against floods under the self-sufficiency scenario since knowledge, wealth and interest in sustainability are assumed to be high.

CHAPTER EIGHT

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

8.1 Introduction

The study sought to assess the impact of changes in population growth and LULC on future flood risk in the GAMA. This final chapter of the study is dedicated to summarizing the study, drawing conclusions based on the results and making relevant recommendations.

8.2 Summary

This study aimed at assessing the impact of changes in population growth and LULC on future flood risk in the GAMA. This objective was sub-divided into three main parts where population growth and LULC changes were explored for the years: 1990-2000, 2000-2010 & 2010-2020. The predictors of flood risk in GAMA with variables of population and LULC were obtained through a regression modelling approach. And forecasts flood risk in GAMA (2030, 2040 & 2050) using population and LULC scenarios.

Data for this study were from a cross-sectional survey (Integrated ClimateSmart Flood Management project), rainfall and temperature data (GMet), district population data (Ghana Statistical Service), and remote sensing data for LULC (LANDSAT & NASA).

Predictors of flood risk were obtained using an OLS regression modelling approach in ArcGIS. The variables included population, slope, rainfall, proximity to a water body, impervious surface, built-up areas and income. These variables and others were first used to develop the outcome variable flood risk in a weighted AHP. After obtaining the outcome variable, the OLS modelling was carried out. Predictors of flood risk in the GAMA were all the variables used in the forward-step procedure. In forecasting flood risk for the years 2030, 2040 and 2050, the flood risk map of 2020 coupled with projected population and LULC were used. Scenarios were used to aid the forecasting. In this study adapting scenarios by Price et al. (2017), scenarios under trend, liberalization and self-sufficiency were contextualized. There were assumptions about population, economic growth and changes in LULC. The trend scenario had assumptions of population growth, economic growth and changes in LULC being similar to the current values using 2020 figures as the benchmark. High economic and population growths characterized the liberalization scenario however, policy interventions on LULC are assumed to be lax. The presence of good and enforced land use policies is one of the different assumptions of the Self-sufficiency scenario, coupled with the population's interest in sustainability.

Population in GAMA shows in this study as in others to be ever-growing. The population in the GAMA is growing at a fast rate not solely as a result of high birth rates. The population of GAMA regarding the demography (age distribution, sex, growth) and the social factors (household headship, presence of safe havens, having social ties) were relevant in the study of flood risk.

There exists a correlation between the population and the LULC classes. This study like others has demonstrated the positive relationship between population growth and changes in some LULCs. Land cover types such as water bodies and vegetations have been converted in most of the seven districts studied into built-up areas and bare lands. The impact of the population on flood risk was evident in LULC practices.

The risk of floods under the three scenarios for the three points of time - 2030, 2040 and 2050 present different impressions of the future but with similarities. The risk of floods is severest under the trend scenario where the future showed how the population in GAMA are susceptible to medium to high flood risks in the future. Therefore, there should be necessary reforms to safeguard the population and livelihoods.

Results from the forecast under the liberalization scenario clearly showed that in the future, medium flood risk will be predominant in GAMA if the situation is similar to the assumptions of this scenario. Economic growth which is a positive in flood risk management alone cannot safeguard the population against flood risk since there will be other important factors which need to be addressed. A vicious cycle is imminent if a sustainability approach to the management of flood risk is not adopted.

In the self-sufficiency scenario where willingness to contribute towards the sustainability of the environment is paramount a virtuous cycle (Petrişor et al., 2016) is attainable. Flood risk under this scenario will be low to medium as sustainability and good policies are assumed. Even though high population growth is assumed, flood risk is more likely to be lower than in the other two scenarios.

8.3 Conclusions

This study is premised on the Vicious Cycle model (VCM) together with the Demographic Transition Theory (DTT) and Vulnerability framework. The VCM postulates how a vicious cycle is inevitable when a mismanaged urban sprawl negatively affects the population by leading to disasters and the population in response to these disasters causes further harm to the environment (Petrişor et al., 2016).

In this study, the GAMA was demonstrated to have evolved from two districts to sixteen at the time of the survey. The administration of the metropolis was decentralized to enhance effective development mainly due to the high population.

Population in GAMA was high and attributable to high birth and in-migration rates. The rate of rural-urban migration from other studies demonstrated its influence on the population of GAMA.

Altogether, the impact of population growth on LULC and associated changes was explored. There is evidence of population growth in GAMA which affected LULC and its changes. The demand for land resources by the population showed how various landcover types were altered for human use. The study established accelerated changes in LULC in the GAMA, where vegetative covers and water bodies were mainly converted to settlements thereby worsening the flood situations by increasing impervious surfaces coupled with other anthropogenic factors linked to built-up spaces. This is therefore consistent with the VCM where flood risk is increased with increasing population and changes in LULC in the GAMA. The impact of population change on land use was the changes observed in land cover types. These factors together with other developmental challenges of a poor drainage system and population attributes of poverty and composition of the population increased flood risk in the GAMA.

Furthermore, the study established the nexus between population growth, LULC changes and flood risk. The predictors of flood risk were population, slope, rainfall, built-up spaces (human settlements), areas covered by impervious surfaces, wealth and proximity of a building (human settlement) to a water body. In an OLS regression in ArcGIS, the aforementioned variables were established as predictors of flood risk in GAMA. The risk of floods in GAMA in 2020 was relatively high which meant most people in GAMA were victims of floods in varying degrees. This proved the motion of a vicious cycle model of the population, LULC and flood risk nexus in GAMA. The study further forecasted flood risk in GAMA.

Flood risk forecast under three scenarios – trend, liberalization and self-sufficiency for the years 2030, 2040 and 2050 established either a vicious or virtuous cycle. The vicious cycle is evident under the forecasted flood risk for the trend and liberalization scenarios where, with the assumptions made, flood risk does not improve for future dates. However, a virtuous cycle proposed under the VCM is possible if the assumptions backing the self-sufficiency scenario are adopted in the GAMA. Therefore, with appropriate policies, strategies for population growth, and enforcement of LULC especially, flood risk in GAMA can be lowered in the future.

8.4 Recommendations

Based on this research the following are recommended:

1. Enforcement of laws on land use and planning. This study found that land use was indiscriminate as land cover types - especially water bodies were altered to make room for buildings. Ghana in 2020 developed a land act- ACT for land acquisition, ownership and use. The District Assemblies in conjunction with the Ministry of Lands and Natural Resources and Ministry of Science, Technology and Innovation (MESTI) - Land Use and Spatial Planning Authority (LUSPA) should ensure that building permits are obtained prior to siting of buildings. This will help utilize land judiciously and ensure protected areas are secured.
2. Assemblies can have a byelaw on paving homes or use it as means of income generation for drainage projects. The technical support on land use and spatial planning provided by LUSPA for the MMDAs under the Ministry of Local Government, Decentralization and Rural Development (MLGRD) can be used in developing byelaws on how people could or could not pave their home spaces. Also, revenue can be generated from

individuals who pave above a predetermined threshold of their spaces and these monies can be channelled to the provision of drains and other mitigating structures to floods in the various districts.

3. Assemblies should task new settlers to plant trees or vegetative covers to increase greenery in the metropolis and aid permeability. When new homeowners are tasked with tree-planting around their homes, the greenery in the metropolitan area will be substantial and reduce the chance of paving entire compounds thus reducing the area of impervious surfaces.
4. Further studies on types of LULC focused on housing types and flood risk. Based on anecdotal knowledge, Ghana has relatively few high-rise accommodations for citizens. This is a cultural and social aspect which requires investigation especially as there is an emergence of such accommodation types, especially in the cities. Ghanaians generally prefer building their own homes, with compounds to themselves thereby increasing built-up spaces. High-rise buildings on the other hand will save space and help minimize built-up spaces occupying larger areas. This will help reduce large impervious surfaces which may arise due to excessive building and paving. And also reduce the chances to build in waterways as the land acquisition on an individual basis is reduced especially in the metropolis.

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Table A1: A partial questionnaire from the ICSFM survey

NO	Questions	CODE
FL01	Is flooding a frequent occurrence in your neighbourhood? Yes---------------------1 No-------------------------2 >> FL04	
FL02	How frequent is this occurrence in the last 5 years? Yearly ---------------------1 Every two years---------2 Seasonally ----------------3	
FL03	How many times has your household experienced flooding within the current season? *>>**FL05** STATE NUMBER OF TIMES*	
FL04	In the last 5 years has your neighbourhood experienced any floods? Yes-------------1 No------------------2	
FL05	What do you think are the possible causes of flooding? Building on water ways ------------A Low lying area ---------------------F Poor settlement planning ----------B Waterlogged area------------------G Poorly constructed drains ----------C Lack of drains ---------------------H Choked drains -----------------------D Surface runoff -----------------------I Heavy storms ------------------------E Paved/concretized surfaces -------J	**CIRCLE ALL THAT APPLIES**
FL06	What are the effects of flooding on your neighbourhood? Destroy houses ---------------A Loss of property----------------D Pollute drinking water -------B Loss of human lives-----------E Cause diseases-----------------C Other (specify)-----------------F	CIRCLE ALL THAT APPLIES
FL07	To what extent does the waste disposal in your neighbourhood contribute to flooding in your area? Very large extent-----------1 Small extent-------------4 Large extent -----------------2 Not at all-----------------5 Not so large an extent----3	

FL08	Does flooding affect your household in any way? Yes, currently -------1 Yes, in the past-------2 No-------3 >> (Skip to FL13)	
FL09	How does flooding affect your household? Destroy my house -----------------A Loss of household assets------D Pollute my drinking water -------B Loss of human lives-------------E Cause diseases----------------------C Loss of income-------------------F Loss of livestock------------------- G Other (specify)-------------------H	CIRCLE ALL THAT APPLY
FL10	What do you think about the frequency of flooding now compared to the past 5 years? Increased ----------------1 Decreased------------3 Remained the same---2 Don't know-----------4	
FL11	Are you or your household able to predict when there is going to be flooding in your neighbourhood? Yes-------------1 No----------------2 *(>>FL13)*	
FL12	If you or your household is able to predict the occurrence of flooding, kindly explain ………………………………………………………………………………… ………………………………………………………………………………… …………………………………………………………………………………	
FL13	How do you prepare towards the floods? We reinforce the house -- 1 We clear our drains -- 2 We use sandbags as barricades ------------------------------- 3 We relocate -- 4 We do not experience flooding ------------------------------5 >>FL16 Other (specify) ---6	
FL14	If flooding affects your household, why are you still living here? Because we bought the land --------------------------------------1 Because we do not have anywhere to go------------------------2 Because we own the land---3 Because of ancestral links --4 Other (specify)---5	

FL15	Were you aware that this area is flood-prone before you moved in? Yes --------------------1 No---------------------2	
FL16	Do you know anyone in this community that is affected by flooding? Yes ---------------1 No---------------------2 >> (Skip to FL19)	
FL17	How seriously has flooding affect this person or household you know? Very seriously ---------1 Seriously ----------2 Not seriously----------3 >>FL19	
FL18	How seriously has flooding affected this person? Destroyed their house ---------------A Loss of human lives-------------E Pollute the drinking water ----------B Loss of livestock-----------------F Caused diseases-----------------------C Loss of income----------------- G Loss of household assets-------------D Other (specify)-----------------H	**CIRCLE ALL THAT APPLIES**
FL19	Are there any benefits of flooding? Yes ------------------1 No---------------2 (>>FL 24)	
FL20	Has your household or any other household benefitted from flooding? Yes ------------------1 No---------------2 *(>>FL22)*	
FL21	What have been the benefit (s)? …………………………………………………………………………………… …………………………………………………………………………………… ……………………………………………………………………………………	
FL22	Has your neighbourhood benefitted from flooding? Yes ------------------1 No---------------2 *(>> FL24)*	
FL23	What have been the benefit (s) for the neighbourhood? …………………………………………………………………………………… …………………………………………………………………………………… ……………………………………………………………………………………	
FL24	What are your household's sources of support after flooding? Financial -------------1 Social---------------3 Other (specify)---------5 Material -----------------2 Not applicable-----------4 >>*FL34*	
FL25	Do you receive information from government institutions on flooding and storms? Yes ---------------1 No------------------2	

FL26	How does the community prepare towards the floods? Clearing water ways--A Clearing drains---B Filing of low-lying areas with sandbags---------------C Creating temporary drains--------------------------------D Awareness creation---E Solid waste removal and decongestion----------------F Other (specify)---G	**CIRCLE ALL THAT APPLIES**
FL27	In your view can flooding be minimised in this neighbourhood? Yes -----------1 No-------------2	
FL28	What can be done to minimize flooding in this neighbourhood? Avoid building on water ways-----A Law enforcement------------------------F Clean clogged gutters ---------------B Provision of safe havens---------------G Construct additional drains --------C Widening/deepening existing drains--H Enhance solid waste collection ----D Other, (specify)---------------------------I Household relocation----------------E	CIRCLE ALL THAT APPLIES
FL29	What have been done to minimize flooding in this neighbourhood in the last 5 years? Avoid building on water ways-----A Law enforcement------------------------F Clean clogged gutters ---------------B Provision of safe havens---------------G Construct additional drains --------C Widening/deepening existing drains---H Enhance solid waste collection ----D Other, (specify)---------------------------I Household relocation-----------------E	CIRCLE ALL THAT APPLIES
FL33	Will you consider relocating from this community because of the trend of flooding? Yes -----------1 No-------------2 ***(>>FL36)*** Don't know------3 ***(>>FL36)***	
FL34	Where do you plan to move or locate to? Name of community--	
FL35	Is this new locality within this same district or municipality? Yes-----------1 No----------------2	
FL36	If NO, why? Because we bought the land---------------------1	

	Because we do not have anywhere to go-----2 Because we own the land------------------------3 Because of ancestral links ------------------------4 Other (specify)---------------------------------------5	
FL37	Was your household living in this community during the June 3, 2015, floods? Yes-----------1 No---------------2	
FL38	After the June 3, 2015, floods have you experienced any other flood? Yes-----------1 No---------------2 (>> FL43)	
FL39	When did you experience the most recent flood event? *INDICATE THE MONTH AND YEAR*	MM/YYYY --------------
FL40	During the current rainy season has your household experience any flooding? Yes ----------1 No---------------2 (>>FL43)	
FL41	When your household got flooded, how many days did it take for the area to completely dry up. STATE NUMBER OF DAYS	
FL42	Please indicate the flood water level on the wall. Enumerator measure level and record in cm	
FL43	Did the flood affect your household access to water? Yes--------------1 No------------2 >>FL45	
FL44	What was your source of water for the household during/after the Floods? Pipe borne inside dwelling-----------01 Bottled water--------------------------08 Pipe borne on compound ------------02 Sachet water -----------------------09 Pipe borne neighbour's house-------03 Tanker supply/vendor provided---10 Public tap/standpipe------------------04 unprotected well--------------------11 Borehole private ----------------------05 Rainwater harvest------------------12 Borehole neighbourhood------------06 Other (specify) ---------------------13 Protected well--------------------------07	
FL45	Did the flood affect your household's toilet facility? Yes--------------1 No----------2 >>FL47 N/A--------------3 >>FL47	

FL46	How did the flood event affect your household toilet/sanitary facility? ………………………………………………………………………………… ………………………………………………………………………………… …………………………………………………………………………………..	
FL47	During the last rainy season did your household experience any flooding? Yes ----------1 No--------------2 (>>FL51)	
FL48	Please indicate the flood water level on the wall. Enumerator measure level and record in cm	
FL49	Who are the three categories of persons most vulnerable to flooding in this community? Men------------------A The aged/elderly-------------E Women --------------B All groups---------------------F Children--------------C Other, (specify)--------------G PWDs -----------------D	CIRCLE THE WORSE THREE
FL50	Rank those indicated from 1 - the most vulnerable to 3 - least vulnerable of the three categories indicated 1. …………………………………………………………. 2. …………………………………………………………. 3. …………………………………………………………..	
FL51	How do households prevent floods in this community? By constructing water channels---------------------------------1 By desilting (cleaning) the gutters------------------------------2 By not dumping rubbish into the gutters----------------------3 Other (specify) ---4	

Table A2: Multi-stage sampling

MMDAs	Communities	Enumeration Areas
AMA	Alajo	Nii Haruna Quaye II House Fountain School First choice spot
	Glefe	Queen Crown Enterprise Public toilet & Bath Glefe Mosque
AdMA	Adenta	Shield International school Timberland Furniture Baptist Church
	Ogbojo	Maa Cee spot Mt. Zion Methodist Church Presbyterian Church
AshMA	Lebanon	Lebanon Police Station Lebanon Community Clinic H/No. T.M.A. Zenu 2
	Tulaku	Angmotor Bio Enterprise Jerry Electrical Mosque
KKDA	Dortia	Chirst Apostolic Church Kpone Methodist Church Kobekro No. 1 Immaculate Spot
	Zenu	Gbetsile Community Health Centre Army House Mashach Academy
LaDMA	South La	Church of Pentecost head office Presbyterian Church New Life International school
	Labone Apapa	Yesu Mo Nativity Presbyterian Church PG Fashion
LeKMA	Teshie	Apostolic Church St. Anne's Catholic Church Plant Medical Company
	Nungua	Regional Maritime University Jehovah's witnesses Church of Pentecost
TMA	Tema Community 5	Presbyterian Church Good Shepherd Catholic Church Ideal College
	Tema New Town	Manheam Miracle Life Church Go Galaxy Gas and Oil filling Station

Appendix A: LULC classes for Districts in GAMA (1990-2020)

Table 26:The area (hectares) and corresponding percentages of LULC types in AshMA (1990-2020)

LULC Class	1990		2000		2010		2020	
	Area (ha)	% Area	Area (ha)	% Area	Area (ha)	% Area	Area (ha)	% Area
Water Bodies	35.33	2.0	40.06	2.0	17.13	1.0	20.66	1.0
Built-up	546.00	31.8	672.96	39.2	903.49	52.7	1156.92	67.4
Bare	0.00	0.0	152.56	8.9	27.92	1.6	115.55	6.7
Vegetative Cover	1133.94	66.0	849.70	50.0	766.73	45.0	422.14	25

Table B2: The area (hectares) and corresponding percentages of LULC types in KKDA (1990-2020)

Landcover	1990		2000		2010		2020	
	Area (ha)	% Area	Area (ha)	% Area	Area (ha)	% Area	Area (ha)	% Area
Water Bodies	290.75	1.0	421.56	2.0	299.10	1.0	323.85	2.0
Built-up	92.18	0.4	507.73	2.4	2515.27	11.7	4187.37	19.5
Bare	984.28	4.6	1265.41	5.9	1752.11	8.2	744.71	3.5
Vegetative Cover	20058.53	94	19231.03	90	16859.25	79.0	16169.80	75.0

Landcover	1990 Area (ha)	1990 % Area	2000 Area (ha)	2000 % Area	2010 Area (ha)	2010 % Area	2020 Area (ha)	2020 % Area
Water Bodies	44.12	0.45	96.57	1.0	84.91	1.0	115.7559	1.0
Built-up	761.43	7.7	2199.88	22.3	4018.11	40.7	4970.80	50.4
Bare	4.67	0.05	42.11	0.4	263.04	2.7	530.98	5.4
Vegetative Cover	9057.82	91.8	7528.95	76.2	5502.13	55.8	4250.211	43.1

Table 27Table B3: The area (hectares) and corresponding percentages of LULC types in AMA (1990-2020).

	1990		2000		2010		2020	
Landcover	Area (ha)	% Area	Area (ha)	% Area	Area (ha)	% Area	Area (ha)	% Area
Water Bodies	902.47	6.2	777.667	5.4	599.6497	4.2	340.5712	2.4
Built-up	7007.18	48.7	9050.73	62.8	10319.10	71.6	9357.29	65.0
Bare	1179.53	8.2	680.80	4.7	343.63	2.4	865.58	6.0
Vegetative cover	5313.18	37	3893.19	27	3139.96	22	3838.34	27

Table 28 B4: The area (hectares) and corresponding percentages of LULC types in TMA (1990-2020).

	1990		2000		2010		2020	
Landcover	Area (ha)	% Area	Area (ha)	% Area	Area (ha)	% Area	Area (ha)	% Area
Water Bodies	742.70	8	477.56	5.5	354.01	4	337.82	4
Built-up	2186.51	25.0	3232.73	36.9	4807.27	54.9	5912.23	67.5
Bare	54.18	6	253.29	2.9	237.56	2.7	257.20	2.9
Vegetative cover	5828.07	67	4731.44	54	2992.83	34	2408.99	28

Table 29TB5: The area (hectares) and corresponding percentages of LULC types in LaDMA (1990-2020).

Landcover	1990		2000		2010		2020	
	Area (ha)	% Area	Area (ha)	% Area	Area (ha)	% Area	Area (ha)	% Area
Water Bodies	11.95	0.5	21.11	1.0	15.45	1.0	9.59	0.4
Built-up	797.38	32.8	1145.77	47.1	1211.98	49.8	1395.22	57.3
Bare	166.65	6.8	147.51	6.1	166.56	6.8	201.35	8.3
Vegetative cover	1457.95	60	1119.54	46	1039.94	43	827.77	34

Table 30Table B6: The area (hectares) and corresponding percentages of LULC types in LeKMA (1990-2020).

Landcover	1990		2000		2010		2020	
	Area (ha)	% Area	Area (ha)	% Area	Area (ha)	% Area	Area (ha)	% Area
Water Bodies	16.59	0.3	16.37	0.3	19.68	0.3	51.34	1.0
Built-up	1271.04	22.6	2787.59	49.5	4243.36	75.3	3961.71	70.3
Bare	80.19	1.4	98.40	1.7	266.86	4.7	537.10	9.5
Vegetative Cover	4273.55	76	2740.86	49.0	1111.20	20.0	1091.23	19

Appendix C: Expert Judgment Weighting Questionnaire

Table 31Table CI: Questionnaire for expert weighting (scale of 1-10)

Dear Expert,

The following table contains factors that contribute to flood risk which need to be assigned weights. I kindly ask that you help me score each factor's contribution to flood risk on a scale of 1-10 (kindly tick the score selected) with 1 being the least and 10 being the highest.

Variable	Score
Precipitation	
Slope	
Impermeable surface	
Standard Error (percentage of impervious surfaces)	
Homebase human built up and settlement	
Probability of HBASE	
Population aged 0-14 years	
Population aged 65+ years	
Location of dams	
Roads	

Table 32Table C2: Questionnaire for expert weighting (percentages)

Dear Expert, Kindly score each factor as a percentage of influence which sums to 100% for all factors.	
For example.	
Variable	Percentage influence
Precipitation	20
Slope	10
Impermeable surface	10
Standard Error (percentage of impervious surfaces)	5
Homebase human built up and settlement	10
Probability of HBASE	9
Population aged 0-14 year	8
Population aged 15-64 years	4
Population aged 65+ years	8
Location of dams	7
Roads	9
Total percentage influence	100
Variable	Percentage Influence
Precipitation	
Slope	
Impermeable surface	
Standard Error (percentage of impervious surfaces)	
Homebase human built up and settlement	
Probability of HBASE	
Population aged 0-14 years	
Population aged 65+ years	
Location of dams	
Roads	
Total percentage influence	

Appendix B: Forecasted Flood Risk for Districts in GAMA under the three scenarios

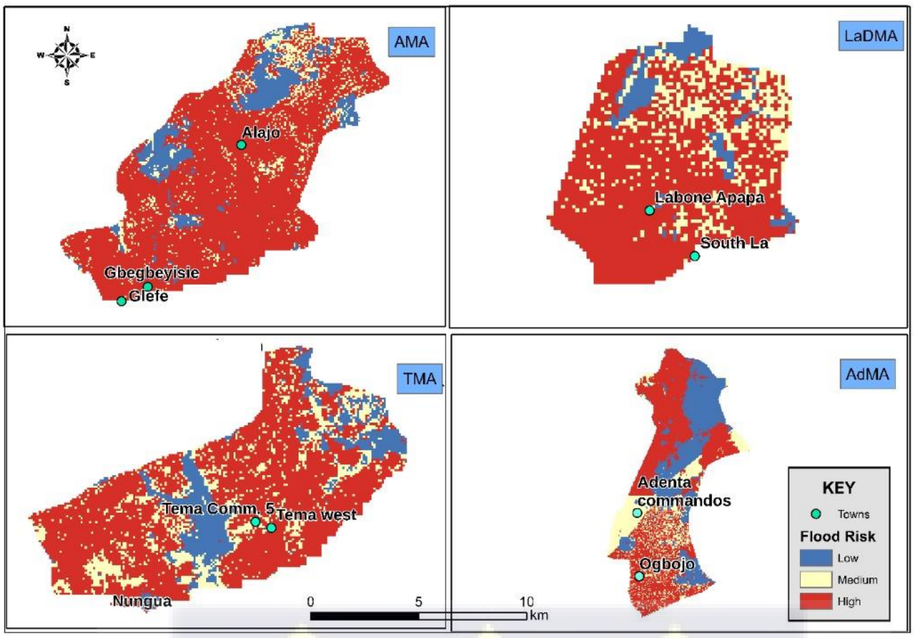

Figure D1: Flood risk maps for AMA, LaDMA, TMA and AdMA (2020)

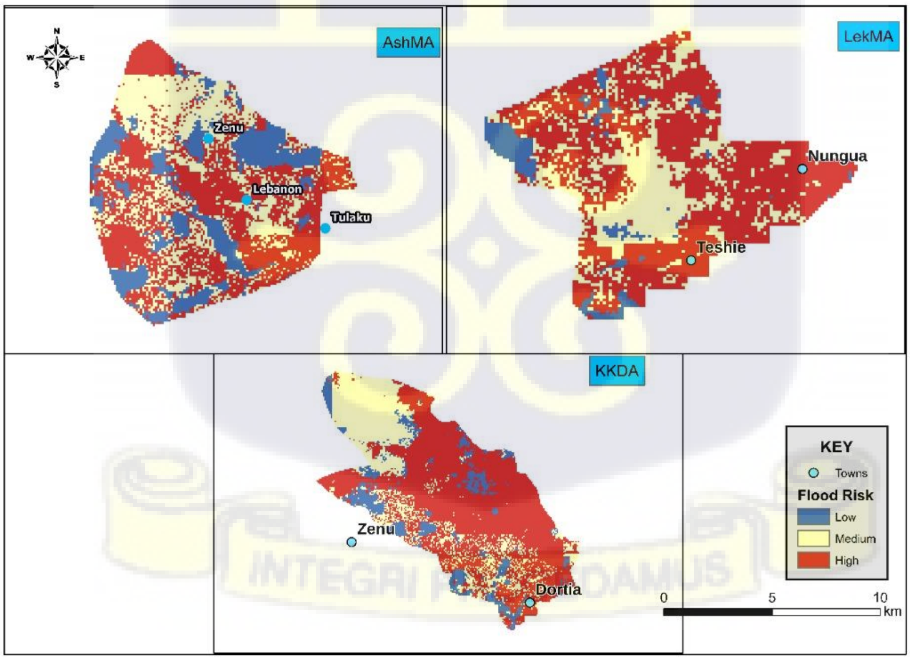

Figure D2: Flood risk maps for AshMA, LeKMA, and KKDA (2020)

Table 33Table D1: Model diagnostics

Number of Observations	26588	Akaike's Information Criterion (AICc) [d]	17148.543235
Multiple R-Squared [d]	0.482523	Adjusted R-Squared [d]	0.482387
Joint F-Statistic [e]	3540.655202	Prob(>F), (7,26580) degrees of freedom	0.000000*
Joint Wald Statistic [e]	21747.349219	Prob(>chi-squared), (7) degrees of freedom	0.000000*
Koenker (BP) Statistic [f]	5008.402268	Prob(>chi-squared), (7) degrees of freedom	0.000000*
Jarque-Bera Statistic [g]	28.637441	Prob(>chi-squared), (2) degrees of freedom	0.000001*

Appendix C: Flood Risk Forecast Figures and Tables

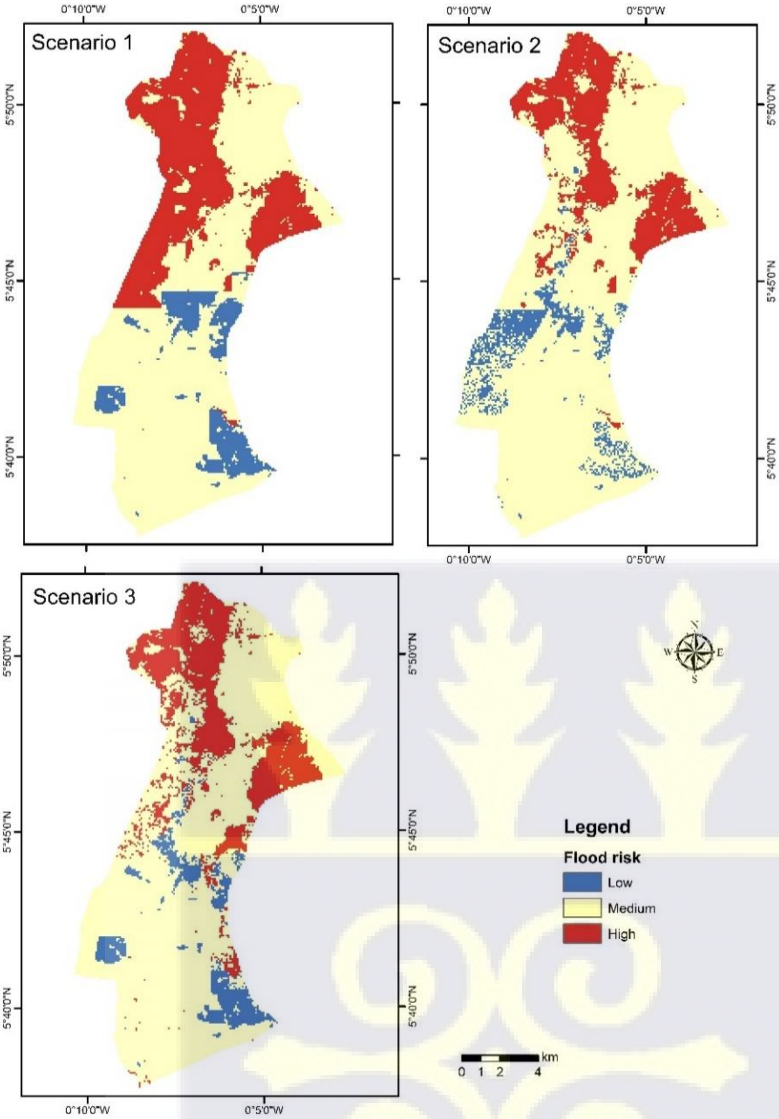

Figure E1: Flood risk maps for AdMA in 2030 under the three scenarios.

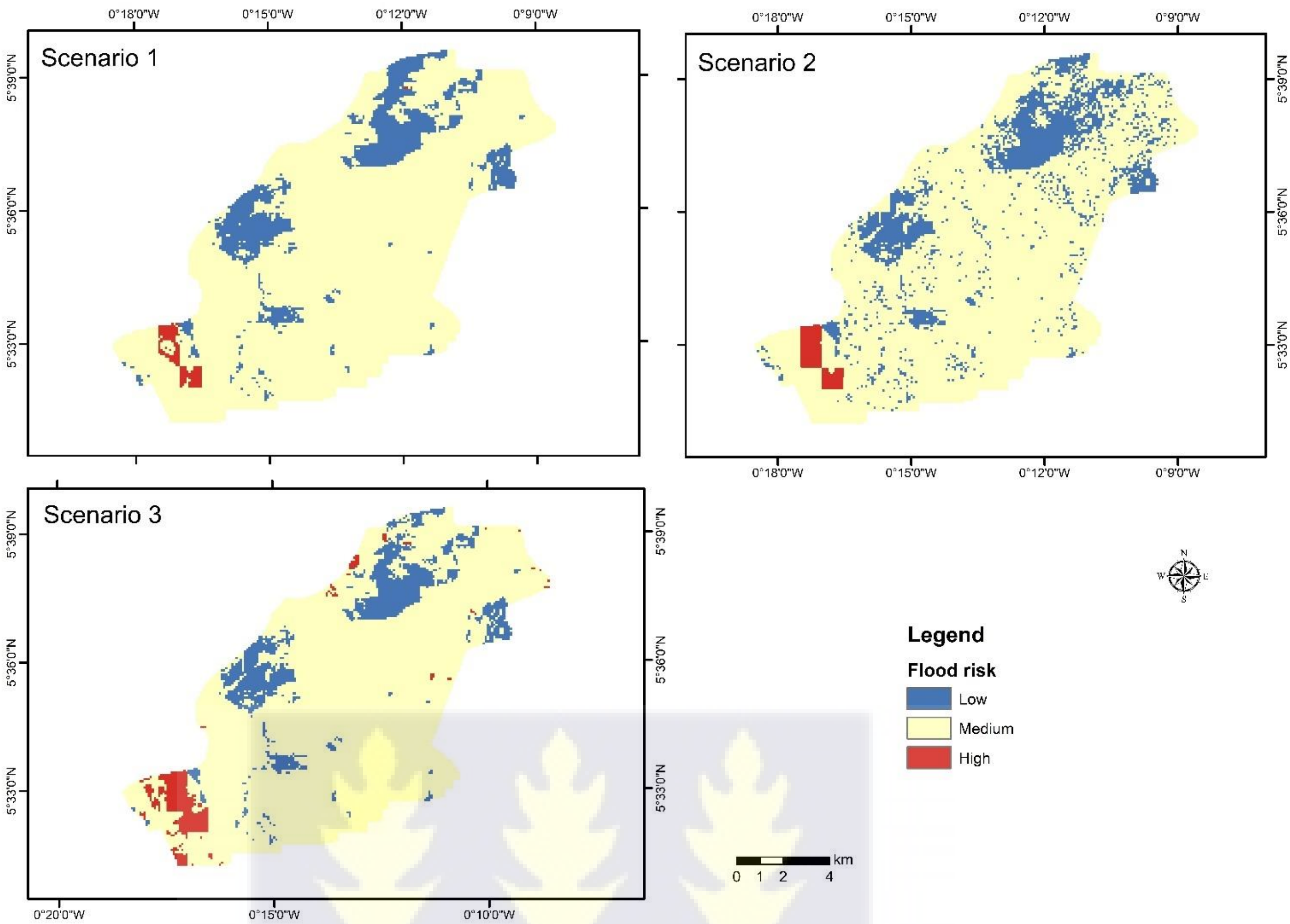

Figure E2: Flood risk maps for AMA in 2030 under the three scenarios.

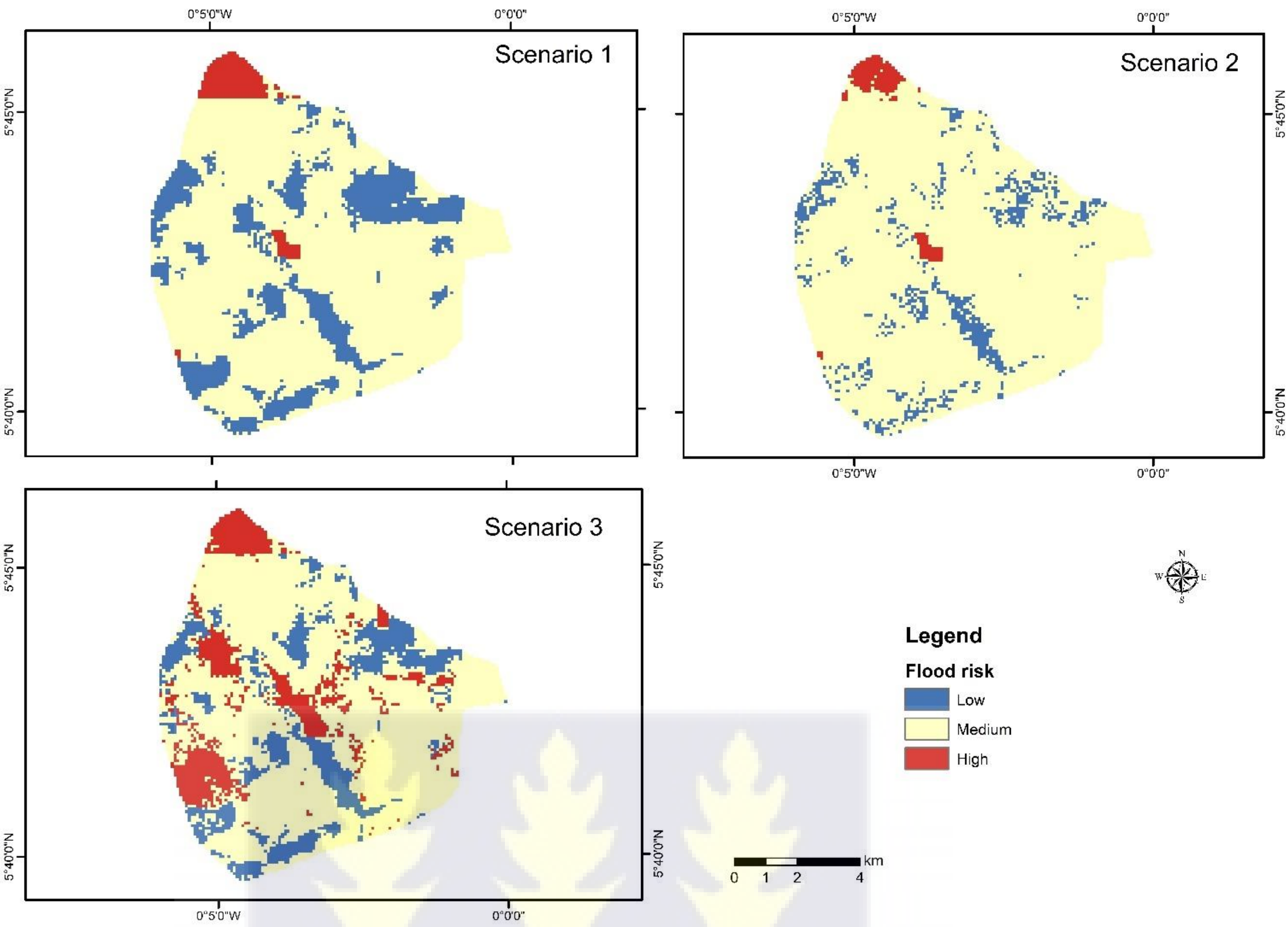

Figure E3: Flood risk maps for AshMA in 2030 under the three scenarios.

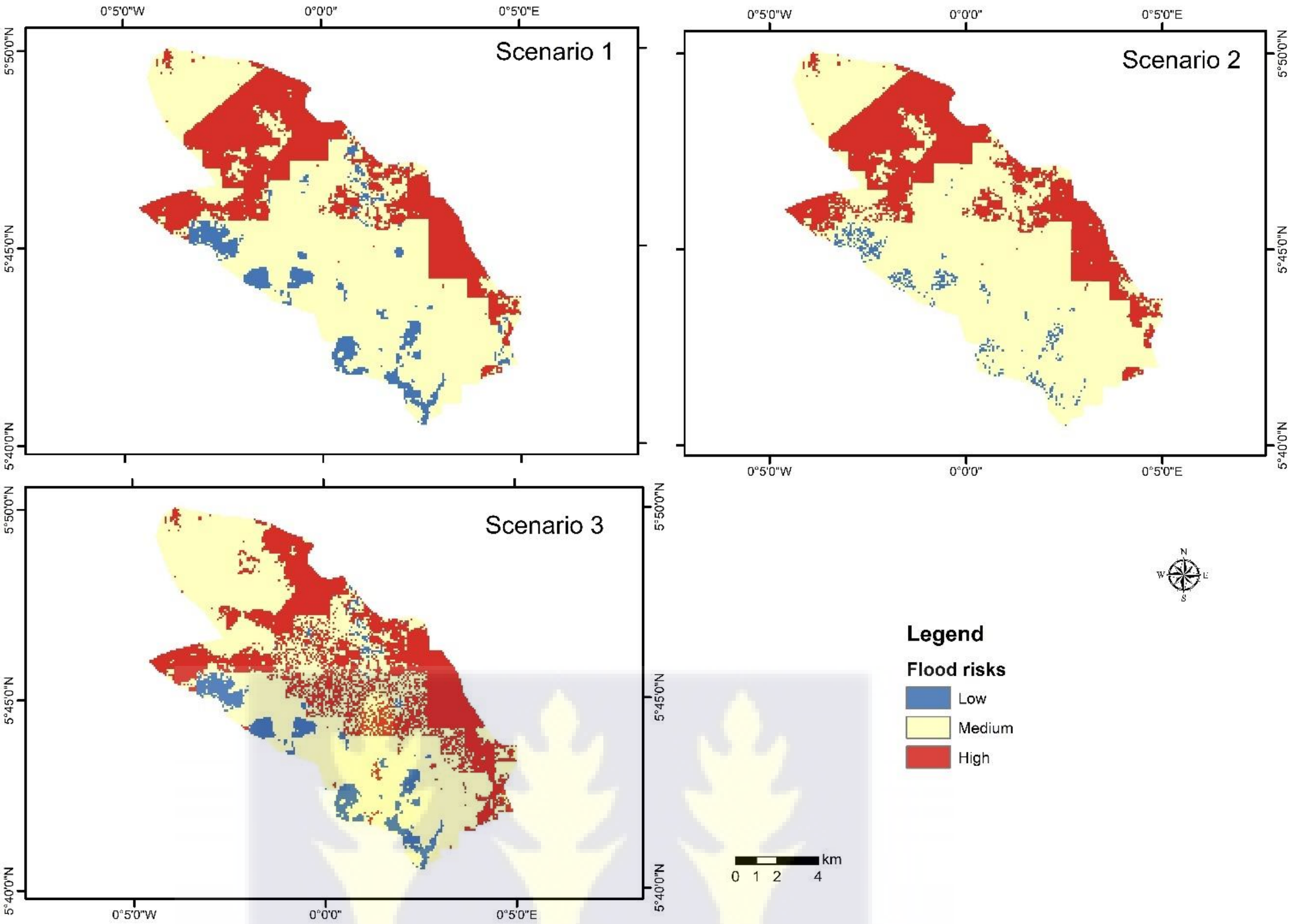

Figure E4: Flood risk maps for KKDA in 2030 under the three scenarios.

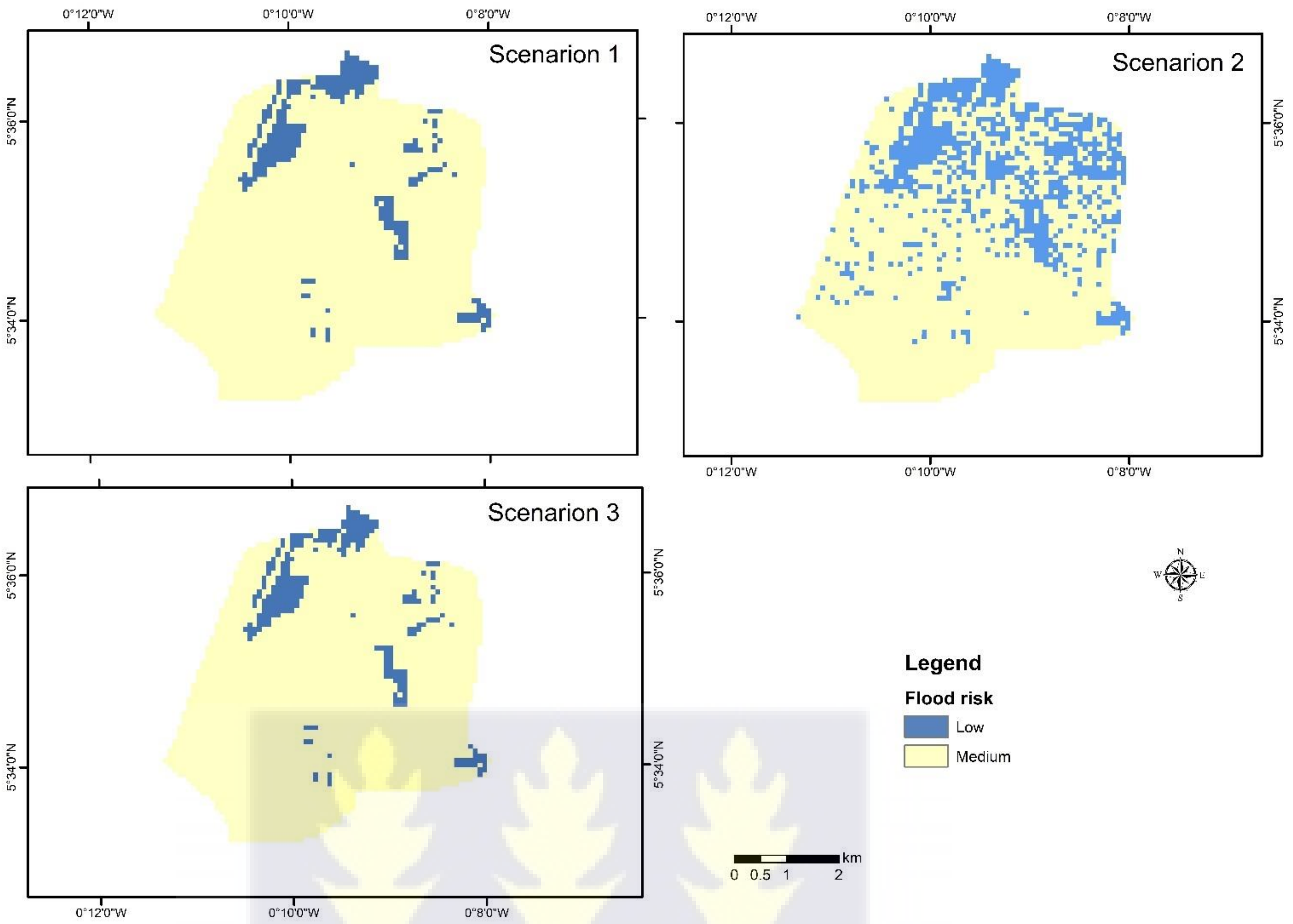

Figure E5: Flood risk maps for LaDMA in 2030 under the three scenarios

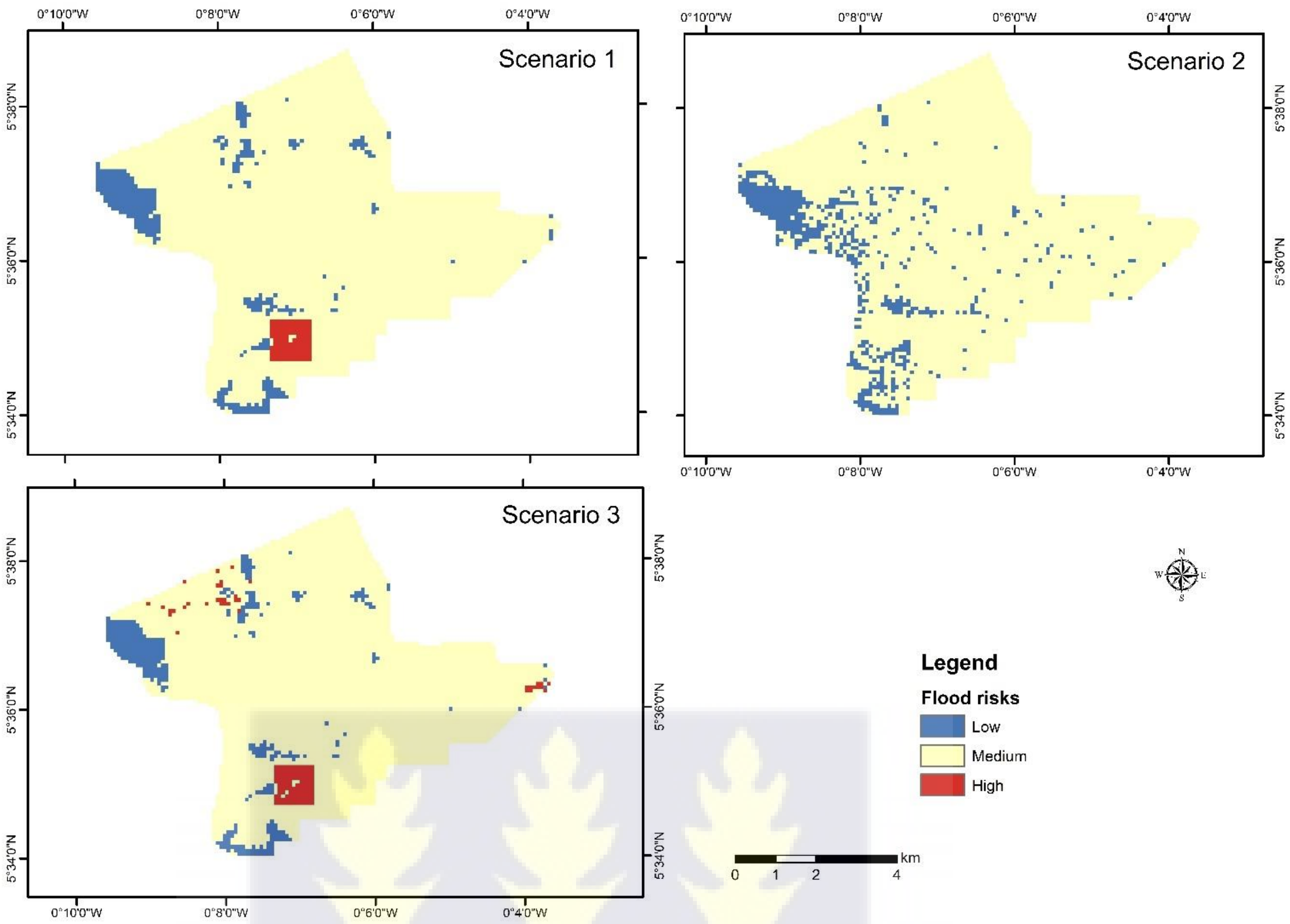

Figure E6: Flood risk maps for LeKMA in 2030 under the three scenarios.

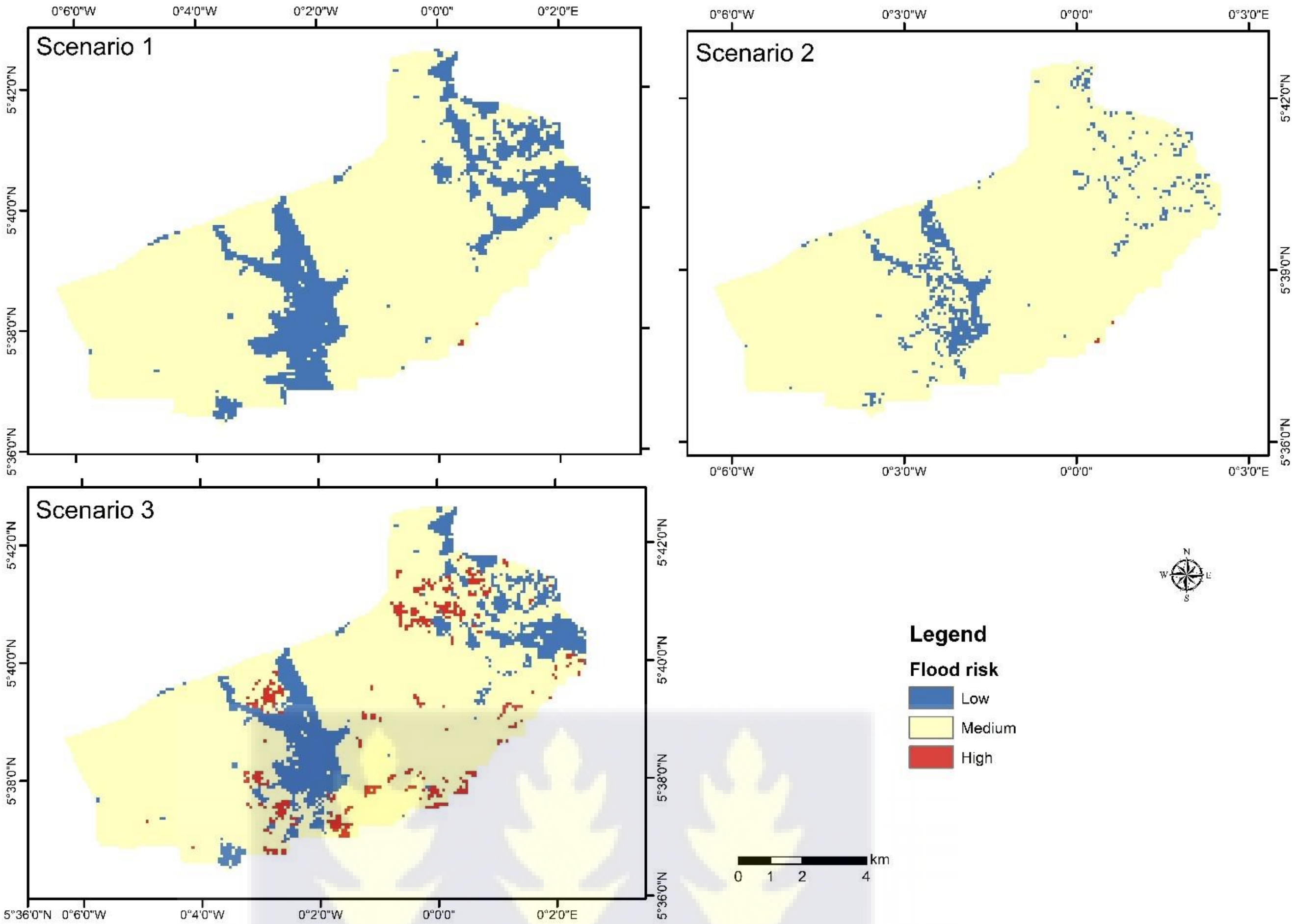

Figure E7: Flood risk maps for TMA in 2030 under the three scenarios.

Table 34Table E1: Forecasted flood risk in the seven districts of GAMA for the year 2030

District	Classification	Category (risk)	Area in hectares (Scenario 1: Trend)	%	Area in hectares ((Scenario 2: liberalization))	%	Area in hectares ((Scenario 3: SS)	%
AMA	0.00-4.00	Low	1906.74	13	2489.94	18	1691.28	12
	4.10-6.00	Medium	12136.23	85	11487.42	80	12013.92	85
	6.1-10.00	High	165.24	2	230.85	2	464.94	3
AdMA	0.00-4.00	Low	1593.27	9	1449.09	8	1330.83	7
	4.10-6.00	Medium	11148.03	62	13083.93	73	12577.68	70
	6.1-10.00	High	5303.88	29	3512.16	19	4125.33	23
AshMA	0.00-4.00	Low	1650.78	20	754.11	9	1377	17
	4.10-6.00	Medium	6142.23	76	7125.57	88	5553.36	69
	6.1-10.00	High	282.69	4	196.02	3	1135.62	14
KKDA	0.00-4.00	Low	1087.83	7	384.75	3	1003.59	7
	4.10-6.00	Medium	9569.34	63	10389.87	68	9076.05	60
	6.1-10.00	High	4519.8	30	4402.35	29	5076.27	33
LaDMA	0.00-4.00	Low	242.19	9	688.5	25	229.23	9
	4.10-6.00	Medium	2495.61	91	2049.3	75	2493.18	91
	6.1-10.00	High	0	0	0	0	0	0
LeKMA	0.00-4.00	Low	325.62	7	483.57	10	319.14	7
	4.10-6.00	Medium	4195.8	91	4131.81	90	4147.2	90
	6.1-10.00	High	93.96	2	0	0	121.5	3
TMA	0.00-4.00	Low	1725.3	18	622.08	7	1351.89	14
	4.10-6.00	Medium	7625.34	82	8728.56	93	7557.3	81
	6.1-10.00	High	3.24	<1	3.24	<1	400.95	4

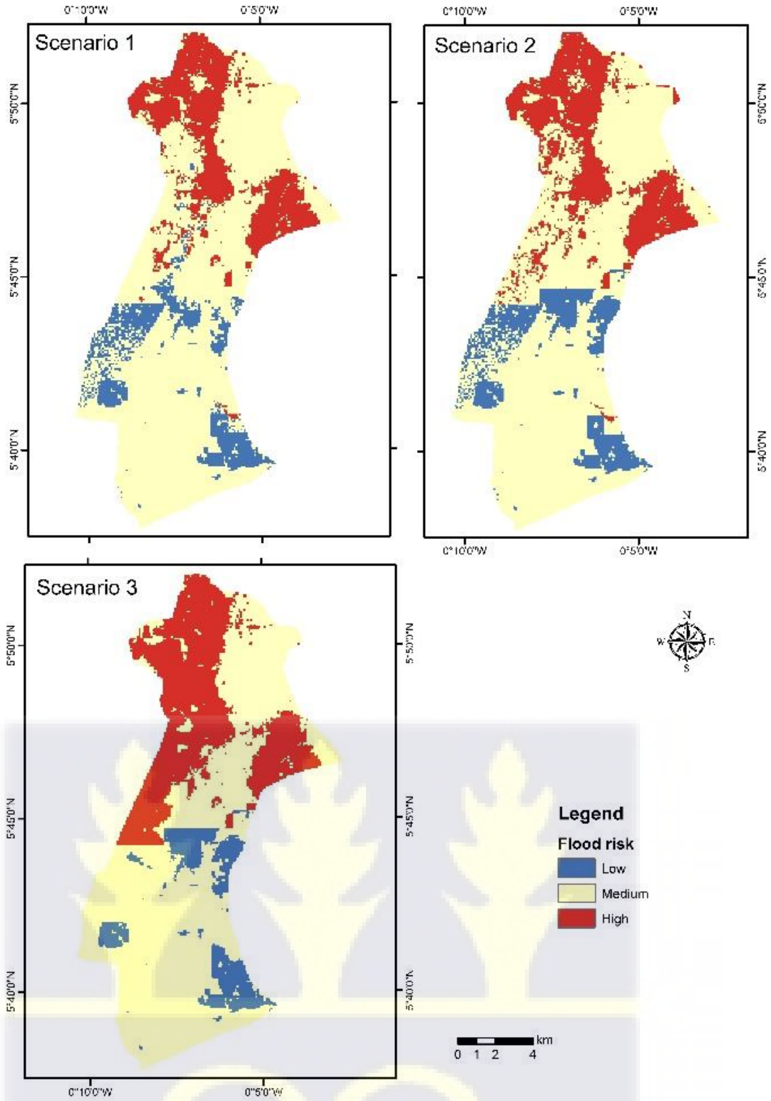

Figure E8: Flood risk maps for AdMA in 2040 under the three scenarios.

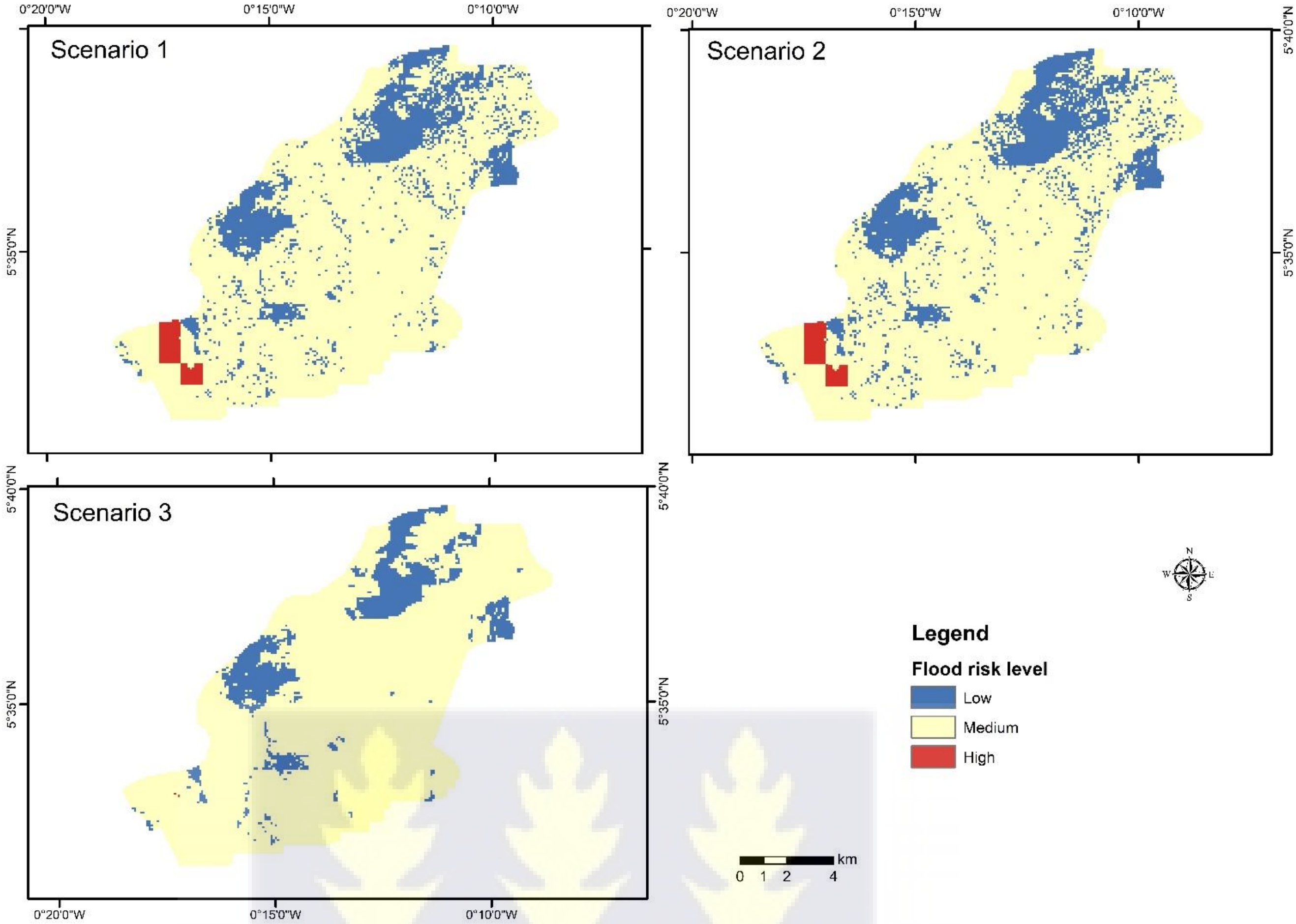

Figure E9: Flood risk maps for AMA in 2040 under the three scenarios.

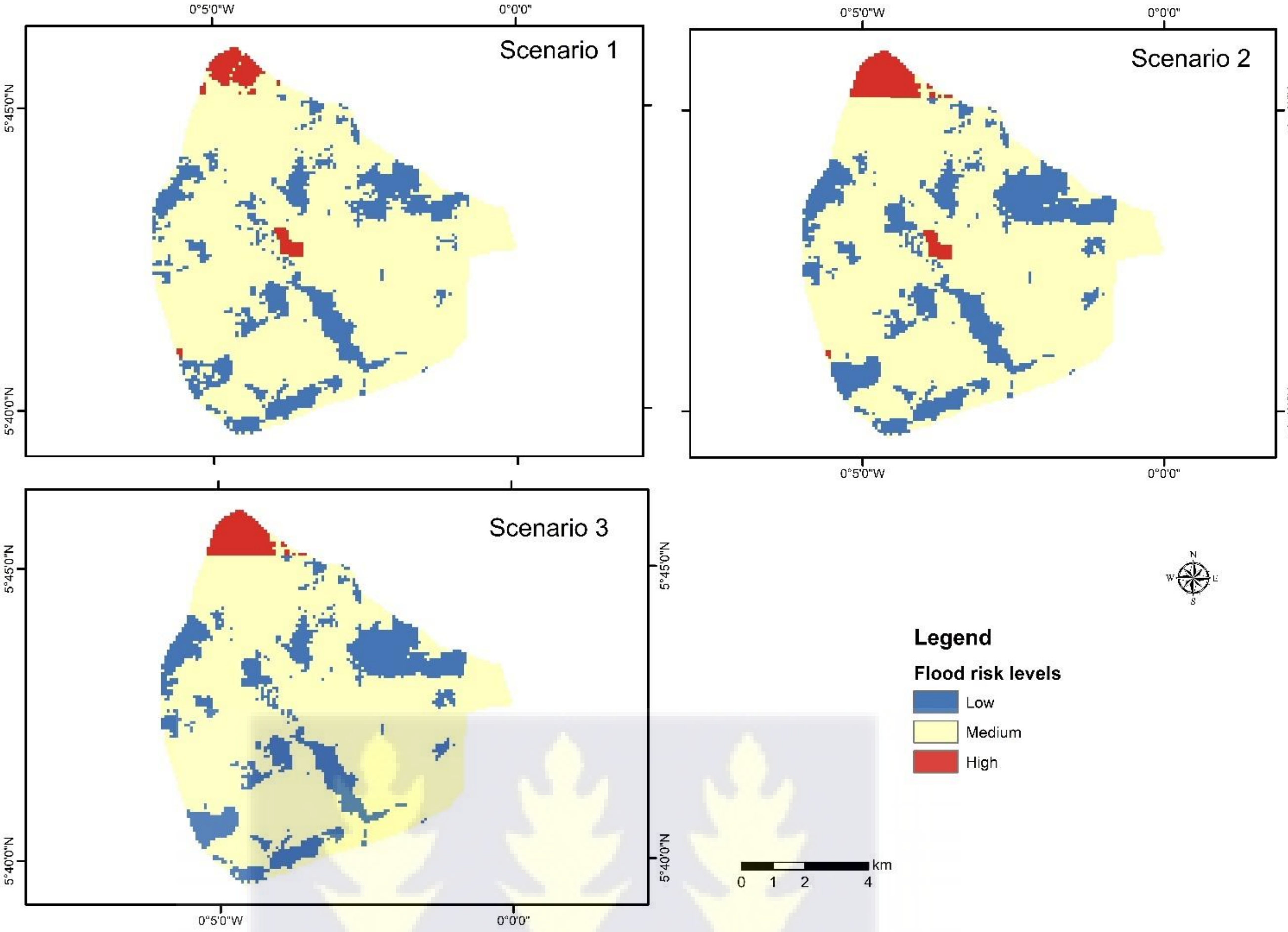

Figure E10: Flood risk maps for AshMA in 2040 under the three scenarios.

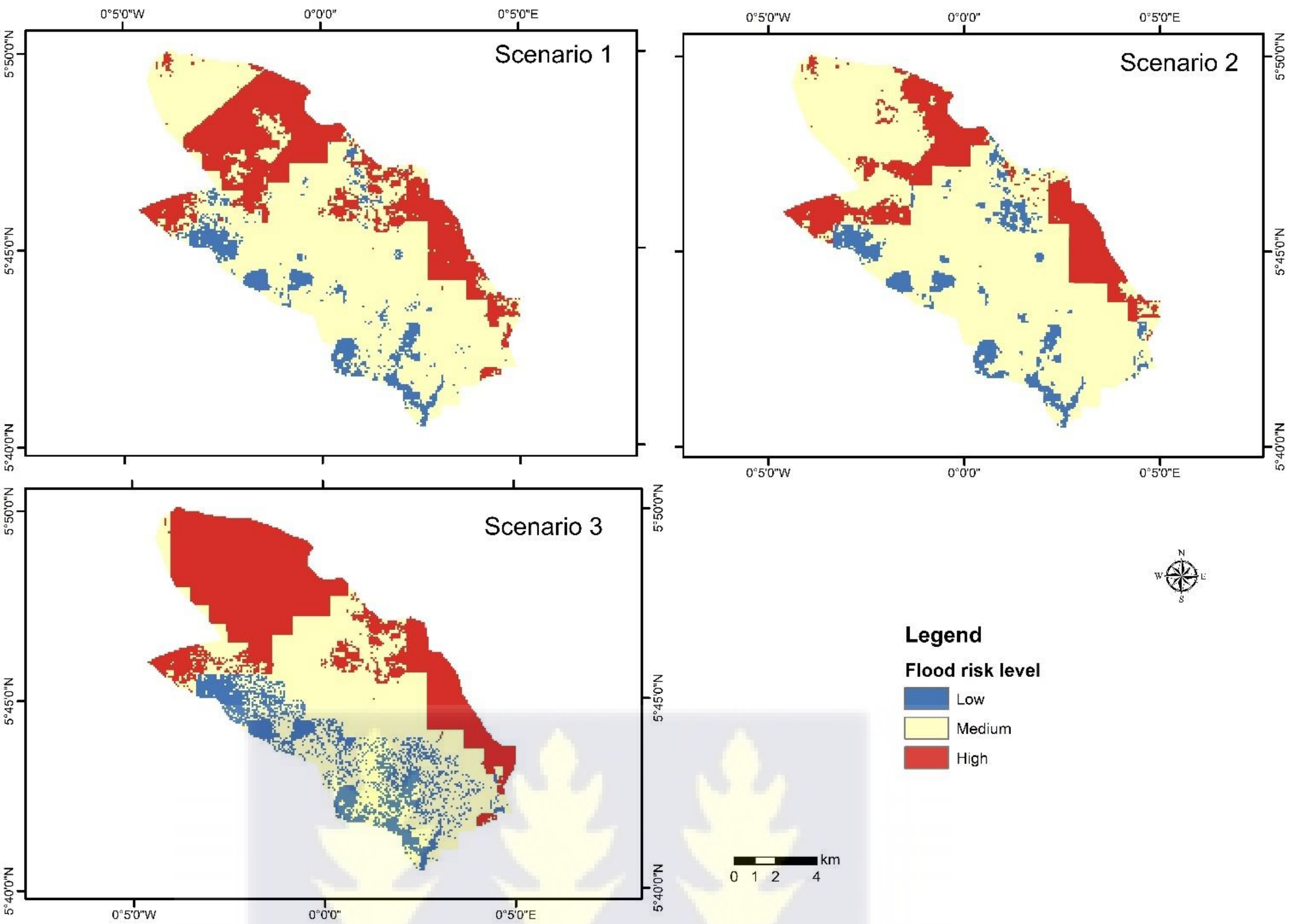

Figure E11: Flood risk maps for KKDA in 2040 under the three scenarios.

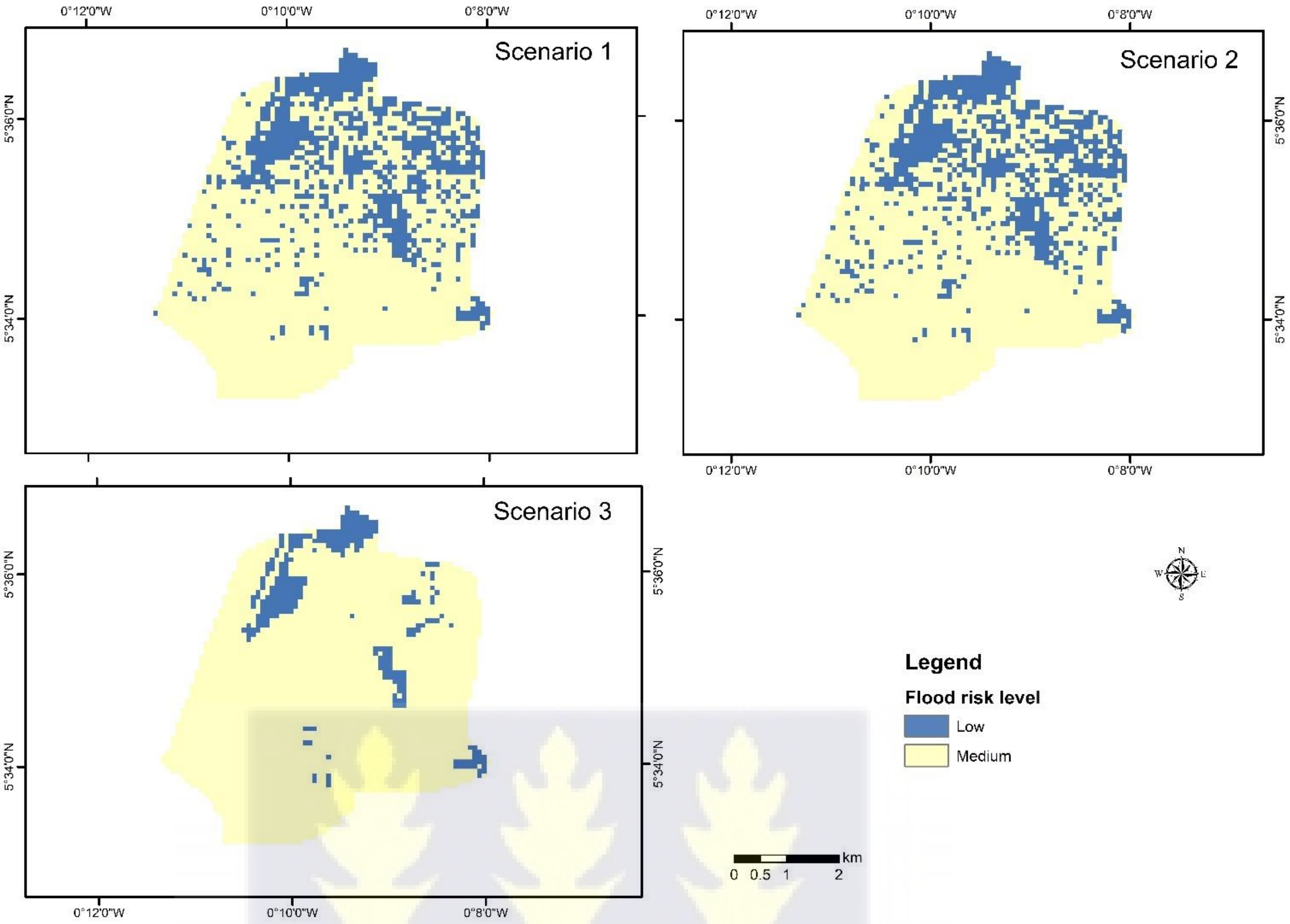

Figure E12: Flood risk maps for LaDMA in 2040 under the three scenarios.

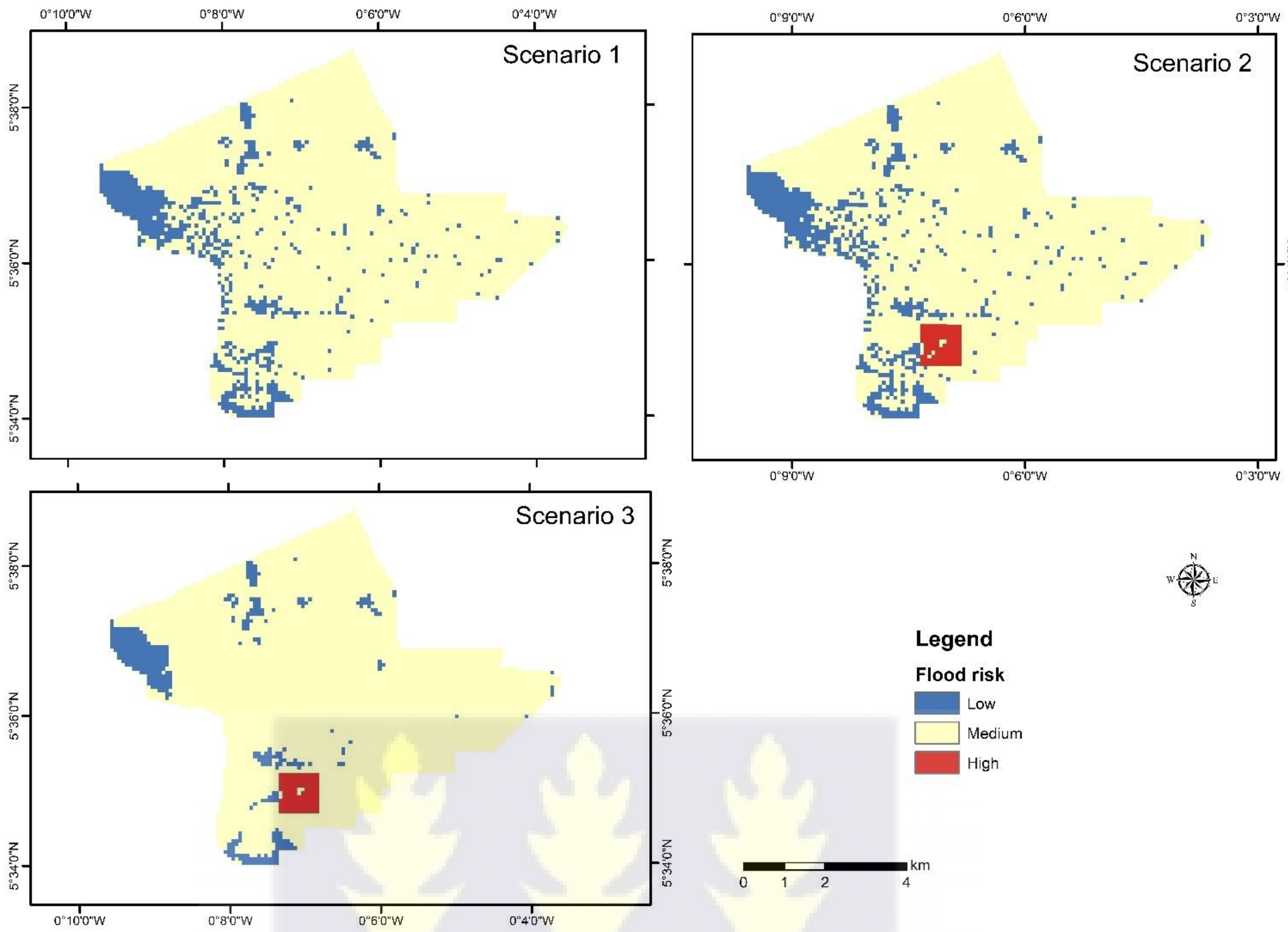

Figure E13: Flood risk maps for LeKMA in 2040 under the three scenarios.

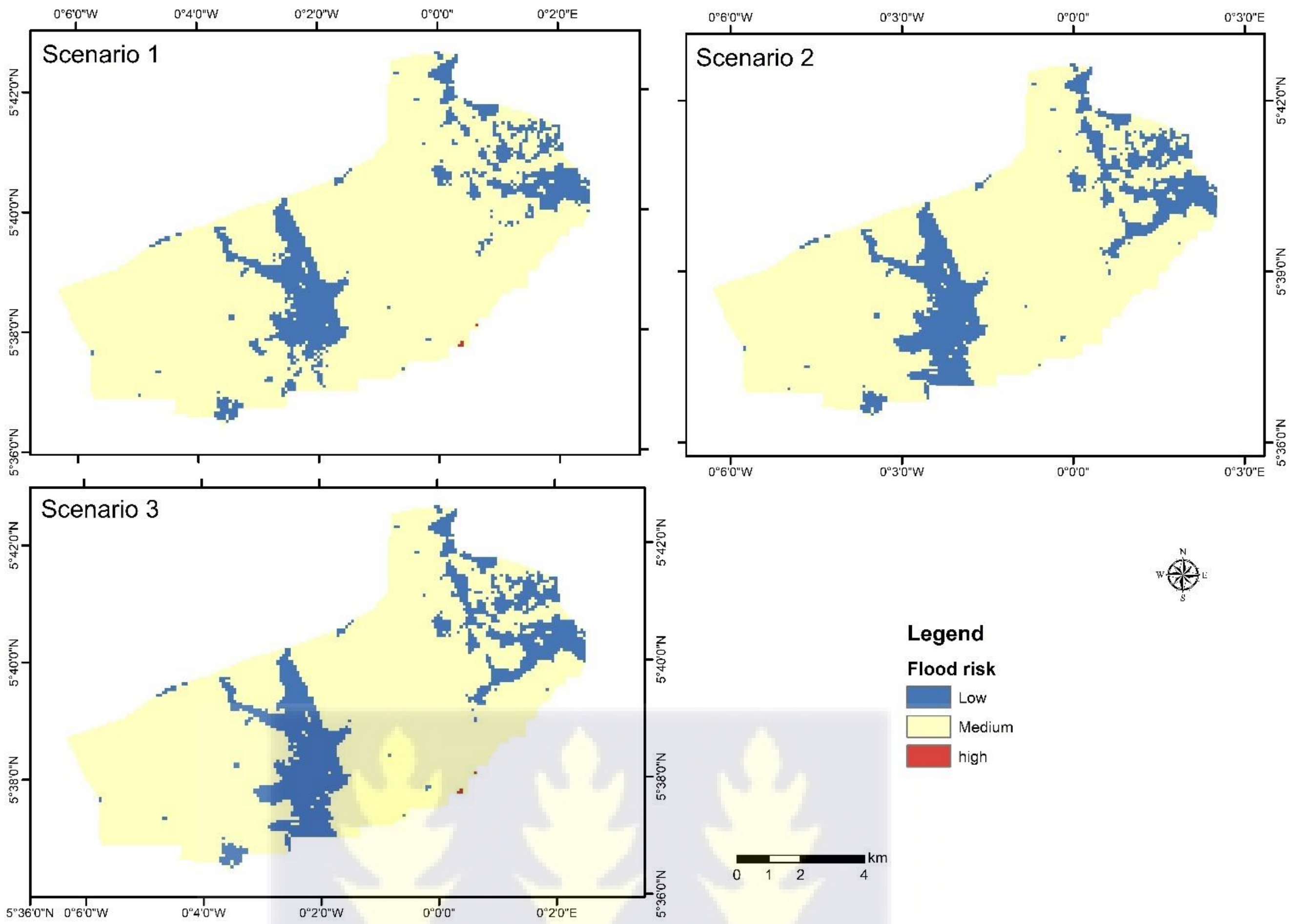

Figure E14: Flood risk maps for TMA in 2040 under the three scenarios.

Table 35Table E2: Forecasted flood risk in the seven districts of GAMA for the year 2040

District	Classification	Category (risk)	Area in hectares	%	Area in hectares	%	Area in hectares	%
AMA	0.00-4.00	Low	2715.12	19	2975.94	21	1908.36	13
	4.10-6.00	Medium	11262.24	79	11001.42	77	12298.23	87
	6.1-10.00	High	230.85	2	230.85	2	1.62	<1
AdMA	0.00-4.00	Low	1946.43	11	2127.06	11	1607.85	9
	4.10-6.00	Medium	12538.8	69	12023.64	67	11213.64	62
	6.1-10.00	High	3559.95	20	3894.48	22	5223.69	29
AshMA	0.00-4.00	Low	1377.81	17	1645.92	20	1652.4	20
	4.10-6.00	Medium	6501.87	81	6147.09	76	6191.64	77
	6.1-10.00	High	196.02	2	282.69	4	231.66	3
KKDA	0.00-4.00	Low	993.06	11	936.36	6	1275.75	8
	4.10-6.00	Medium	9781.56	69	8178.57	54	11011.95	73
	6.1-10.00	High	4402.35	20	6062.04	40	2889.27	19
LaDMA	0.00-4.00	Low	698.22	26	719.28	26	242.19	9
	4.10-6.00	Medium						
			2039.58	74	2018.52	74	2495.61	91
	6.1-10.00	High	0	0	0	0	0	0
LeKMA	0.00-4.00	Low	579.96	13	591.3	13	325.62	7
	4.10-6.00	Medium	4035.42	87	932.55	85	4195.8	91
	6.1-10.00	High	0	0	91.53	2	93.96	2
TMA	0.00-4.00	Low	1351.89	14	1726.11	18	1726.92	18
	4.10-6.00	Medium	7998.75	86	7627.77	82	7623.72	82
	6.1-10.00	High	3.24	0	0	0	3.24	<1

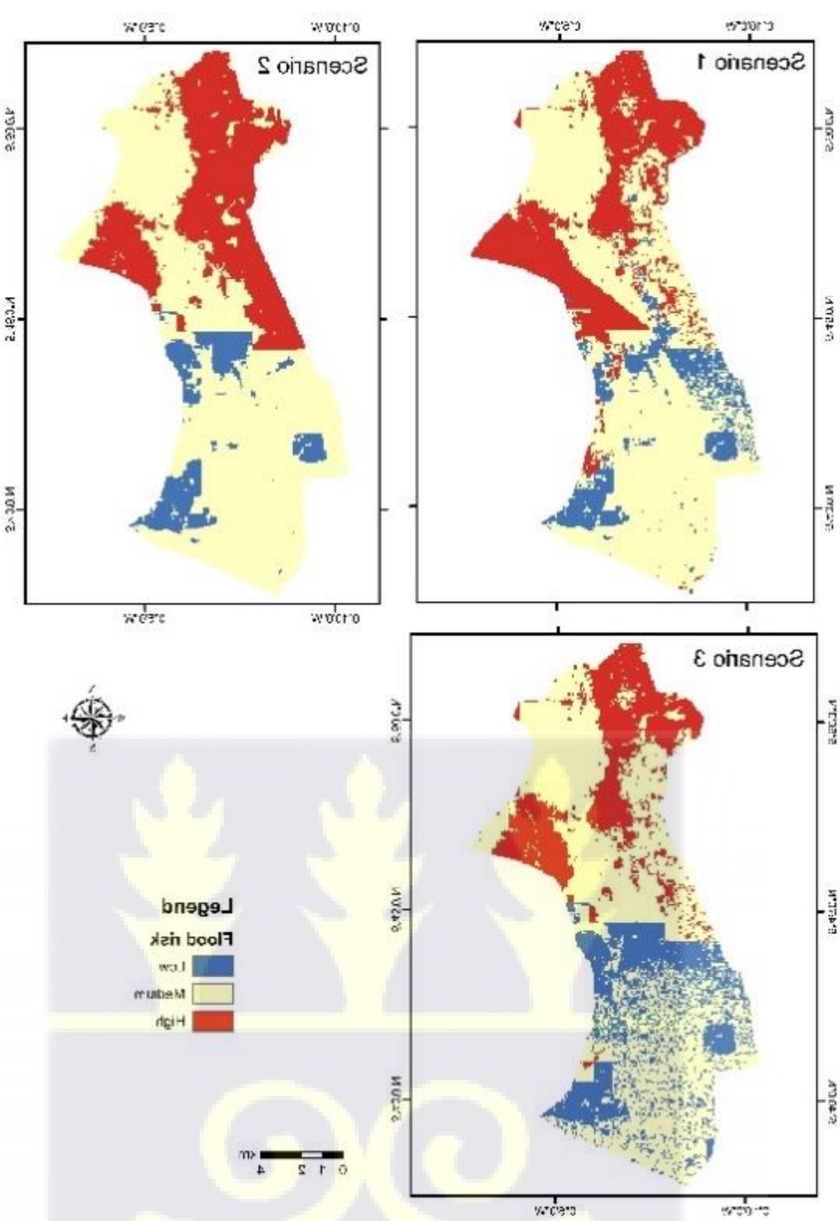

Figure E15: Flood risk maps for AdMA in 2050 under the three scenarios.

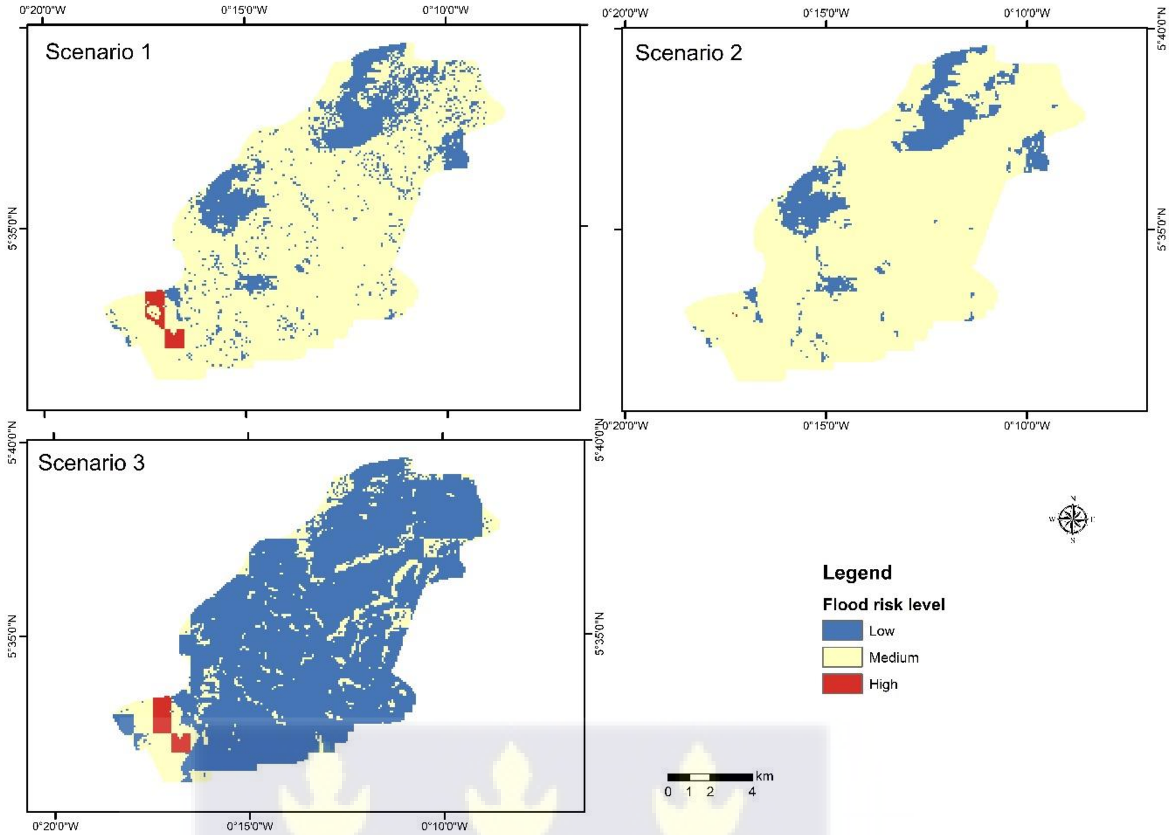

Figure E16: Flood risk maps for AMA in 2050 under the three scenarios.

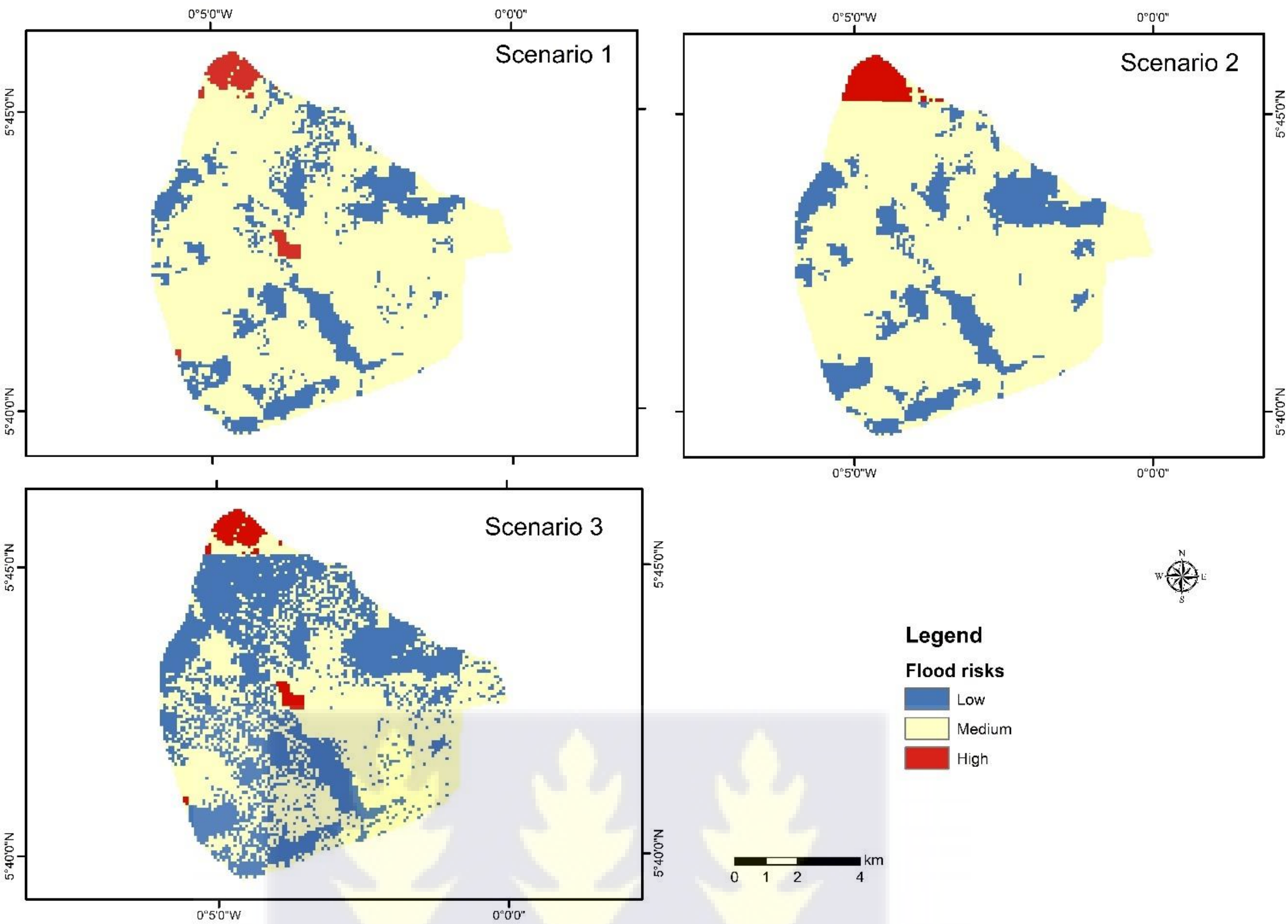

Figure E17: Flood risk maps for AshMA in 2050 under the three scenarios.

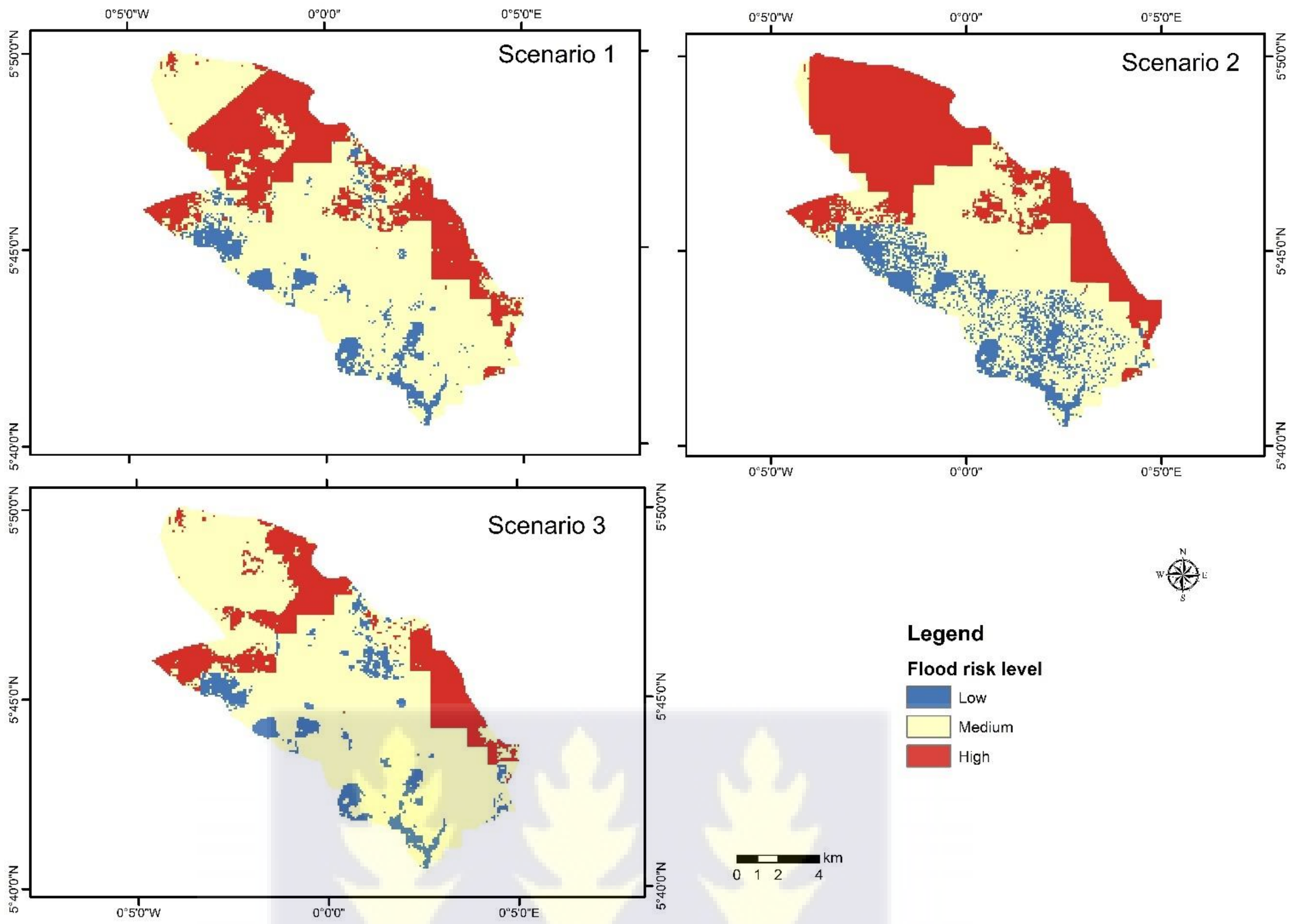

Figure E18: Flood risk maps for KKDA in 2050 under the three scenarios.

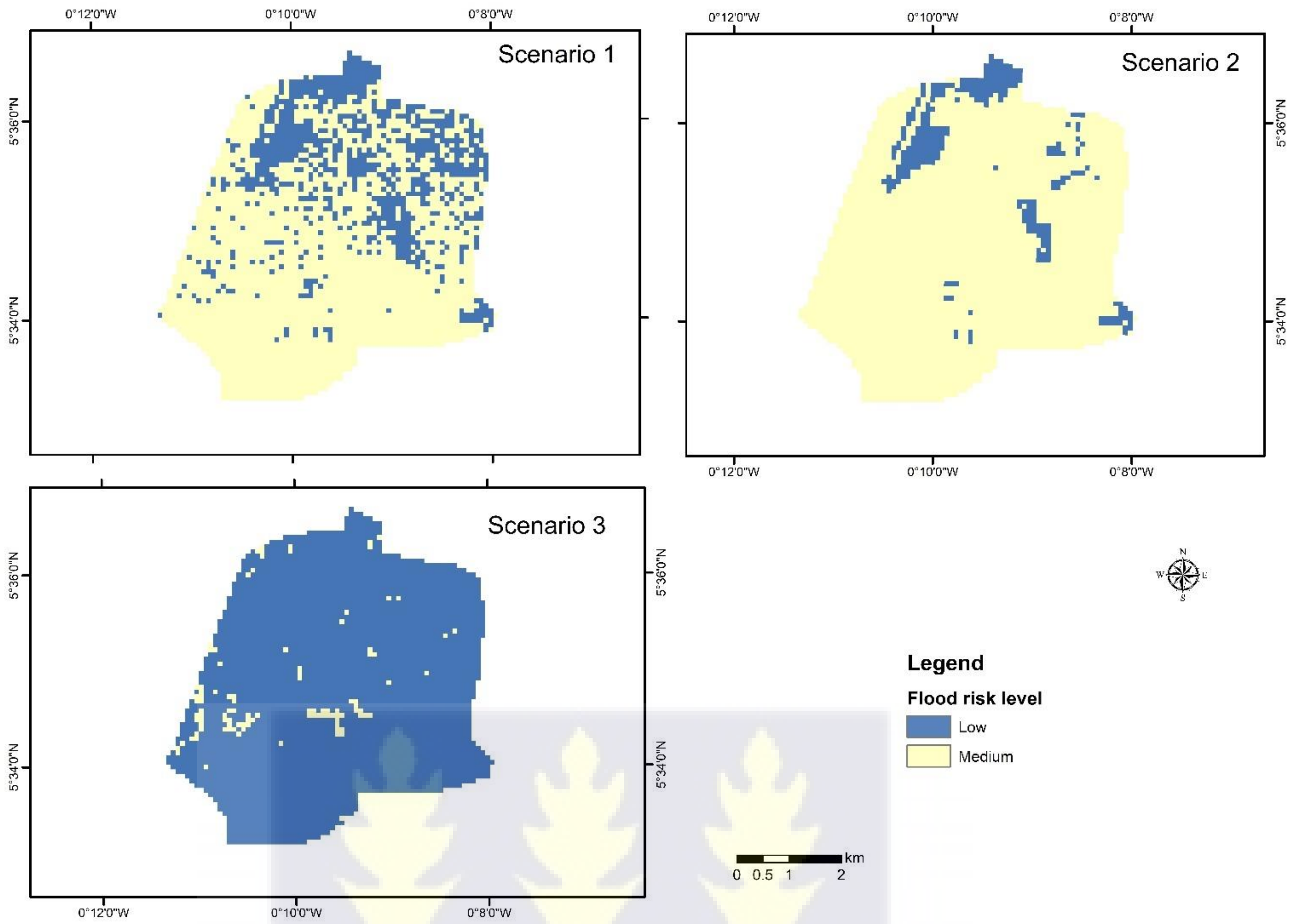

Figure E19: Flood risk maps for LaDMA in 2050 under the three scenarios.

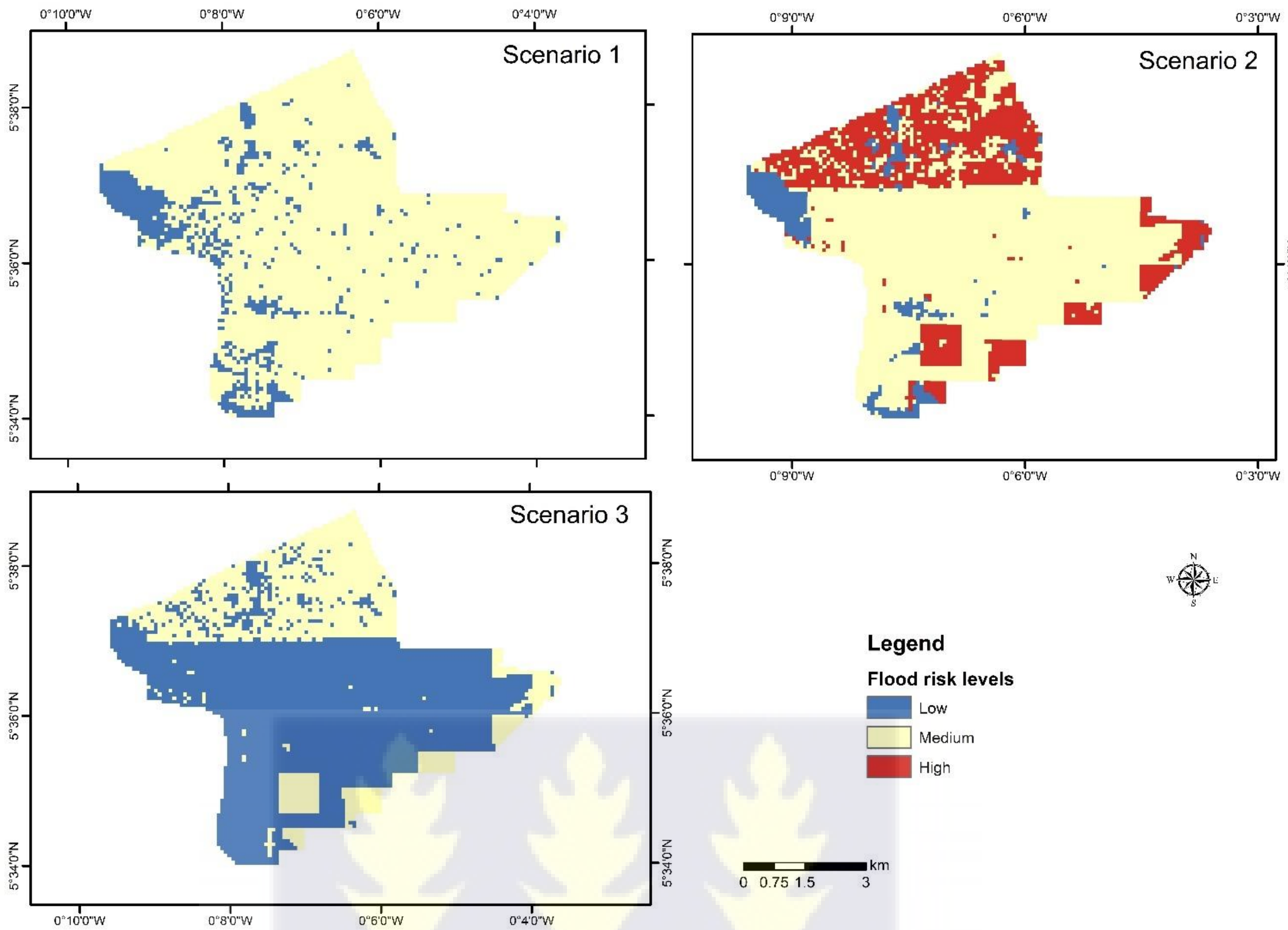

Figure E20: Flood risk maps for LeKMA in 2050 under the three scenarios.

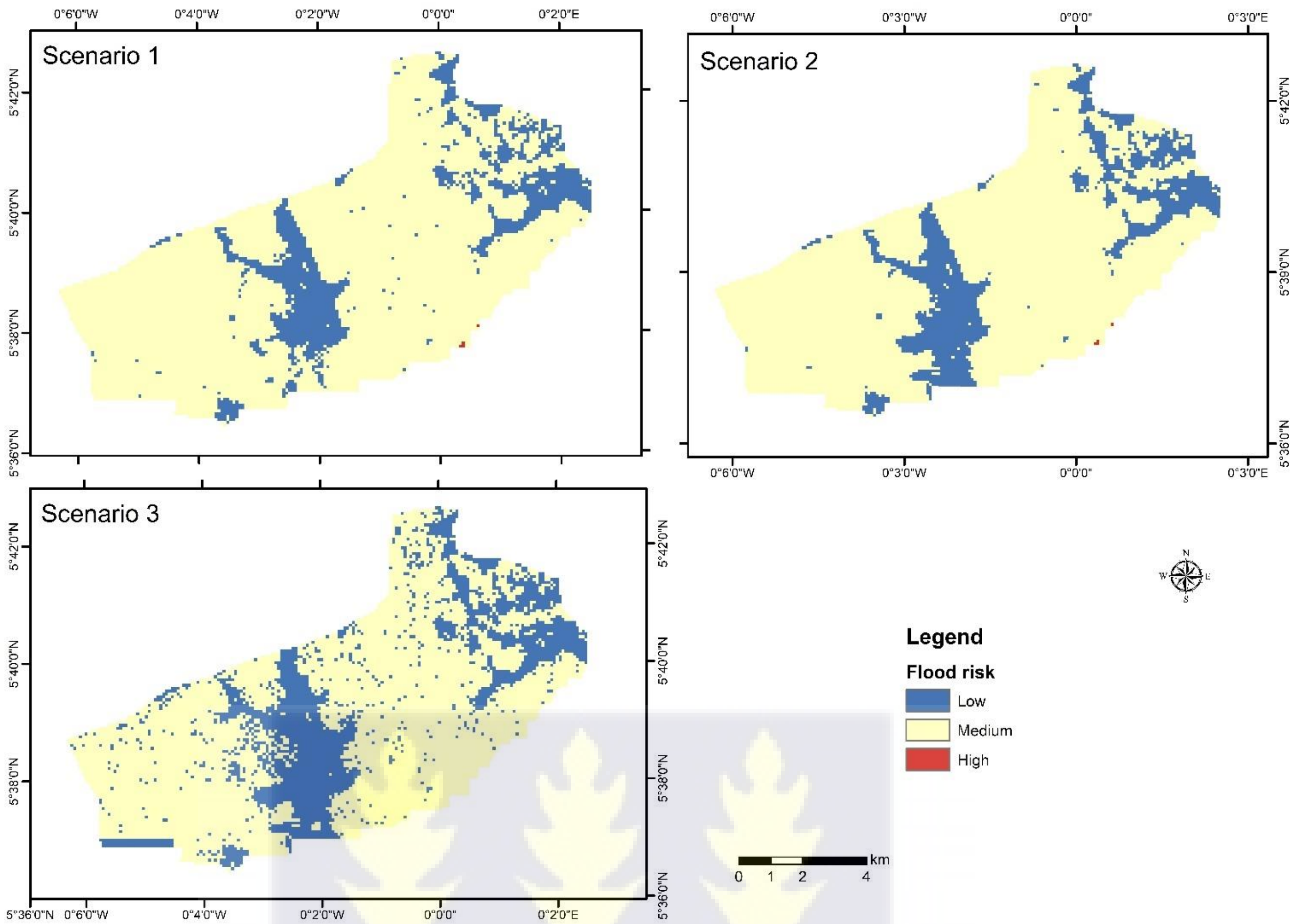

Figure E21: Flood risk maps for TMA in 2050 under the three scenarios.

Table 36Table E3: Forecasted flood risk in the seven districts of GAMA for the year 2050

District	Classification	Category (risk)	Area in hectares	%	Area in hectares	%	Area in hectares	%
AMA	0.00-4.00	Low	2781.54	20	1908.36	13	11880.27	84
	4.10-6.00	Medium	11247.66	79	12298.23	87	2097.09	15
	6.1-10.00	High	179.01	1	1.62	0	230.85	2
AdMA	0.00-4.00	Low	1999.89	11	1607.85	9	3762.45	21
	4.10-6.00	Medium	12567.96	70	11213.64	62	10551.06	58
	6.1-10.00	High	3477.33	19	5223.69	29	3731.67	21
AshMA	0.00-4.00	Low	1628.91	20	1652.4	20	3666.06	45
	4.10-6.00	Medium	6251.58	77	6191.64	77	4213.62	52
	6.1-10.00	High	195.21	2	231.66	3	196.02	2
KKDA	0.00-4.00	Low	1219.86	8	1275.75	8	2199.15	14
	4.10-6.00	Medium	9695.70	64	11011.95	73	7045.38	46
	6.1-10.00	High	4261.41	28	2889.27	19	5932.44	39
LaDMA	0.00-4.00	Low	698.22	26	242.19	9	2655.18	97
	4.10-6.00	Medium	2039.58	74	2495.61	91	82.62	3
	6.1-10.00	High	0.00	0	0	0	0	0
LeKMA	0.00-4.00	Low	599.40	13	325.62	7	3171.96	69
	4.10-6.00	Medium	4015.98	87	4195.8	91	1443.42	31
	6.1-10.00	High	0.00	0	93.96	2	0	0
TMA	0.00-4.00	Low	1512.27	16	1726.92	18	2476.17	26
	4.10-6.00	Medium	7838.37	84	7623.72	82	6877.71	74
	6.1-10.00	High	3.24	0	3.24	0	0	0