Detecting and Predicting Land Use and Land Cover Change in the Cross-Sanaga-Bioko Coastal Forest Region for Sustainable Forest Management.

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A dissertation submitted in partial fulfilment of the requirement of degree of

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Dedication

I would like to thank my supervisor, Dr Hull, for his encouragement and support throughout my master's degree studies, as well as Mr Thomas Slingsby, Mr Nicholas Lindenberg, and Ms Mignon Wells for their assistance, as well as my family, particularly my uncle, Dr Charles Akwe Masongo, and his wife, Mrs Emade Masango, for making my coming to South Africa and continuing my education possible. I'd like to thank my lab collaborators Alex Yumbu, Dianah Abeho, and Itumeleng Musa, as well as the University of Cape Town's Division of Geomatics. Special thanks to God Almighty for making everything possible and providing me with the strength and energy I needed throughout the most difficult periods.

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List of Abbreviations and Acronyms

ART: Architecture for REDD+ Transaction

ATLAS: Laboratory for Application and Science

AWS: Amazon Web Services

CA: Cellular Automata

CA-MC: Cellular Automata Markov Chain

CART: Classification and Regression Trees

CBD: Convention on Biological Diversity

CO: Carbon Monoxide

CSB: Cross-Sanaga-Bioko

DEM: Digital Elevation Model

ENVI: Environment for Visualising Images

ERDAS: Earth Resources Data Analysis System

EU: European Nations

FAO: Food and Agriculture Organization

FLEGT: Forest Law Enforcement Governance and Trade

GEE: Google Earth Engine

GFRA: Global Forest Resource Assessment

GIS: Geographic Information System

GPS: Global Positioning System

Ha: Hectares

IAF: International Agreement on Forest

IGBP/IHDP: International Geosphere-Biosphere Program and International Human Dimension Program

ITTA: International Tropical Timber Agreement

ITTO: International Tropical Timber Organization

IUCN: International Union for Conservation of Nature

LCC: Land Cover Change

LCM: Land Change Modeller

LULC: Land Use Land Cover

MLP: Multi-Layer Perceptron

MLPNN: Multi-Layer Perceptron Neural Network

MODIS: Moderate Resolution Imaging Spectroradiometer

NESREA: National Environmental Standard and Regulation Enforcement Agency

NFWP: National Forest and Wildlife Policy

NLBI: Non-Legal Binding Instrument

NO_2: Nitrogen Dioxide

NOAA: National Oceanic Atmospheric Administration

O_3: Ozone

OFAC: Observatory for Forest of Central Africa

$PM_{2.5}$: Particulate Matter 2.5

QGIS: Quantum Geographic Information System

REDD+: Reducing Emissions from Deforestation and Forest Degradation

R-Studio: Integrated Development Environment for R Programming

SDG: Sustainable Development Goal

SFM: Sustainable Forest Management

SNAP: Sentinel Application Platform

SO_2: Sulphur Dioxide

SPOT: Satellite Pour L'Observation de la Terre

TerrSet: Integrated Geospatial Software System for Monitoring and Modelling

UG/M^3: Micrograms per Cubic Meter

UN: United Nation

UNCED: United Nation Conference on Environment and Deforestation

UNFCCC: United Nations Framework Convention on Climate Change

UNFF: United Nation Forum on Forest

VGGTS: Voluntary Guidelines on the Responsible Governance of Tenure

VPA: Voluntary Partnership Agreement

WHO: World Health Organization

Abstract

This study assesses forest, agriculture and built-up areas change in the Cross-Sanaka-Bioko (CSB) region from 2000 to 2021, aiming to provide reliable data for sustainable forest management practices. This analysis will be accomplished with the aid of GIS tools (Google Earth Engine and ArcGIS Pro) and remote sensing data (LULC maps and digital elevation models) in the CSB region. Land use and land cover (LULC) changes in forested regions are critical indicators of environmental transformation, contributing to deforestation, forest degradation, and biodiversity loss, with significant impacts on the environment and human well-being. Sustainable forest management is essential for maintaining ecological balance and ensuring forest resources for future generations. A supervised LULC classification map was created for 2000, 2007, 2014, and 2021 using a decision tree-based machine learning algorithm. Loss, gain and post-classification change detection analysis were used to pinpoint significant LULC changes in the region. Identifying the potential impacts of LULC changes to the environment, air pollutants (CO, NO_2, SO_2, and PM2.5) were used to first evaluate the variation of emission of the pollutants over the years using a descriptive statistic. Furthermore, a point biserial correlation analysis was used to test the strength of association between the supervised LULC classes with the identified pollutants. Lastly the Multi-Layer Perceptron and Cellular Automata-Markov chain models were used to predict land cover change in the region in the year 2063 and validated by comparing the predicted 2063 map with the 2000 and 2021 classified maps in the CSB region. The study revealed a significant reduction in forested areas (35.55% loss), with the most substantial decline (14.69%) between 2007 and 2014. Agricultural and built-up areas increased by 28.05% and 13.73%, respectively. The primary LULC transition was from forests to agricultural areas, followed by built-up areas. Pollutant emissions, except for NO_2, exceeded WHO-recommended values in the region. The results from the correlation analysis showed positive and negative correlations between the LULC changes and air pollutants. For example, agriculture had a moderate positive correlation with NO_2 and a moderate negative correlation with CO. There is a projected 21.03% loss in forested areas by 2063, with agricultural lands expanding by 19.69% and built-up areas by 10.88%. These findings highlight the urgent need for sustainable development practices to balance forest conservation, agricultural growth, and urban expansion, aligning with Goal 7 of the African Union Agenda to promote environmental sustainability, and Goal 15, Target 15.2 of the United Nations Sustainable Development Goals.

Keywords: Sustainable Development, LULC, Correlation Analysis, Change Detection, Descriptive Statistics, Machine Learning, Land Cover Forecasting, and Air Pollution.

1. INTRODUCTION

1.1 Background

In terms of natural resources, forest regions are essential for economic growth and environmental protection. When inland forest and woodland extends to the sea in different climatic conditions of the world, they form coastal forest regions. Coastal and tropical forests are valuable due to their abundant biodiversity and natural resources. The formation of these regions may be powered by climatic factors, topology and soil types which may create coastline forest such as mangroves, beach forest, peat swamp forest, and riparian forest (Filotas et al., 2014). The Food and Agriculture Organization (FAO, 2020) describes deforestation as an occurrence where forest areas are being converted into different land use or where there is long-term deduction of more than 10% of the tree canopy cover. Furthermore, it is important to note that deforestation is an active process which if allowed to continue will give rise to forest loss which is regarded as the complete removal of tree canopy. Between the years 2015 and 2020, the global deforestation rate was measured to be 10 million hectares per year (Food and Agriculture Organization, 2020).

Deforestation across Africa and the world has been influenced by increased population growth and economic development. Coastal countries like Equatorial Guinea, Cameroon, and Nigeria cannot afford to stop the destruction of their natural forest resources, mainly because they need the forest resources to generate revenue and create more agricultural lands for food production. This in turn helps to support their ever-growing population and economy (Food and Agriculture Organization, 2015). It is widely recognized that the forest and trees provide a certain level of environmental protection and increase socio-economic development of the continent. Rural and urban communities depend for their livelihoods on the different varieties of forest products and resources which include wild foods such as honey, mushrooms, fruits, medicine, wood fuel, construction poles, and other materials for their livestock. The resources produced by the forest also helps to increase the economy of the country through the trading of timber in the Congo basin countries (Food and Agriculture Organization, 2009).

Even though there is global, national, and local awareness of the importance of forests and their ecosystems, their conservation must be juxtaposed against the assurance of human socio-economic development and poverty reduction. The decline of forest regions in Africa is still expected to occur at high rates due to forest degradation and deforestation. FAO estimated that during the years 1990 to 2005, there was a 9% loss in forest resources in the Congo basin which was about 4 million hectares annually (Food and Agriculture Organization, 2009). Although sustainable forest management is practiced, the loss of forest resources is still significant in most African countries because the management procedures have not produced any concrete results (Food and Agriculture Organization, 2020). Within the member states of the International Tropical Timber Organization (ITTO) of Central Africa, less than 8% of the permanent forest estates are under sustainable management, despite more than 27% being allocated for sustainable management (International Tropical Timber Organisation (ITTO), 2005).

Sustainable forest management (SFM) is a concept that seeks to balance the needs of both the consumers and producers (humans and the environment), embracing environmental values for all types of forest for the benefit of the present and future generations see Figure 1-1 below (Prabhu, et al., 1996). Increasing environmental concerns of the public, professionals, and the worldwide media can be addressed with the help of SFM (Tainter, 2001). For example, SFM can be used to promote an understanding between uncontrolled logging and ban on logging. SFM may be defined as follows:

"The process of managing permanent forest land to achieve one or more clearly specified objectives of management with regard to the production of a continuous flow of desired forest products and services without undue reduction of its inherent values and future productivity and without undesirable effects on the physical and social environment" (International Tropical Timber Organisation (ITTO), p2 1992).

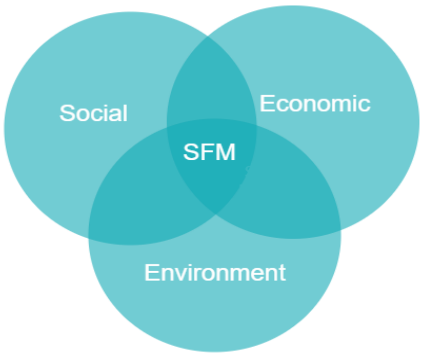

Figure 1-1: The three pillars of Sustainable Development, showing the relationships amongst social, environmental, and economic sustainability.

With the introduction of SFM in the early 1990's, the idea has been seen as a driving force in the protection of environmental services of major ecological values and as a reasonable way of promoting local, national, and international objectives. Since the implementation of SFM, preservation of forest regions was the main concern in the United Nations Environment and Development forum in 1992. Deliberations on forest sustainability led to the allocation of finance for the preservation of forest regions close to extinction (Food and Agriculture Organization, 2005). In the 9th session of the United Nations Forum on Forests (UNFF9) on October 30, 2009, policies for SFM implementation were established. These policies, monitored by the United Nations Forest Forum Non-Legal Binding Instrument (NLBI), aimed to achieve four Global Objectives on Forests: reversing forest loss, enhancing forest-based benefits, increasing sustainably managed forests, and mobilizing financial resources. The focus on mobilizing financial resources was particularly critical, leading to the creation of an open-ended intergovernmental ad hoc expert group and the establishment of facilitative constraints. (Food and Agriculture Organization, 2009).

Effective SFM requires collaboration between policymakers and forest users. This necessity was highlighted at the 2012 United Nations Conference on Sustainable Development Goals (SDG) in Rio de Janeiro. The SDGs aimed to balance human development with natural resource sustainability, identifying poverty eradication as a fundamental challenge. The goals, designed to be integrated, indivisible, and balanced, also emphasized human rights and gender equality (United Nation Development Programs, 2016). Besides the UN SDGs there also exist the African Union Agenda 2063 which was formed in May 2013. The aim of the agenda is to transform Africa into a global powerhouse by attaining inclusive and sustainable economic growth and development (African Union, 2015).

This research focuses on UN SDG 15 and African Union Agenda Goal 7, both of which underscore the need for SFM. SDG 15 targets the protection, restoration, and sustainable use of terrestrial ecosystems, aiming to combat desertification, halt and reverse land degradation, and halt biodiversity loss by 2030 (United Nations, 2012). Similarly, African Union Agenda Goal 7 aims to create environmentally sustainable and climate-resilient economies and communities (African Union, 2015). The significance of sustainable management to forest environment is that it creates a steady and continuous flow of forest resource products, mitigates climate change, and provides renewable energy, biodiversity, and good quality water supply. Furthermore, the quality of oxygen exchange in the atmosphere is made possible by the forest. Hence, the protection of the world’s forest regions, including the Cross-Sanaka-Bioko (CSB) forest region, is highly important.

1.2 Motivation

Humanity relies heavily on forest resources for survival and quality of life. Forests play a critical role in biomass allocation, carbon storage, biodiversity, and environmental productivity (Simard et al., 2011; Zhang and Zhou, 2016). The Global Forest Resource Assessment (GFRA) estimated the global forest area in 2015 to be approximately 4,000 million hectares, or 30.6% of the world's land area. The United Nations (2017) reported a decline in forest cover from 31.6% in 1990 to 30.6% in 2015, primarily due to deforestation, especially in Latin America, sub-Saharan Africa, and the Caribbean, as well as natural factors. Deforestation in coastal and tropical regions has led to significant greenhouse gas emissions, contributing to global warming (Food and Agriculture Organization, 2020). The CSB forest region is a biodiversity hotspot located in Central Africa, encompassing areas in Nigeria, Cameroon, and the island of Bioko in Equatorial Guinea. This region is known for its rich biodiversity, including numerous endemic species.

The CSB forest faces significant threats from human activities, including illegal logging, mineral extraction, and human encroachment, leading to deforestation and species extinction by destroying natural habitats and reducing species richness, while introducing non-native species at the expense of native ones (McKinney, 2002; George et al., 2008). Protected areas attract settlements, increasing human activity and posing a threat to wildlife habitats, flora, and fauna (Oates and Linder, 2004). Infrastructure development promotes growth but also destroys forests, altering ecological processes (Kowarik, 2011; McKinney, 2006; Shochat et al., 2006). These activities endanger species such as chimpanzees, forest elephants, and African Teak. Sustainable development in the CSB region is crucial for preserving biodiversity and mitigating global warming (United Nations, 2019).

The challenge lies in balancing forest conservation with agricultural and urban expansion. Addressing deforestation through sustainable management can restore forest regions while supporting agricultural and urban needs (Wade and Theobald, 2009). Forest ecosystems provide essential goods and services such as water, food, fuel, climate regulation, soil formation, and photosynthesis, crucial for both humans and wildlife. While agriculture combats global hunger (SDG 2) and provides income for rural inhabitants, sustainable practices are needed to support its multi-functional role (Tscharntke et al., 2016a; Kanter et al., 2018). This implementing sustainable development will preserve landscapes, cultural heritage, and protected areas for future generations (Viccaro et al., 2019).

1.3 Problem Statement

Population growth, climate change, and human activities such as agriculture and urbanization are putting immense pressure on forests, leading to deforestation and biodiversity loss. This deforestation not only threatens the availability of forest resources but also contributes to negative environmental impacts such as increased greenhouse gas emissions, global warming, soil erosion, desertification, and habitat loss (Singh et al., 2016). Without effective management strategies, forests could disappear within a century (Food and Agriculture Organization, 2015). Sustainable Forest management is crucial for preserving forests and their resources from permanent loss. However, achieving this requires comprehensive monitoring and analysis of forest changes using tools like GIS and remote sensing. This dissertation therefore leverages the use of earth observation in addressing this concern. Applying these technologies can provide accurate data for better resource allocation and forest policy governance, thus aiding in the preservation and sustainability of forests.

1.4 Aim and Objective of the Study

1.4.1 Aim

This study focuses on promoting sustainable forest management in Cross-Sanaga-Bioko (CSB) coastal forest region. The aim is to assess changes in forest, agriculture and built-up areas in the CSB region from 2000 - 2021, all in the interest of providing reliable information for sustainable forest management.

1.4.2 Objective and Research Questions

The following objectives and associated research questions support the aim:

1. Objective One: To assess the change in the land cover in the CSB region from 2000 to 2021 using time series Landsat 7 and 8 images.
    - 1.1. How can land cover change be detected, with particular focus on deforestation, urbanization, and agriculture?
    - 1.2. What is the historical and current land use and land cover status in the CSB forest region, including the direction of change and trends over time?
2. Objective Two: To identify potential causes and effects of LULC change in the CSB forest region using results from objective one.
    - 2.1. What insights can the analysis provide into the causes of LULC change in the CSB region, such as deforestation, urbanization, or agricultural expansion?

2.2. What are the effects of LULC change in the CSB region, with a specific focus on air pollution?
3. Objective Three: To predict potential land cover change in the CSB forest region without interventions.
   3.1. How can land cover change be modelled to predict potential outcome of the forest region without interventions?
   3.2. Without any additional interventions, what could the land cover situation look like in the future?
4. Objective Four: To view the results from the analysis within the context of sustainable forest policies applicable in the CSB region.
   4.1. What structures have been put in place to protect the forests in the CSB region?
   4.2. How can a balance be found between forest conservation and the need for urbanization and agriculture, and what recommendations are required to meet United Nation SDG 15, and African Union goal 7?

1.5 Scope of Study

This project utilizes various GIS tools, including Google Earth Engine (GEE), ArcGIS Pro, R-Studio, and TerrSet, to achieve its objectives. These tools are essential for monitoring and detecting land cover changes using data from space-based earth observatory instruments like Landsat and SPOT. GEE, being a cloud-based platform, is particularly useful for processing large geospatial datasets, which is crucial for this study covering three countries. It allows for the integration of different datasets at different scales and is accessible to a wide audience due to its high-performance computing capabilities (Gorelick et al., 2017). ArcGIS Pro is used for change detection analysis, especially for categorical raster data, providing detailed outputs for class transitions (Environmental Systems Research Institute (ESRI), 2023). For R-Studio this tool was employed for statistical analysis, offering various correlation functions to analyse relationships in the data (Prabhanjan et al., 2016). Finally, TerrSet software is chosen for predicting land cover changes, offering tools like Markov Chain and Cellular Automata models, which proved effective in training datasets without memory issues (Eastman, 2020). Each tool serves a specific purpose, contributing to the comprehensive analysis of land cover changes in the CSB region from 2000 to 2021.

1.6 Research Outline

Chapter two of this study will review past and current literature relevant to the assessment of land cover change in the CSB region, providing a theoretical framework for understanding the factors driving LULC change. Additionally, it will examine international and national forest and environmental policies adopted by CSB region governments to prevent deforestation and promote sustainable forest management. In chapter three, the methodologies used to assess land cover change in the CSB region from 2000 to 2021 using time series Landsat 7 and 8 images will be described. The chapter will describe the various spatial data analysis methods to achieve the aim and objectives. It also elaborates on the pre- and post-processing of data in preparation for correlation analysis. Chapter four of the study will present the results and discusses the outcomes of each of the analysis that was used in the study. This will comprise of objectives one to three and its required research questions excluding research question 2.1. Chapter four will present the results from the methodologies by answering the various objectives and research questions identified above. Chapter five will discuss the implications of the research findings in relation to the potential causes of LULC change in the CSB forest region which is related to research question 2.1. The chapter will also answer objective four and its research questions. Finally, chapter six will address the limitations of the study, draw conclusions based on the results obtained, and provide recommendations for sustainable forest management policies in the CSB region, aligning with objective four. See Table 1-1 for a summarised view.

Table 1-1: Showing how each objective will be addressed based on the research question, chapter and sections.

Chapters	**Objectives**	**Research Questions (RQ)**	**Sections**
Chapter one	N/A	N/A	Sections 1.1, 1.2, 1.3, 1.4, 1.5, 1.6, 1.7
Chapter two	N/A	N/A	Sections 2.1, 2.2, 2.3, 2.4, 2.5, 2.6, 2.7, 2.8
Chapter three	Objective 1	RQ 1.1	Section 3.6
		RQ 1.2	Section 3.7
	Objective 2	RQ 2.2	Section 3.8
	Objective 3	RQ 3.1	Section 3.9
		RQ 3.2	Section 3.9
Chapter four	Objective 1	RQ 1.1	Sections 4.1, 4.2, 4.3
		RQ 1.2	Section 4.5
	Objective 2	RQ 2.2	Section 4.5

	Objective 3	RQ 3.1	Section 4.6
		RQ 3.2	Section 4.6
Chapter five	Objective 4	RQ 2.1	Section 5.2
		RQ 4.1	Section 5.3
		RQ 4.2	Section 5.4
Chapter six	N/A	N/A	Sections 6.1, 6.2 and 6.3

1.7 Summary

This chapter addresses the need for a sustainable forest management practice in the CSB forest region. Addressing this section is the background of the study which introduced forest as a natural resource, deforestation, sustainable development and sustainable forest management and its importance to protecting and preserving the forest environment. Furthermore, the motivation outlined the role forest ecosystems play in the environment and examples of some factors that are contributing to deforestation. The problem statement in section 0 defines the factors contributing to deforestation and its consequences to the environment and how it can be mitigated. The guideline to which the study/research will be structured is based on the aim, objective and research questions which have been stated in section 0 above. Lastly, the scope of the study was based on identifying and describing the tools and method suitable for use in this study.

2. LITERATURE REVIEW

2.1 Overview

In this chapter, relevant literatures are reviewed to provide insight on how various research methods have been used to answer similar studies. This chapter comprises five sections:

- Forest Sustainability
- Geo-spatial Data in Exploring and Analysing Forest Cover
- LULC Change Detection
- The Application of GIS and Remote Sensing in Environmental Monitoring
- Forest Cover Change and its Consequences on the Environment

2.2 Data Collection for Literature Review

Using the topic of the dissertation, a review of the literature was implemented with the key string search ((remote sensing OR remote-sensing) AND ("Google earth" NOT "Google maps") AND engine*) AND (forest) AND (sustainable development) AND (land use) AND (land cover) in the University of Cape Town library website. The website hosts several databases such as Web of Science, Scopus, Academia, and Google Scholar. After the search, 3 061 articles were found. These were screened as useful or not useful per the following criteria below, after which 150 articles remained.

- **Relevance**. This criterion was achieved by reading through the abstract which provides a concise summary of the study's objectives, methods, and key findings, to assess whether the article aligns with the research topic.
- **Data compatibility**. This method checks if the data used in the article is open source (freely available to the public) or proprietary (not meant for public use). The open-source articles were used which encourages data collaboration.
- **Methodology and processes**. Check whether the data used in the study is relevant to my study or whether I have access to similar data, and assess the processes used for data collection, pre-processing, and analysis to ensure they are reliable and consistent with the scope of my study.
- **Comparable environments**. This was based on comparing whether the study's environmental settings, such as the geographical region, climate, or ecological characteristics, are comparable to my study area.

- **Access to article**. This criterion verifies if the article is published in a reputable peer-reviewed journal and if its access is limited or open source. Based on the criteria, the open-source articles were selected.

A full-text-review was performed on the articles in which I screened for articles that provided background information, theoretical framework, and relevant concepts to my study. Of the 150 articles, 120 were used for literature review which were categorized into theories, concepts, historical developments, and relevant findings. The remaining 30 articles were used to identify empirical data, experiments, case studies, or methodologies relevant to my objectives and research questions.

2.3 Forest Sustainability

2.3.1 Background of Sustainable Development

The Brundtland commission published a report titled *Our Common Future* which was based on the development of the link between everyday life issues that have to do with economic development and environmental stability. Identifying the links that exist between these two entities fulfils the concept sustainable development, which is defined as

> *"The development that meets the needs of the present future without compromising the ability of the future generations to meet their own needs"* (Brundtland, p1 1987).

The definition above was aimed at maintaining economic development on a continuous basis that preserved the value of the environment on a long-term agenda. Using this concept, a framework of environmental integration policy and developmental strategies was created (Brundtland, 1987).

The integration of sustainable development in forest environment can be traced back to Hans Carl von Carlowitz, an administrative member of the mining department at the Saxony electric court. In his position as an administrative member, he published a systematic exposition in 1713 titled *Economics of Silviculture.* In the published systematic exposition, the introduction of the concept of sustainability was raised. He advocated that for a continuous, stable and sustained use of the forest environment, sustainability should be implemented (Schmithüsen, 2013). Eventually, the idea of sustainable use of natural resources was integrated and implemented in the forest environment. The integration has over the years been helpful in managing forest resources. The results have contributed to a 17 percent increase in forest conservation areas in the CSB and Congo basin region in the past decade. With all these results, sustainable development is still the cornerstone of forest management and planning, which is dependent on present-day forest operations around the world (Bettinger et al., 2017).

Dernbach, (1998) explained that the appreciation of our natural resource constraints will be beneficial for us to truly understand the role it plays in their protection. A truly national and effective system of governance requires a country to consider and protect the environment and its natural resources on which its current and future development depends. Any further approach in this environment will be self-defeating. Thus, the connection between the environment and development (economic) provides a powerful rationale for developmental protection and enlightens self-interest. The existing inter-dependence between the long-lasting stability of the environment and the economy is the founding block in the field of sustainable development.

Though there have been different definitions of sustainable development, the most used definition is the one described by the Brundtland commission as seen above. The idea of conserving the forest future is regarded as an important feature that separates the developmental policies for sustainability from conventional environmental degradation externalities. The main aim or goal of sustainable development is developing a long-term stability of the environment and economy, which is only achievable via acknowledgment and integration of environmental, economic, and social factors throughout the decision process.

The important principle guiding environmental protection and controlling all the other principles is the integration of economic, environmental, and social factors into all the decision-making concepts as seen in **Error! Reference source not found.** (on page 2) (Stoddart, 2011). The concept of integrating sustainable development with other principles lies deeply within the way in which it can interact with other concepts which is the advantage that separates or distinguishes it from other policies. Achieving sustainable development relies on different principles. However, the most talked about principles concerning sustainable development are related to social equity, economic feasibility, and environmental protection. The interrelation amongst the sustainable development principles helps develop conservation and ecosystem model, population control, production systems, and human resource management (Mensah and Enu-Kwesi, 2019).

2.3.2 Sustainable Development and Forest Management

Concerns regarding uncontrolled forest resource destruction together with unresolved degradation in many parts of the world were addressed in the 1992 United Nations Conference on Environment and Development (UNCED). The conference was based on sustainable development (including forest protection), in which a non-binding statement of forest principles was developed covering the guidelines and ways of protecting forests around the world. This represents the global ideology of sustainable development (Siry et al., 2005).

Sustainable forest management covers environmental, social, and economic dimensions of the forest and all their uses. Many definitions have been used to describe SFM, for example:

"The stewardship and use of forest land in a way, and rate, that maintains their biodiversity, productivity, regenerative capacity, vitality and their potential to fulfil now and future, relevant, economic and social functions at local, national and global levels, that does not cause change to the other ecosystem" (Helsinki Resolution, p1, 1993).

Presently, the United Nations general assembly defines SFM as:

"a dynamic and evolving concept that aims to maintain and enhance the economic, social, and environmental value of all types of forest for the benefits of present and future generations" (Food and Agriculture Organization, np 2018).

Though the definitions of SFM vary, the criteria and indicators (objectives and measures for progressive management) that have been developed for describing SFM are constant and relate equally to a small (temperate, community, and tropic forest) or large (international and national) forest regions. The 1992 Earth Summit Conference Agreement, organized by the United Nation Conference on Environment and Development, was aimed at reconciliation of worldwide economic development and environmental protection. Backed by its indicators and criteria, principles for monitoring, measuring, and reporting the progress on SFM were modelled for different contexts and different scales. Information gathering on forest resources is made possible with the help of criteria and indicators. They help in facilitation, policy, decision making processes, assessing sustainability, and development of SFM programs through certifying the indicators and criteria (Food and Agriculture Organization, 2018).

Forest regions around the world (tropical, temperate, and boreal) have been in a state of deforestation versus protection. The forest environment is home to many of the world's biodiversity systems, carbon storage systems, and protections of a wide variety of ecosystem services. This has caused a strict conservation rule by government agencies and environmentalists when it involves the management of forest resources (Hartshorn, 1995). However, the forest region is connected to the everyday life of the inhabitants of the communities on a local, regional to national scale. This sometimes propagates conservation as a negative influence on both the use of natural resources and developmental factors (Malhi et al., 2014). As there is a constant increase in world population, followed by increase in urbanization, the conflict between extraction of forest natural resources and conservation of forest natural resources will become more complex (Seymour and Busch, 2016). Notwithstanding, within the global development and conservation communities, there has been an increased recognition of the complex, dynamic and intertwined relationship between ecological and social systems (Folke et al., 2002).

In response to the issue of forest conservation and deforestation problems and other human challenges, a large-scale response to global factors and developmental challenges was made in the form of the United Nations sustainable development goals. The goals were adopted in September 2015, which were referred to as the world's response to the challenges or difficulties ravaging the finite global resources and services, and a platform to subdue the complex problems faced in the present and future generation (Helgason, 2016). Among the UN SDGs there also exist the African Goals 2063, "The Africa We Want", which focuses on creating a blueprint and master plan for transforming Africa into a global powerhouse for the future with the help of 20 goals adopted in the same year as the UN SDGs.

Practicing sustainable use of resources across the globe may play an important role in restoring and conserving terrestrial ecosystems via combatting deforestation, reversing, and reducing loss in biodiversity and gradation (Keenan et al., 2015). The release of the SDGs by both the United Nations and the African Union includes the creation of a sustainable environment. Regarding sustainable environment goals, the protection and conservation of forest regions is in line with UN goal 15 targets 15.1, 15.2, and 15b. The goals are based on ensuring restoration and conservation of forest, mobilizing resources for restoration, and promoting sustainable forest management (United Nations Development Programs, 2016). For the African Union agenda on promoting sustainable environment, goal 7 (environmentally sustainable, and climate resilient economies and community) was in line with forest regions. The priority areas for goal 7 were biodiversity, conservation and sustainable natural resource management, followed by promoting water security, and finally climate resilience and natural disaster preparedness (African Union, 2015).

The importance of forest ecosystem to the environment is that it acts as a buffer against climate change (FAO, 2016). This has prompted the fight for conservation of terrestrial land and has led to the protection of about 15% of the world's terrestrial biodiversity. Fortunately, some forest regions have seen less destruction due to uneven terrains and strict laws making it difficult to access by humans. For example, the Daintree Forest and Queensland Forest in Australia, Monteverde cloud forest in Costa Rica, and Redwood national park in California, United States of America. This has led to the preservation of biodiversity thereby contributing to the health of forest regions (Barlow et al., 2016).

The management of forests to promote sustainable development has been difficult in most developing or 3rd world countries that are dependent on the forest natural resources, such as the development and exportation of tropical timber to support their national economy and global demands (Vincent, 1992). Nevertheless, the interlinked and interwoven nature of SDG 15 and African Union goal 7 is relevant to SDG 1 (end poverty in all its forms everywhere). The connection between the SDGs seeks to deliver a prosperous society that provides dignity and justice for people while preserving the planet for our future generation (United Nations Development Programs, 2016). So, the understanding of all types of changes (land use and land cover) and the expected effect on the behaviour of animal and plants including their migratory patterns, is important. This will aid in the creation of a flexible and realistic criterion for SFM, especially when developing national and global standards for private, public, and community stakeholders (Bradshaw et al., 2015).

2.4 Geospatial Data in Exploring and Analysing Forest Cover

Information gathering by different satellite sensors tasked with monitoring of different objects (land, water, and atmosphere) required for analysis undergoes different stages (acquisition, pre-processing, processing, and classification) before the final image is used. The remotely sensed waveform obtained from space is then converted into data such as images. The instrument used in the acquisition of the data is based on energy detected by the sensors from the reflected object (Nijland et al., 2019). The advantage of this system is that it can monitor and measure electromagnetic variation of the earth's surface and then display the subsequent data as a unique view of the desired target. Additionally, data sourced from the satellite, drone or manned aircraft can be enhanced to fit a particular purpose and later used in model validation (Razavi-Termeh, Sadeghi-Niaraki and Choi, 2020; Abedi Gheshlaghi, 2019). Examples of geo-spatial data in model validation can be seen using aerial photography to gather important information such as soil, vegetation index, limit of lakes, geologic information, and sheets of water movement (Ghorai and Mahapatra, 2020).

Environmental changes accompanied with increased urbanization and agricultural expansion can be identified with the help of land use / land cover change detection (Agaton et al., 2016). Changes in land cover may signify the presence of human and/or natural activities that can lead to loss of biodiversity and land degradation or deforestation (Butt et al., 2015). Monitoring and assessment of land use change is an important component in the development of an integrated land resource management policy. Forest destruction can be documented and visualized over time using remote sensing and GIS techniques. For example, disturbance of forest cover has been monitored using remote sensing in United States of America from 1985 to 2012. The report revealed that the rate of disturbance ranged between 1.5% to 4.5% of the total forest per year which was negatively affecting the health of the forest (Cohen et al., 2016).

The availability of high-resolution images or data has encouraged environmentalists and researchers to study, process and analyse data from various satellites to obtain temporal and long-term effects of forest change in different regions. (Gómez et al., 2016) explained that non-stop usage of time series Landsat images can spot trends of disturbance (land-trends) that help in the recovery process of the forest. This method captures gradual and real-time changes based on the short-term trajectory of the spectral index of the images. A vegetation change tracker developed by (Huang et al., 2010) detected forest change with the help of integrated forest Z-score value. Using dense satellite time-series images for detecting land/forest cover change, detailed information can be provided with respect to the area of interest yearly (Hadi et al., 2018).

2.4.1 Cloud Processing Platforms

The past years have seen an increase in the number of platforms used to obtain and process remotely sensed data by various space and air borne sensors. With the availability of more remote sensing (open source) data sets, this trend is expected to increase, and this will aid in the advancement in satellite sensors, better image processing platforms, and computer technologies (Amani et al., 2019; Tamiminia et al., 2020). Working with large amounts of remote sensing data (petabytes) is resource-intensive and may prove to be challenging in terms of processing and analysing the data. A comprehensive solution has been created that has met these challenges. The system is a well-developed, efficient, safe, and advanced cloud computing platform, that does all the required processes without any difficulties (Chi et al., 2016).

One of the most efficient ways of accessing, storing, and analysing remote sensing data is through cloud computing platforms because they have powerful, and high-speed servers. Not only does the system provide super-speed processing, but it also provides storage services and software packages for use by its customers (Chi et al., 2016). Examples of some cloud-based computing platforms that make use of Sentinel-2, Landsat, and moderate resolution imaging spectroradiometer (MODIS) datasets, are:

- **Amazon Web Service (AWS):** This is a comprehensive cloud computing platform provided by Amazon. It offers a wide range of services such as compute services, storage services, database services, networking services, machine learning services, GIS, and analytical services. The services provided on this system have been made free for study purposes but paid for business use.
- **AZURE** is another cloud computing platform, and it is hosted by Microsoft. The platform offers the same services as the AWS platform.

Another cloud-based computing platform consisting of remote sensing datasets is GEE (Gorelick et al., 2017). GEE is the most popular data processing platform, which helps in facilitating and providing numerous datasets that can be freely accessed for scientific and geographic discovery purposes. The system's design is user-friendly and can be accessed via an internet-based application programming interface and interactive web-based development environment. Also, with the simplicity of the platform interface, high level expertise such as web programming is not needed on the system. The GEE platform also contains some built-in algorithms that help in the classification of data at a planetary scale (classification algorithm) and gives room for improvement and development of new algorithms for analysis of data (Kumar and Mutanga, 2018).

GEE comprises of a web portal that has the capability of providing time series global satellite images, cloud-based computing, access to software, vector data and has a built-in algorithm for processing the required data. GEE is a product of Google and has a data collection repository with over 40 years of satellite images of the whole world, the data collections available in the system are summarised in Table 2-1 below.

Table 2-1: Available remote sensing datasets on GEE (Google Earth Engine, 2010)

Satellite Systems	**Satellite Collections**	**Spatial and Temporal Resolution**
Moderate Resolution Imaging Spectroradiometer (MODIS)	MODIS Atmosphere products	1 kilometre spatial and 2 days temporal resolution.
	MODIS Land products	250 meters to 1 kilometre spatial and 2 days temporal resolution.
	MODIS Ocean product	250 meters to 1 kilometre spatial and 2 days temporal resolution.
	MODIS Cryosphere products	250 meters spatial resolution and 2 days temporal resolution.
Landsat	Collection 1 (Landsat 1 - 9)	10 meters to 60 meters spatial resolution and 16 days temporal resolution.
	Collection 2 (Landsat surface reflectance 4 - 9)	10 meters to 60 meters spatial resolution and 16 days temporal resolution.
Sentinel	Sentinel 1 (C-band synthetic aperture radar)	Sentinel 1 operates in different imaging modes, each with its own spatial resolution; for example, Interferometric Wide (IW) Mode has a Spatial Resolution of approximately 5 m x 20 m (range x azimuth) and a temporal resolution of 6 days.
	Sentinel 2 (Multispectral instrument)	10 meters to 60 meters in spatial resolution and a temporal resolution of 10 days.
	Sentinel 3 (Ocean and land colour instrument)	300 meters to 1.2 kilometres spatial resolution and temporal resolution of 27 days.
	Sentinel 5 (Tropospheric monitoring instrument)	3.5 km x 7 km spatial resolution and a temporal resolution of 24 hours.

GEE is recognized as an important platform for the large-scale mapping of remote sensing datasets due to its powerful abilities in processing and accessing massive volumes of multi-temporal, multi-scale, multi-source earth observation data through a cloud-based platform (Gorelick et al., 2017). The varieties of datasets available in the GEE catalogue are categorized into satellite images, geophysical, weather, climate, and demographic data. With this data, GEE has the capability of providing exciting opportunities for large-scale land cover and multi-temporal mapping (Sidhu et al., 2018). Unfortunately, complex machine learning algorithms which require longer training sites or large training data sets cannot be performed in GEE because of sample restrictions. Selection of data mining models in GEE is limited when the classification and regression model is implemented. It only makes use of the Random Forest classification and regression tree algorithm (CART), and the Support Vector Machine algorithms (Amani et al., 2019). Also, one of the important approaches in image classification is increasing training site number or samples for better accuracy, but GEE has limited training site samples as compared to other tools (ArcGIS Pro and ENVI) (DeLancey et al., 2020).

Notwithstanding, GEE has been widely used by researchers over the world in terms of big data processing and analysis. Using the platform, powerful models and algorithmic functions have been developed for everyday use in terms of processing and analysing remote sensing images and advanced spatial datasets such as:

- **Forest loss and estimation analysis**: GEE can be used to extract the forest area of a specific region by applying the forest loss and estimation algorithm on canopy cover and minimum area requirement. A similar method has been used by (Jena and Pradhan, 2019) to detect forest change relating to mining using GEE in Belitung Island, Indonesia. Change detection of forest region related to mining was achieved using the normalized difference vegetation indices, modified normalized difference water indices, normalized difference water indices and digital elevation models to identify water bodies and active mining areas that are responsible for forest loss. The results obtained from the analysis revealed a change in the forest cover within the time frame used in the analysis.
- **Supervised classification analysis**: Supervised classification in GEE is made possible via the classifier algorithm used in the classification of land cover areas. The algorithm includes classification methods such as CART, Support Vector Machine, Random Forest, and NaiveBayes method. The latter is dependent upon 5 basic workflows in GEE which are collection of training data, initiating the classifier, training the classifier, classifying the image, and finally estimating the classification error with independent data. Using this approach on GEE, (Amani et al., 2019) created a generalized supervised classification scheme to produce provincial wetland inventory maps: an application of GEE for big geodata processing. Their method was based on defining optimal classification features, processing of satellite data, classifying the land cover data in which the Random Forest classifier method was utilized, and finally performing accuracy assessment to check the effectiveness of the classification system.

2.4.2 Forest Cover Mapping

To successfully establish sustainable management and development strategies that balance the preservation of wildlife habitats with the fulfilment of human needs like building materials and fuels, forests regions necessitate thorough and precise inventory and monitoring practices. These efforts aim to provide a comprehensive understanding of the forest's makeup and changes over time. Achieving this objective entails the requirement for well-planned data collection initiatives and mapping. These campaigns serve to characterize and create maps detailing the forest's structural features. These features encompass a range of attributes such as the extent of the canopy cover, the height of trees, the biomass they hold, their stem volume, as well as critical aspects like age distribution, species composition, land cover patterns, and the history of disturbances that have affected the forested area (Matasci et al., 2018).

The creation of the global land cover map promoted the mapping of regional land cover across central Africa (Congo basin) and nearby forest regions using the Advanced Very High-Resolution Radiometer sensor due to its high temporal resolution of 1 day (Hansen et al., 2000). Modern sensors have enhanced spectral and spatial characteristics, for example Satellite Pour L'Observation de la Terre (SPOT) and MODIS, which increase the spatial resolution of forest monitoring for better management (Chen et al., 2015). The land cover map of Africa in the year 2000 was developed with the aid of remote sensing and knowledge from experts (Mayaux et al., 2004). Hansen et al., (2008) created a methodology for multi-resolution (Landsat and MODIS) 250 m binary mapping of forest and non-forest in the Congo basin regions. (Vancutsem et al., (2009) developed a map of the Cross-Sanaga-Bioko Forest region at 1 km spatial resolution using a semi-automatic process and one year's worth of satellite data gathered by the SPOT vegetation sensor.

Forest cover mapping provides a clear picture of the level of reduction that has occurred in the land. Deforestation via urbanization and expansion of agricultural land, which have been amongst the causes of forest cover change (Potapov et al., 2015). Deforestation is occurring mostly in the tropical forest regions (the continent of South America, Africa (Congo basin and some parts of western Africa), and Middle Eastern Europe) and in terms of forest regrowth, the process is occurring in temperate forest that is Western Europe and Eastern North America and southeast Asia (Food and Agriculture Organization, 2020).

In terms of vegetation cover and forest loss in the Congo basin, the atmospheric laboratory for application and science (ATLAS) and Landsat sensors were used in the mapping of various vegetation cover and forest loss from the year 2000 to 2010 (Verhegghen et al., 2012). National and regional forest monitoring capabilities have been a growing concern in forest regions of Africa. This has led to the creation of several modelling techniques to protect and monitor the forests of these regions, for example the Observatory for Forest of Central Africa (OFAC) was created in 2006 to monitor the forest region of the Congo basin. The system was controlled by the different stakeholders of the Congo basin forests partnership. The initiative was aimed at using experts in the different forestry norms and the available data to monitor and protect the forest (Mayaux et al., 2009).

2.5 Land Use/Land Cover (LULC) Change Detection

As defined by the (National Oceanic and Atmospheric Organization (NOAA), 2023), land cover refers to the physical land type present in the area such as forest, built-up areas, and water bodies, while land use refers to how the land is being used, for example for agriculture. Although these terms are separate, my research focuses on both land use and land cover, hence for simplicity, the terms will be jointly referred to as land use/land cover (LULC) throughout the research.

Change detection is the identification of phenomena or objects by observing them over time (Singh, 1989). Climate and environmental conditions have been affected by changes occurring in land use and land cover. Performing change detection on forest cover is an important tool in understanding the extent of land gain and loss occurring over time to help with decision making (Tolessa et al., 2017). Environmentalists and decision makers have been relying on change detection techniques for easy management of the environment in terms of population increase, technological advancement, and natural resource management (Kiswanto et al., 2018). The changes occurring in the different LULC classes display their own spectral signatures which can be detected by satellite sensors. The different spectral signatures can be detected by comparing the past and present images using the different change detection algorithms. However, there are many factors that must be considered before change detection can be performed, such as topographic conditions, atmospheric correction, complexity of the landscape, quality of the remote sensing image, and the desired change detection method.

Change detection is a complex process involving the consideration of various factors. Understanding the different variables that are responsible for change in an area and developing a method of measuring the change be it remotely or physically is important for mitigating the changes (Prabu and Dar, 2018). The implementation and use of the various change detection techniques have proven to be helpful in identifying areas affected by change (Hussain et al., 2013). The identification of the best method for a specific study area and the availability of data is dependent on the analyst's knowledge and skills (Samal and Gedam, 2015).

Change occurs on the earth's surface by either natural or anthropogenic forces, and for easy identification of these changes many platforms have been designed to analyse and detect the changes (Muhati et al., 2018). There are many powerful platforms, and tools designed to analyse and detect changes and amongst the many are ArcGIS enterprise products (Map and Pro), Image Processing and Analysis Software by L3Harris Geospatial, QGIS, SNAP Desktop, ERDAS Imaging, Amazon Web Server, and AZURE. Though all the tools and platforms available for classification are good, each platform and tool are suitable by the user according to how best they understand the platform and tool interface. Below are examples of change detection approaches.

2.5.1 Pixel-based Approach

This method is based on the utilization of image pixels as the basis of processing to account for the change between two datasets. The method analyses the spectral discrepancy between the given images including their transformations. A pixel-based approach examines the changes in land use and land cover at the spectral level that may result in the difference in their radiance values. The change difference measurement should be larger than the changes caused by other factors such as surface moisture, sun angle, and atmospheric conditions. Some examples of pixel-based approach include.

- **Image Differencing**: This method refers to the subtraction of the radiometric values of two geo-referenced images. The implementation of image differencing technique is made possible through image pre-processing where relative/absolute radiometric correction, followed by pixel-wise co-registration methods, have been performed. The end results of image differencing are a binary difference map showing the statistical measurement of the mean and standard deviation of the two images obtained by applying the appropriate threshold spectral values (Tian *et al.*, 2013).
- **Image Ratio**: This method computes the ratio between the radiometric values of the two images at different time frames with one or more bands. Change detection using image ratioing is represented by the pixel values lower than or higher than 1, while pixels with no change will have a value of 1 (Gao, 2009).

- **Change Vector Analysis**: This method is based on the spatial representation of changes occurring in a spectral band. When pixels have undergone changes between two dates, their positions in n-dimensional spectral space are expected to change, which is represented by a vector defined by two factors: the magnitude, which provides the information about the change, and the direction, which provide the information about the nature of change. Using this method, any number of bands can be processed concurrently, and detailed information about the change can be produced. However, the challenges using this method are based on discriminating between change and no change followed by interpreting the vector direction in relation to the change (Tian et al., 2013; Ye et al., 2016).

2.5.2 Object-based Approach

Object-based change detection methods are usually done on images with very high resolution (below 5 m), which may be composed of different categories of pixels (Blaschke, 2010). Using this approach, images can be analysed on an object basis where groups of image pixels are obtained from textual or spectral criteria. Objects can be classified using image segmentation or vector data methods. The object-based approach produces accurate results and usually requires less computing power. Furthermore, using the shape of the segments, objects that are not easily identified can be differentiated using spectral information (Chen et al., 2012). The object-based method can be used in one of the following ways.

- **Image-object Overlay**: In this method, the segmentation is executed on one of the two images, then the change detection analysis is performed within each segment of the images (Listner and Niemeyer, 2011).
- **Image-object Comparison**: This method makes use of both images during segmentation. The change detection analysis is performed separately on both images and then combined for comparison (Ehlers et al., 2014).
- **Multi-temporal Segmentation**: This method comprises of a time series raster image in which the segmentation is executed on the entire time series image by taking intersections of the individual segments (Tian et al., 2013).

2.5.3 Classification-based Approach

This approach is generally related to supervised and unsupervised classification methods, which then labels the objects/pixels after image-based change detection. This approach can be further divided into two processes (pre-classification and post-classification), with each method having its ways of identifying change detection (Longbotham et al., 2012).

- **Pre-classification**: This method executes image classification calculations independently for the given years then assigns the labelled image as an input for the change detection. The pre-classification method consists of comparing the changes in the images in terms of differences in intensities. It further detects feature changes, which can sometimes be affected by the variation of physical conditions during data capture. So, understanding the image scenes before and after classification may lead to improved change detection results (Chughtai et al., 2021).
- **Post-classification:** Commonly referred to as delta classification, which consists of overlaying two or more classified images together to perform change detection acquired at different time frames. The post-classification method is the most widely used method because it identifies changes from one time to another. The method works by rectifying the classified images independently and then generating a thematic map by comparing the identified pixel changes of each class in the images (Chen et al., 2012)

In terms of identifying the suitable change detection method for this project (as per research question 1.1 of objective one which focusses on identifying suitable methods of detecting change), the post-classification method will be used. This method reduces discrepancies caused by variations in sensors, atmospheric conditions, and the environment. This is achieved by independently classifying data from two different dates, which mitigates the need for complex normalization processes to account for atmospheric and sensor variations between the separate dates. Moreover, it generates a comprehensive matrix that depict land cover changes when multiple images are employed. These matrices comprise of various types, including pixel conversion/change matrices, percentage conversion matrices, and area conversion matrices, which are established by comparing pixel values on a one-to-one basis (Tolessa et al., 2017). Furthermore, the change matrix generated allows for easy interpretation of the changes that have occurred in the different classes thereby separating real changes from false alarms (Chaabouni-Chouayakh et al., 2013).

2.6 The Application of GIS and Remote Sensing in Environmental Monitoring

The term GIS is believed to have originated around the 1960s from the Canadian natural resource inventory program led by Roger Tomlinson. The program became popular around the world as computing became more powerful to run mapping and spatial analysis software's through the analysis of patterns and information related to weather and traffic data. GIS, as described by (Longley et al., 2005), refers to a system that is designed to capture, collect, observe, store, manage, and analyse geographic data for interpretation and visualization.

Remote sensing originated as a term used by geographers during the period when satellite images became commercialized by the military, and the term is often being used to describe the collection of data from artificial satellites. Remote sensing refers to the non-contact recording of information by means of cameras and scanners from the visible, infrared, ultraviolet, and microwave regions of the electromagnetic spectrum, mounted on a mobile platform such as spacecraft or aircraft hovering above the earth (Nagendra et al., 2013).

Remote sensing and GIS are "complementary technologies that, when combined enable improved monitoring, mapping and management of forest resources"(Franklin, 2001). The use of GIS and remote sensing data in the mapping of natural resources, for modelling environmental processes, have been growing over the years. With the increase in availability of remotely sensed data from various satellite platforms, accompanied by a wide range of radiometric, spectral, and spatiotemporal resolutions, GIS tools have become one of the best sources of exploring, analysing, and modelling (Manfreda et al., 2018). Below is a summary of the application of remote sensing and GIS in the monitoring of the environment.

2.6.1 Remote Sensing and GIS in Land Cover Change Forecasting

Change forecasting refers to the prediction of LULC beyond the timeframe of the available data. The most used models for forecasting land cover changes are based on analytical equation-based models, statistical models, evolutionary models, cellular models, Markov models, multi-layer perceptron models, and hybrid models (Singh et al., 2015; Subedi, Subedi and Thapa, 2013). These models can be implemented on their own or in combination with other models to produce a more robust forecasting result. The most widely used models in land cover change forecasting are cellular and multi-layer models (Sohl and Claggett, 2013;Zhao and Peng, 2012). Examples of the functionality of some models for land cover change forecasting are as follows.

- **Multi-Layer Perceptron (MLP):** This model consists of a neural network of interconnected nodes which process elements based on the weighted inputs transmitted from the nodes. Using the MLP model, non-linear data can be modelled in different layers for easy classification (Taud and Mas, 2018). The MLP functions by allowing data flow in a feed-forward neural network from the input layer through the hidden layers and then the output layer. The interconnected nodes are linked via a web of connections. Training the model is dependent on a back-propagating algorithm which spreads the errors from the output layer to the input layer by correcting the nodes to reduce error between the predicted and observed outcomes (Megahed et al., 2015). The ability of the model to learn and predict complex problems is based on its hidden layers of nodes which increases the training performance of the data (Taud and Mas, 2018). Data training creates a generative process of network outputs used to predict the unseen inputs. The network output is further compared with the predicted output which then computes the error matrix through a back-propagating algorithm through the network of nodes to adjust the prediction (Pérez-Vega et al., 2012).

- **Cellular Automata**: Cellular Automata (CA) consist of a bottom-up spatiotemporal dynamic model, that simulates different scenarios of variables over space-time, no matter the complexity of the data. Calculation of the CA model is based on data present in a cell, neighbouring cell, cell space, rule, and time, in which the data in every cell are decided by the cell and its neighbouring cell (He et al., 2014).
- **Markov Chain:** A Markov chain consists of a stochastic algorithm used to simulate complex land cover change to identify the transition probability of the initial state of one variable to another. It assumes that the probability of a variable in each state and time can be determined if its prior state and time is known. The assumption is true provided the rate of change observed during the calibration period (T1 to T2), will remain constant during the simulation period (T2 to T3) (Fathizad et al., 2015). The integration of CA and Markov chain models provides the simulation of expected variables over a long period, with each model playing a specific role. The temporal dynamics of the transition probability of each variable are controlled by the Markov chain while the changes in the spatial dynamics of the variables are controlled by the CA model (Singh et al., 2017).

2.6.2 Wildlife Habitat Monitoring Using Remote Sensing and GIS

Remote sensing and GIS have led to better wildlife resource evaluation and monitoring processes. Using remote sensing, appraisal of habitat attributes can be examined with ease, and new sites identified for protection and conservation (Varghese et al., 2012). GIS and remote sensing in wildlife habitats can help identify depleting habitats and avert the consequences, leading to better monitoring and management. The basic requirement for managing and protecting these areas relies on identifying their risk factors, development of preventative infrastructure measures, and sensitive categorization of the various habitats (Suryavanshi et al., 2013).

Wildlife species conservation is important because it helps preserve and maintain animals and plant species. Remote sensing data and GIS tools play an important task in the conservation process through geographic space or landscape processing. Landscape process monitoring occurs in patterns called spatial ecology. The process is studied to see how the patterns influence characteristics of animal and plant populations such as density, movement, and distribution (Stapleton et al., 2014). Ecological monitoring using remote sensing and GIS is versatile and its potentials have been tested in the fields of wildlife habitat prediction and have proven encouraging. Automated data retrieval technology such as General Packet Radio Service (GPRS) and Argo's satellite uplink have been used for wildlife tracking. The tracking method uses global positioning system (GPS) for wildlife tracking in which researchers, biologists, and conservation agencies can track the movement patterns of animals remotely (Kabir and Lee, 2021).

2.6.3 Forest Fire and Risk Mapping via Remote Sensing and GIS

According to the International Union for Conservation of Nature (IUCN) and the United Nations Environment World Conservation Monitoring Centre, there exist about 202 467 protected land surface areas measuring about 20 million km^2 of the world (International Union for Conservation of Nature, 2015). IUCN described protected areas as a defined geographic space which is recognized and managed using legal means.

Fire is a major environmental transformation system (Food and Agricultural Organisation, 2007). It is regarded as a process of important ecological value as a management tool for a healthy ecosystem. However, fire is a paradoxical entity in that if planned properly, the expected outcomes (for example vegetation regeneration through micro-organisms and fungi, fuel accumulation regulation, insect and disease control, mineral soil exposure, and nutrient release) will be achieved (Pausas and Paula, 2012). Nevertheless, uncontrolled or unwanted fire can lead to ecological disturbance which will cause bush encroachment, loss of biodiversity, reduction of soil water content, or invasion of alien plant species (Jhariya and Raj, 2014). Fire risk assessment has been made available using vegetation greenness related indices with the understanding that chlorophyll content of vegetation reduces in proportion to the water content of the vegetation. The assessment depends on the spectral signature of the vegetation greenness in the near infrared and red regions of the spectrum. The inner structure of healthy leaves plays a vital role in reflecting the near infrared wavelength. This helps in distinguishing healthy vegetation from non-healthy vegetation. To minimize the effects caused by forest fires, extra precautions must be set in place to prevent or control the fire. The use of a fire map is the first precaution to be set in place, which can be very helpful in terms of planning and managing fire risk areas or forest regions.

GIS and remote sensing techniques have proven useful over 10 years in terms of natural hazard prediction and environmental modelling. Integrating GIS and remote sensing data into forest fire management and mapping tools is an added advantage in the field of fire and risk assessment mapping (Feizizadeh et al., 2021). For example, forest fire and risk management may be assessed by artificial neural network (Goldarag et al., 2016). Using this method, high potential areas for fire occurrence were identified in the Golestan region in Iran. The model was based on different field data and satellite images in which 12 static and dynamic parameters responsible for forest fire were used. The data used in the creation of the model ranged from 2001 to 2004 after which the 2005 data was used to evaluate the created model. The data collected was used to create two fire risk prediction models which were based on the logistic and artificial neural network models which were later compared and evaluated. The logistic regression was based on the value of the estimated probability of occurrence of a certain binary outcome (high fire risk), and the probability of the opposite outcome (low fire risk). Based on the estimated probability, the Artificial Neural Network model was used to predict the forest fire successfully.

2.7 Forest Cover Change and Its Consequences on the Environment

Different conceptual models have been developed to help explain the LULC changes as a factor of a country's economic and social status (Foley et al., 2005). Many parts of Africa have undergone dramatic changes in terms of LULC over the last 3 decades which has either been because of human or climatic variability. Information obtained from such changes may help in terms of management, planning, protection, and conservation of natural forest systems. LULC changes can disrupt the normal supply of service in an ecosystem, affecting the health of the ecosystem of the forest and other living organisms (Rimal et al., 2019). Changes in land or forest occurring in an area could influence the organic (biological) process and change the provision of services within the ecosystem (Gibson et al., 2018). The occurrence of change in the forest or land areas does not only affect living organisms but it also affects the hydrological fluxes, agricultural production, regional climate, and greenhouse gas exchange in the area (Guzha et al., 2018).

Changes in forest cover have been recognized to affect not only the immediate environment, but a whole range of earth systems processes tied to the forest/land (water cycle, air quality, plant, and animal habitats). This cycle of interconnected processes is based on the ecosystem functions which are affected in one way or the other when there is a change in forest cover (Vellend et al., 2017). Alteration of forest or land cover in our world is a direct cause of human and natural action and the ideology of global forest change must be structured around human influence directives on land surface (Guzha et al., 2018). The International Geosphere-Biosphere Program and International Human Dimension Program (IGBP/IHDP, 1999) explained that the aim of forest change is to know:

- Changes in the forest cover patterns.
- Forest cover change processes
- Human response to forest cover change.

Forest cover is the 'last biotic frontier' which houses habitats conducive to the evolution of millions of micro-organisms, birds, plants, insects, and animals (Parker, 1995). It is believed to be an important factor in the maintenance of the diversity and functioning of the ecosystem. The structural complexity and ecological importance of forest cover plays a vital part in the forest environment. Forest cover plays a primary role in the exchange of gases that occurs between the atmosphere and vegetation, thus a loss in forest regions may lead to increased environmental problems (Guzha et al., 2018). It also facilitates many ecosystem processes that are of great importance in the maintenance of forest biodiversity. Land use and land cover are key elements in the study of global forest cover change. Each category of land cover change is accompanied by several environmental consequences that affect the carbon cycle (Gibson et al., 2018).

According to (Boakye et al., 2008), the primary causes of forest cover change are anthropogenic factors and variability in natural climate. They reported that exploitation in tropical forest occurs because of timber harvesting and pasture development. Over several years, the forest loss affects the water catchment quality and biochemical cycles of the area of interest leading to water shortage and erosion. Destroying the forest does not only reduce water catchment and increase soil erosion, but it destroys the habitats of forest animals, biodiversity, hinders tourism and other recreational activities (Parviainen and Päivenen, 1997). The lack of appropriate agricultural technology in agricultural areas along forest to land boundaries is amongst the factors causing forest destruction. The centralization of management policies in some countries have led to the misuse of forest resources which has also been considered as a factor causing forest cover loss in some countries. Moreover, logging operations that have no planned method of selective logging destroys the young forest trees thereby reducing the forest's ability to reduce greenhouse gases (Bokpin, Mensah and Asamoah, 2015).

In the Cross-Sanaga-Bioko region, loss of forest through LULC change (urbanization and agricultural expansion) is amongst the recorded cause of deforestation, which also influences the loss of many plant species (Amindeh, 2022). Zhuravleva et al., (2013) created a GIS based system of assessing forest loss in the Congo basin. They explained that the primary determinant of forest loss in the Congo basin was through small scale subsistence farming occurring along the edges between the forest and non-forest land. Furthermore, they concluded that the loss of forest region may be related to increased soil degradation, increased vulnerability to natural disasters, and biodiversity loss. Increased infrastructures, mainly construction of roads and factories, is also regarded as a proximate cause of land cover change which has promoted the disruption of ecosystem functions and alteration of microclimates. For example, in the Congo basin forest, the construction of the Douala (Cameroon) to Bangai (Central African Republic) road cuts across 1 400 km of forest land (Duveiller et al., 2008).

The transformation of forest lands into agricultural and urban areas, as well as the conversion of water bodies into urban areas, has caused the deterioration of air quality, because the regulating effect of natural vegetation has decreased (Du et al., 2010). When studying the effects of LULC on the environment, correlation analysis can be used to evaluate the strength of association between the variables (Zhu et al., 2019). Correlation can be categorised into two methods: spatial autocorrelation and spatial correlation. Spatial autocorrelation refers to the statistical relationship between values of a variable and their spatial locations. It occurs when similar values tend to cluster together in space, indicating spatial patterns or trends in the data, for example population density. Spatial cross correlation is defined as the relationship between one variable to another (e.g., population and urban area) in terms of size and spatial contiguity (Lichstein, Simons, Shriner, 2002; Braun, Auerswald and Geist, 2012). These fall under the umbrella of spatial correlation modelling, which has been widely used to account for the correlation of human and natural phenomena in different fields of study, e.g., the prediction of crime rates in different neighbourhoods of a city based on various socio-economic and demographic variables (Beck and Sieber, 2010).

When studying correlations, it is important to differentiate between correlation and causation. Correlation can only identify the relationship between two variables but cannot prove causation between the variables. Therefore, while the results of the correlation analysis can statistically show the relationship between the variables such as changes in LULC and air pollution, the results cannot prove that these factors are *causing* the observed change in air pollution (Zou et al., 2016). With the aid of Landsat imagery for observing changes in land use pattern, and ground observation stations for monitoring air quality change, specifically particulate matter 2.5 from the years 1998 to 2010, a moderate to high correlation was discovered between the change in urban land use surrounding the monitoring sites of the particulate matter 2.5 stations in Central Alabama, United States of America. The correlation indicated that the changes in land use in the area had a significant relationship to the change in particulate matter 2.5 concentration in the region (Superczynski and Christopher, 2011).

Weng and Yang (2006) examined the relationship between land use patterns and air quality in Guangzhou, a mega city in southern China. In their examination, a series of buffers were created in two city centres using ArcMap. Using the buffered areas, the built-up density within each buffer was calculated and then correlated against the air quality of that area. The results produced a positive correlation coefficient between air quality and land use. The distribution of different land cover areas attracts different varieties of settlement which either contributes to increase in air pollution or helps to mitigate the pollution rate of the area (Bandeira et al., 2011). However, natural land surfaces like large-scale water bodies and forest regions have positive effects on air quality so preserving the resources is important for environmental preservation (Irga et al., 2015).

2.8 Summary

The availability and assessment of the different status of both environmental and biological resources is among the first step in the fight towards the creation of sustainable resource development and management planning. The creation of sustainable systems is a continuous process that requires the determination of the major baseline data of different levels or stages. Section 2.3 above was used to address research question 1.5 of objective one which addresses the structures that have been designed to protect the forest (see section 1.4.2). As seen in the section above (2.3), the countries of the region have established forest conservation policies (for example the ITTA agreement and the REDD+) to help protect the forest region against deforestation. Implementing forest policies is a complex and multifaceted process that requires careful consideration of various factors to ensure their effectiveness and sustainability.

Additionally, GIS tools aids in enhancing the effectiveness and efficiency of forest policies by providing spatial data, analysis tools, and visualization capabilities. It allows policymakers to make evidence-based decisions, monitor policy outcomes, and address environmental and social challenges related to forests. However, the introduction of modern geospatial technological tools such as GIS has aided in very efficient and effective methods for identifying, classification, surveying, mapping, characterization, monitoring and tracking in various fields of study. Furthermore, research question 1.1 of objective one (how LULC change can be detected with focus on deforestation, urbanization, and agricultural expansion) was addressed in section 2.5.3. The section identified the method that will be used to detect LULC change in the region: the post-classification approach. Further explanation of the method will be addressed in section 3.7 below.

3. METHODOLOGY

3.1 Overview

Having reviewed the literature regarding deforestation, sustainable management (balancing forest conservation with urbanization and agriculture expansion), as well as land cover change modelling and prediction, let us now turn to the methods that will be used to achieve the aims and objectives of the study. The study focusses on promoting sustainable management in the CSB region; thus, the chapter will cover the following topics: description of study area and data used in the study, identifying the past and present state of LULC in the CSB region, and how LULC has been changing over the study period. Additionally, a correlation analysis will be done to test between LULC change and air pollution, followed by modelling land cover change to predict future outcomes of land cover change in the region.

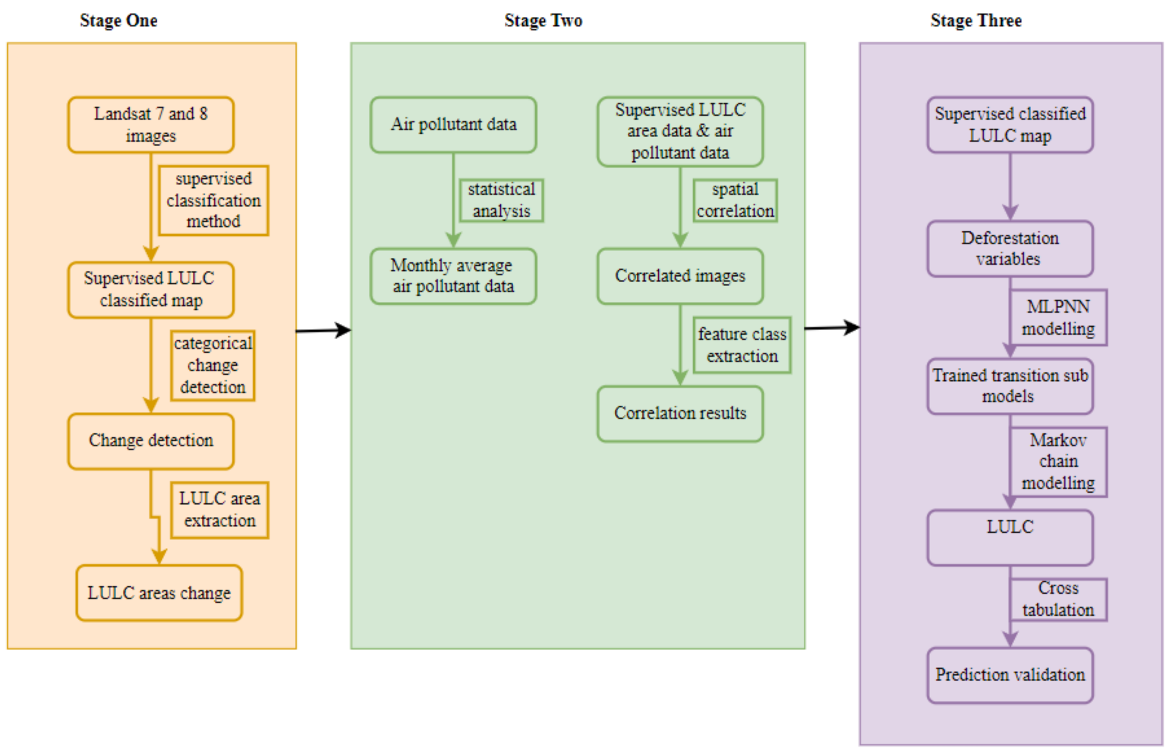

Figure 3-1: Overall flowchart of methods and techniques to be used in the study.

3.2 Study Area

As explained earlier, the region cuts across Nigeria, Cameroon and Bioko Island (see first paragraph in section 1.2) comprising of different terrestrial ecoregions which makes it difficult in generating an actual geographic extent of the area see Figure 3-2 below. This analysis will make use of the map extent listed in the figure below (Figure 3-2). Using the extent below will be essential for a comprehensive understanding of the factors driving these changes. This approach allows for the identification of broader regional trends and indirect pressures, such as economic activities, population dynamics, and climate patterns that influence the study area. It also helps in understanding ecological connectivity and habitat corridors, which are crucial for biodiversity conservation. Additionally, incorporating external regions enhances the accuracy of prediction models by accounting for a wider range of variables and interactions.

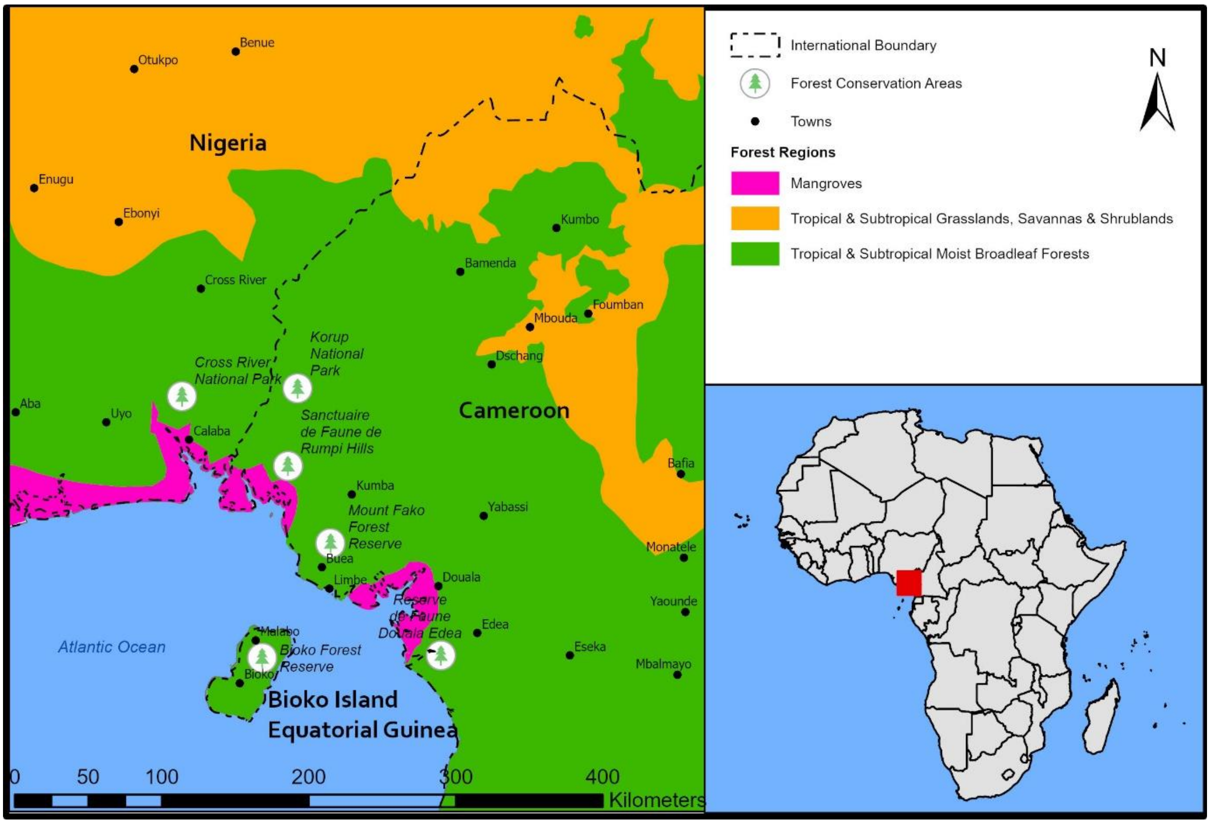

Figure 3-2: CSB study areas showing the forest areas present in the region.

The region is made up of the Cross-Sanaga-Bioko coastal forest including the Cameroon highland forest, Cross-Niger transition forest, mount Cameroon and Bioko montane forests located in the vicinity of Buea, Limbe and Bioko Island, and part of the central African mangroves (located in the coast of Calabar and Douala). The entire forest region falls within the humid tropics. Rainfall measurement in the south-west foothills of Mount Cameroon and that of Bioko (south-western section) can exceed 10 000 mm per annum with small seasonal changes. In the south-eastern section of the Cross River region in Nigeria, rainfall can average about 3 000 mm per annum along the coast and can drop to about 2 000 mm per annum inland. The dry seasons of the entire forest region can be short but very severe and can last for about 3 to 4 months (November to February). Humidity in the forest region reaches about 90% and it rarely goes below 75%. The temperature in the forest regions varies from 30° Celsius to 15° Celsius with little seasonal changes (Neil Burgess and Emma Martin, 2018).

Calabar, the capital of Cross River State, is amongst the most densely populated region in the study area with an estimated 2019 population of 4 175 020 and a density of >500 people per kilometre square. Although Cameroon's population is less dense than Nigeria's, the section of Cameroon covered by the CSB region is the most populated area in the region. The Littoral and Southwest region have an estimated population of 8 504 986. of which Douala and Buea are the most densely populated cities. Bioko is the most sparsely populated area of the three regions, with a population of 411 914 inhabitants of which most of its inhabitants are in Malabo in the northern section of the island (United Nations, 2022).

3.3 Data Description

The timeframe for this study was set at 21 years (2000 to 2021). Within the 21 years it was further broken down to a period of seven years (2000 – 2007, 2007 – 2014, 2014 – 2021) to aid in further analysis such as LULC gain and loss, change detection, and point biserial correlation. For the seasons in which the images were captured the dry seasons were selected (November to February). This season was selected because during the dry season, there exist lower moisture content in the atmosphere and more stable atmospheric conditions generally lead to fewer clouds. This thus produces clear skies and less cloud cover which is a characteristic of dry periods in the region because there is less moisture available to condense into clouds and precipitation. Additionally, this study makes use of both raster and vector data types, and for a better understanding of the data used in this study the data will be grouped into their different data type formats as seen in Table 3-1 below.

Table 3-1: Description of the different data used in this research.

Raster Data Types		**Vector Data Types**	
Data Name	**Description**	**Data Name**	**Description**
LULC data	Used for supervised LULC class classification.	Population Density	Provides the Euclidian distance of the population density of the study area.

Raster Data Types		Vector Data Types	
Global forest change data	Utilized for the calculation of global forest cover loss analysis.	Roads	Provides the Euclidian distance of the transportation roads in the study area.
Slope	Provides suitable areas for future development based on the rise and fall of the terrain.	Rivers	Provides the Euclidian distance of rivers present in the study area.
Aspect	Provides the direction or face of a terrain.	Towns	Provides Euclidian distance from towns in the study area.
Digital Elevation Model (DEM)	Provides the topographic surface of the earth excluding trees.		
Air pollution data	Provides the level of NO2, SO2, CO, O_3, and particulate matter 2.5 pollutants in the atmosphere.		

3.4 Data Acquisition

The data acquired for analysis in this research was as follows. The data types below are grouped according to their method of acquisition.

Table 3-2: Description of the source and spatial resolution of the data types utilized in this study.

Data types	**Source and Data Types (Raster and Vector)**
Land Cover data	The data was captured by Landsat 7 and 8 sensors with a spatial resolution of 30 m, then hosted by the GEE platform for analysis and visualization
Air pollutant data	The air pollutant data, which is made up of NO2, SO2, and CO captured by the terra and aqua MODIS, then hosted by the GIOVANNI earth data website. They all have a spatial resolution of 500 m
DEM was used as ancillary data for slope and aspect	The DEM data was captured by the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) with a 30 m spatial resolution, then hosted in the United States Geological Survey (USGS) EarthExplorer platform.
Population density	Population data was obtained from the world bank data catalogue with a range of 20 years for Nigeria, Cameroon, and Equatorial Guinea based on the region of interest.
Towns	Town or places data was generated from OpenStreetMap website which is an open-source data platform
Rivers and roads	Data for rivers and roads was obtained from OpenStreetMap website

3.5 Image Pre-Processing

Amongst the different types of the data format used (see Table 3-2 above), only the image-based datasets were pre-processed by applying atmospheric, topographic, terrain, and radiometric corrections. The purpose of radiometric correction is to correct for variation in the recorded brightness in a remotely sensed image which may occur from factors such as atmospheric conditions, sensor characteristics and illumination differences. The correction is meant to enhance the accuracy and consistency of the image data, allowing for better interpretation, analysis, and comparison of the imagery. Atmospheric correction aims to remove atmospheric effects (such as haze and clouds) from a satellite image to obtain the true surface reflectance values of the earth’s surface. This reflectance occurs in the form of scattering and absorption of the solar energy and identifying and correcting the effects.

Topographic and terrain corrections are applied to remotely sensed images to account for the influence of the earth's topography on the recorded radiance values. These corrections aim to remove or minimize the effects of variations in terrain elevation, slope, and aspect on the image data. Examples of a few methods include slope and viewshed corrections (Afify, 2011).

In terms of geometric correction (exact positioning of an image to an identifiable feature on the earth), the process aligns the images in a systematic order and makes sure they are relative to each other. The consistency is achieved by applying georeferencing and orthorectification methods through ground control points (Young et al., 2017). The datasets present in GEE have already undergone pre-processing techniques (geometric, atmospheric, terrain, and topographic corrections). However, there are still some GEE functions that have been created to help enhance the images (Amani et al., 2019). The datasets used for image classification in this project were Landsat 7 and 8 Tier-1 collection calibrated top-of-atmosphere reflectance. The top of atmosphere reflectance is a measure of the amount of solar radiation reflected by the Earth's surface or atmosphere, as observed from the top of the Earth's atmosphere. It represents the raw, uncalibrated reflectance values recorded by remote sensing instruments like satellites or airborne sensors (Amani et al., 2019).

3.6 Detecting Past and Present States of the LULC in the CSB Forest Region

The focus of this section will be based on addressing objective one and research question 1.1. Forest areas in the CSB, Africa, and the world are in a constant state of flux which is leading to accelerating loss of forest in some areas and gain in other areas (Hansen et al., 2013). The state of the CSB forest refers to the total amount of tree cover present in the forest. Changes occurring in forest regions do not only affect the flow of vital ecosystem services but also affect climate regulation, biodiversity richness, carbon storage, and water supply (Foley et al., 2005). To fully understand the past and present state of the forest region, a historical change of the different LULC classes including the forest areas of the region is needed to show how they have been changing over time. Within the given study time, four dates were selected (2000, 2007, 2014, and 2021) to create a supervised LULC classification. Supervised classification is a technique used for analysing remote sensing images quantitatively. It involves the use of training samples, where the user identifies and labels specific areas of the image corresponding to different classes. These labelled samples are then used to train a classification algorithm to recognize and classify similar features in the rest of the image (Richards, 2013).

Using GEE, a supervised classification package called CART (which is a decision tree-based machine learning algorithm used for classification and regression analysis) was used. Its functionality and interpretable algorithm make it suitable for handling both categorical and continuous data. Furthermore, the classification was performed on two separate satellite sensors (from 2000 and 2007 for Landsat 7, and from 2014 and 2021 for Landsat 8) as follows.

1. A cloud masking function was created in GEE to produce a cloudless or near cloudless image. The cloud masking function was used because the location of the study area falls in the equatorial rain forest region, and it is covered by cloud on most days (rainy seasons) of the year.
2. A variable containing the Landsat 7 and 8 image collection was created.
3. Using the created image collection variable, the dates for the classification were selected as seen above by filtering the specific season of interest (years, months and days) from the image collection using a GEE filter (ee.Filter) function.
4. To reduce the image load and processing time, filter bounds were used to clip the images to the study area extent.
5. The image bands (1 to 11) were then added as variables to aid visualization. They are essential for supervised classification as they contain the spectral information necessary to differentiate between land cover classes. Additionally, distinctive spectral signatures of different classes captured in various bands serve as the basis for training the classification algorithm and accurately categorizing pixels in the image.
6. The season in which the images were selected as explained above (see section 3.3, first paragraph) covered a period of four months. Furthermore, an image median variable was created by calculating the median of all the pixel values across the image collection. The image median does not only add the most recent pixel to the image collection, but it also calculates the median of all the pixel values in the stack to help remove shadows and clouds.
7. After visualizing the image collection, the supervised classification method was performed as follows.
    a. Collection of training data was done by creating 4 variable feature class collections to store the known LULC classes (forest, built-up areas, agriculture, and water bodies) labels on the images.
    b. The different training point variables were then merged into one training point variable, followed by overlaying the training points to the images to get the

training samples by using the Sample Region filter (converts each pixel of an image that intersects one or more image regions to a feature collection).

c. The classifier variable package was initiated followed by selecting the CART classifier algorithm and its parameters which are then trained using the training samples. The training samples are then classified using the CART.

d. Finally, the confusion matrix or accuracy assessment (used to define the performance of a classification algorithm) was checked by testing the classified images with independent validation data. The script used in GEE for the supervised classification can be found in the appendix. The Figure 3-3 below shows a screen grab of supervised classification in GEE.

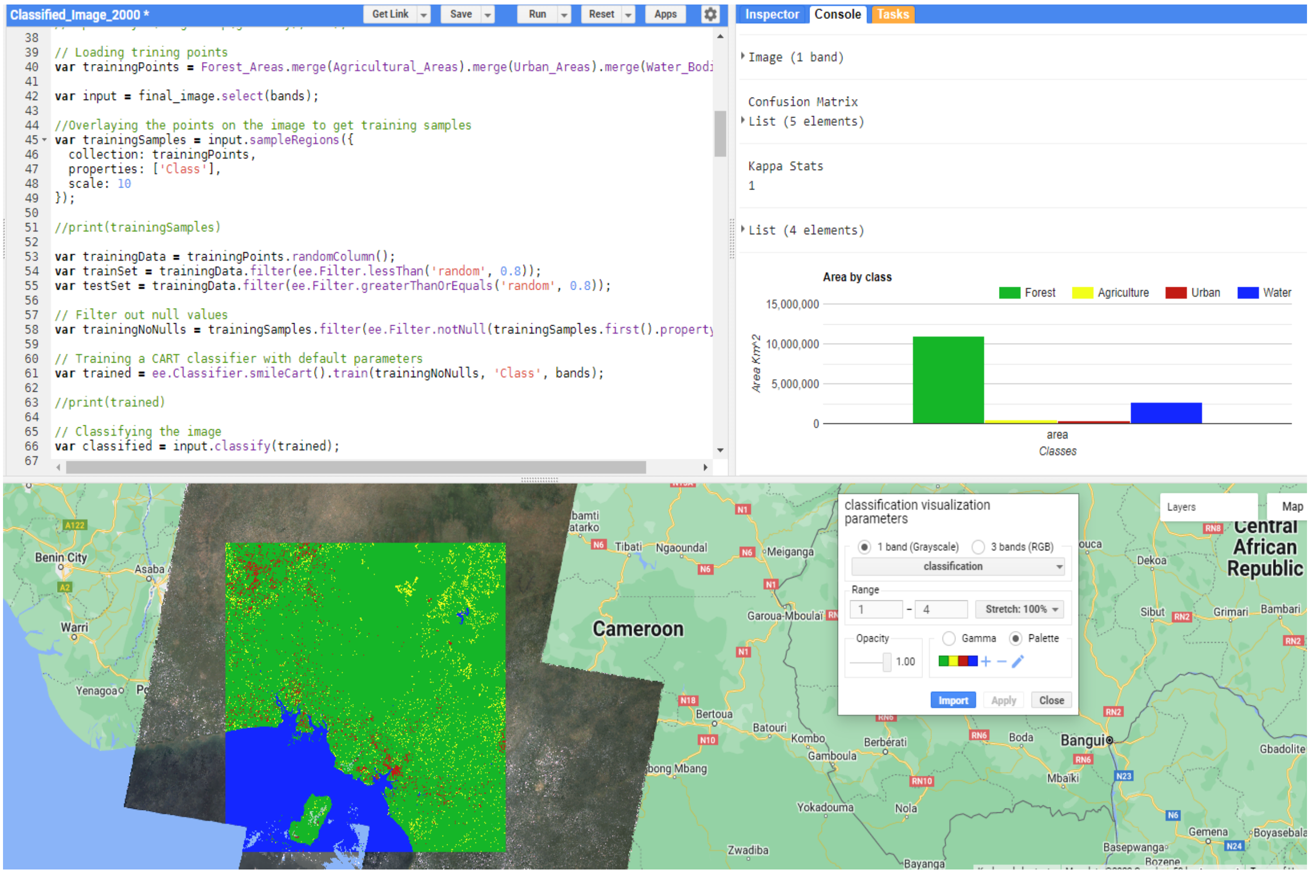

Figure 3-3: Screen grab of supervised classification using GEE.

Figure 3-4 below describes the workflow methodology used in detecting the past and present state of the different LULC classes present in the region.

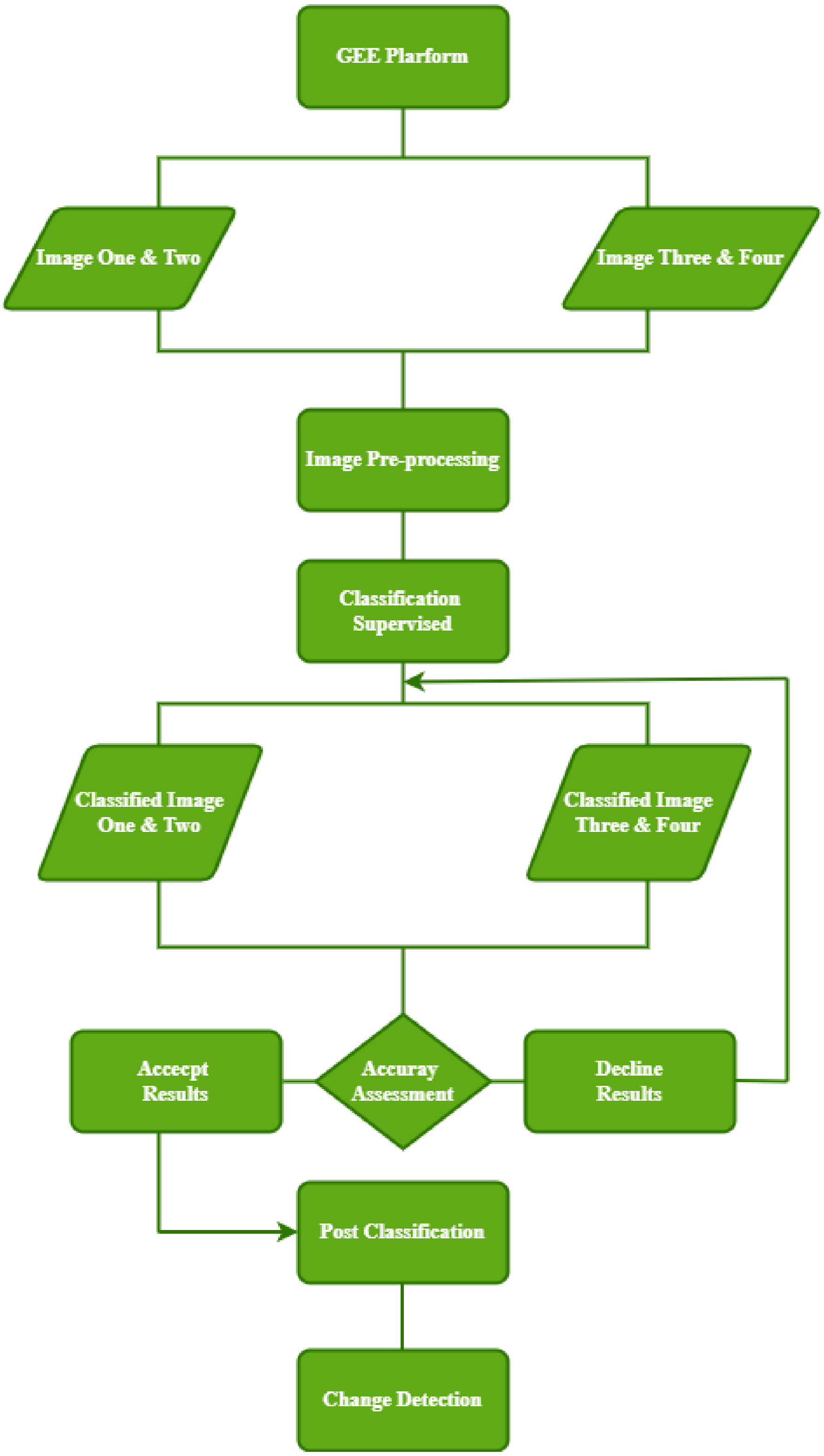

Figure 3-4: Flow diagram of supervised classification and change detection identifying the different processes of the analysis.

Additionally, to identify the distribution of the different LULC class areas overtime in the CSB forest region, the following process was used. The areas of each LULC classes were obtained by multiplying the pixel numbers of each LULC class from each classified image (2000, 2007, 2014 and 2021) with the spatial resolution of the satellite image, which was 30 m, then converted to hectares which is a standard measurement of land area. Obtaining the past and present state of the LULC classes in the region aided in the examination of the distribution of the different LULC classes in the region such as gain and loss analysis of the various classes. The analysis was done to highlight the LULC dynamics in the region thereby indicating which LULC area had the most gained and loss as seen in the explanation below.

Following the prior analysis (identifying the past and present state of LULC classes), the LULC areas of each class in the years above were then exported to a spreadsheet file which showed the historical changes in LULC areas in the region. The timeframe of the study was separated into three periods based on the dates used for LULC classification which were period one (2000 – 2007), period two (2007 – 2014), and period three (2014 – 2021). This was done to show not only the start and end points of the change occurring in the different LULC classes in the region, but also to show the changes in-between such as 2007 and 2014. Using the (Dibaba et al., 2020) equation, the net loss and gain calculation was performed on the classified images (see **Error! Reference source not found.**). The equation two below was used to calculate the rate of change of the different LULC classes over the study periods (see section 4.2 below), while equation three it was used to calculate the percentage change of the LULC areas (see the equations below). For better visualization, a column graph was created to show the variation of the loss and gain of the different LULC from past to present (see Figure 4-4 to Figure 4-6).

$$Total\ LULC\ Gain\ = Area\ in\ image\ 2 - Area\ in\ image\ 1 \quad \text{Equation 3-1}$$

$$Total\ LULC\ Loss = Area\ in\ image\ 1 - Area\ in\ image\ 2 \quad \text{Equation 3-2}$$

$$Rate\ of\ Change\ = \frac{Image\ 2 - Image\ 1}{T} \quad \text{Equation 3-3}$$

$$Percentage\ Change\ = \frac{Number\ of\ Pixel\ change\ for\ LULC\ class}{Area\ of\ LULC\ class\ in\ later\ map} * 100 \quad \text{Equation 3-4}$$

$$Percentage\ Area\ = \frac{Number\ of\ Pixel\ change\ for\ LULC\ class}{Total\ area\ of\ LULC\ map} * 100 \quad \text{Equation 3-5}$$

where images 1 and 2 are the classified LULC (ha) map of the region, and T is the total area of LULC (ha) of a later land cover image.

3.7 Assessing LULC Change in the CSB Forest Region Over Time

Changes in LULC classes over time can be determined using change detection analysis, which is an important aspect in remote sensing applications. The aim of the procedure is to analyse and compare two separate images covering the same area obtained at different times. The application of change detection has been applied in a wide range of disciplines such as disaster assessment, urban expansion, agriculture investigation, and ecological or environmental monitoring. As discussed in section 2.5, change detection can be carried out in many ways which are dependent on the satellite sensors and the methodology used. For this project, a supervised classification image was prepared as explained in section 3.6 above, followed by exporting the classified images from GEE to ArcGIS Pro (see section 1.5 specifying why the data was exported to ArcGIS Pro for change detection analysis). Furthermore, this section will fulfil objective one and research question 1.2

As stated in section 2.5.3 (on page 23), the post-classification change detection method was used to identify the direction of change between the different LULC classes. After exporting the classified images from GEE, they were then added to ArcGIS Pro and post-classification change detection was performed. The method is used to examine the categorical change difference between two classified raster datasets for land cover change analysis and allows two input datasets for analysis (the initial date and the final raster date). For this analysis the start and end dates of the different periods as identified in the last paragraph of section 3.6 above was used. The computational method that was used to account for change was the categorical method which shows the transitional change from every LULC class on the images. Using this method, it provided the option of limiting the analysis on a specific number of land cover classes and excluding others like water bodies.

3.8 Analysing the Effects of LULC in the CSB Region

This section will be based on addressing the research question 2.2 of objective two. Analysing the effects of LULC change to the CSB region will in this section will be accomplished by using descriptive statistics and correlation analysis. Correlation analysis between air quality and LULC change can be a valuable tool for assessing the environmental impact of LULC change in the sense that air quality is readily affected by changes in the environment. Air pollution is being considered in this study due to its significant impact on both environmental and human health. In the context of LULC changes, alterations in land use such as deforestation, urbanization, and agricultural expansion can lead to increased emissions of pollutants. Forests act as natural air filters, absorbing pollutants such as carbon dioxide, while urban and agricultural activities can contribute to higher levels of pollutants like particulate matter and nitrogen oxides. By examining the correlation between LULC changes and air pollution, the study aims to understand how shifts in LULC can affect changes in air quality, providing insights into the broader environmental and public health implications (Guzha et al., 2018).

By looking at how air quality changes alongside LULC modifications, we can gain insights into the potential environmental consequences of those modifications. Furthermore, satellite sensors have been created which makes obtaining air quality date through remote sensing techniques easy. Additionally, the nature of this research being an earth observation, there is no ground-based data, I will have to rely on what is visible from space. So, correlation analysis will be used to help identify the relationships between LULC changes and air pollution levels, which will serve as a proxy for environmental impact (see section 2.7 page 29 for literature on correlation analysis). The methodology described in this section comprises descriptive statistics and spatial cross correlation (point biserial correlation analysis).

3.8.1 Descriptive Statistics

Descriptive statistics provides a quantitative method of describing data in a graphical and summary form by measuring the central tendency and degree of distribution of the values present in the variables. Using the degree of distribution, it is possible to show the frequency of occurrence and the possible values present in the variables (Gudivada, 2017). In this section, descriptive statistics were calculated on the monthly average concentrations of the air pollutants to determine their degree of distribution and the central tendency of the air pollutants over the study period. This was achieved by downloading the yearly pollution concentration datasets of the different pollutants, followed by extracting the pixel values of the different air pollutants in the region and finally calculating the mean of the values. The values were then plotted to show the distribution of the pollutants in the study area over the study period.

The selection of the air pollution variables was based on the pollutants that pose a greater health risk to the environment such as carbon monoxide, nitrogen dioxide, ozone, particulate matter 2.5 (pm 2.5 are tiny particles in the air that are two and one-half micron in width), and sulphur dioxide. These pollutants were chosen because they are the major contributors to air pollution causing major public health to humans globally. They are also reportedly responsible for causing a yearly global mortality rate of 3.2 million people dying from household air pollution, and 4.2 million yearly deaths from ambient air pollution (World Health Organization, 2021a).

3.8.2 Spatial Cross Correlation (Point Biserial Correlation)

Spatial cross correlation (specifically point biserial correlation) is used to account for the correlation between LULC change and air pollution in the CSB forest region. Point biserial correlation was used in this study because the variables used in the study are made up of a continuous (air pollution) and a categorical (LULC) variable. When dealing with variables that are not normally distributed, the use of a point biserial correlation is recommended because it is designed to measure the strength and direction of the association between a continuous variable and a categorical variable. Like other correlation coefficient calculations, in point biserial correlation the measurement of the strength of association between two variables ranges between +1 and -1.

The analysis in this study was based on exploring if the change in LULC areas is associated with an increase in concentrations of a specific pollutant (for example NO_2 pollution due to industrial emissions). However, the correlation (point biserial) analysis was based on changes in LULC but did not consider other factors such as weather and topography which may affect the concentration of the air pollutants used in the study. For example, rainfall washes away water-soluble pollutants such as particulate matter and may affect the dispersal and dilution of pollutants in different areas. The correlation calculation between LULC (forest, agricultural and built-up areas) and air pollution variables (carbon monoxide, nitrogen dioxide, ozone, pm 2.5, and sulphur dioxide) is based on equation 4 (Diana Kornbrot, 2005).

$$rPb = \left(\frac{\bar{y}_1 - \bar{y}_0}{sy}\right)\sqrt{\frac{N_1 N_0}{N(N-1)}} \qquad \textit{Equation 3-6}$$

Where rPb is point biserial correlation, $\bar{y}_1$ and $\bar{y}_0$ are means of the metric observations coded 1 and 0 respectively; N_0 and N_1 are the number of observations coded 0 and 1 respectively; N is the total number of observations; and sy is the standard deviation of all the metric observations. The process of point biserial correlation was performed as shown in Figure 3-5 below.

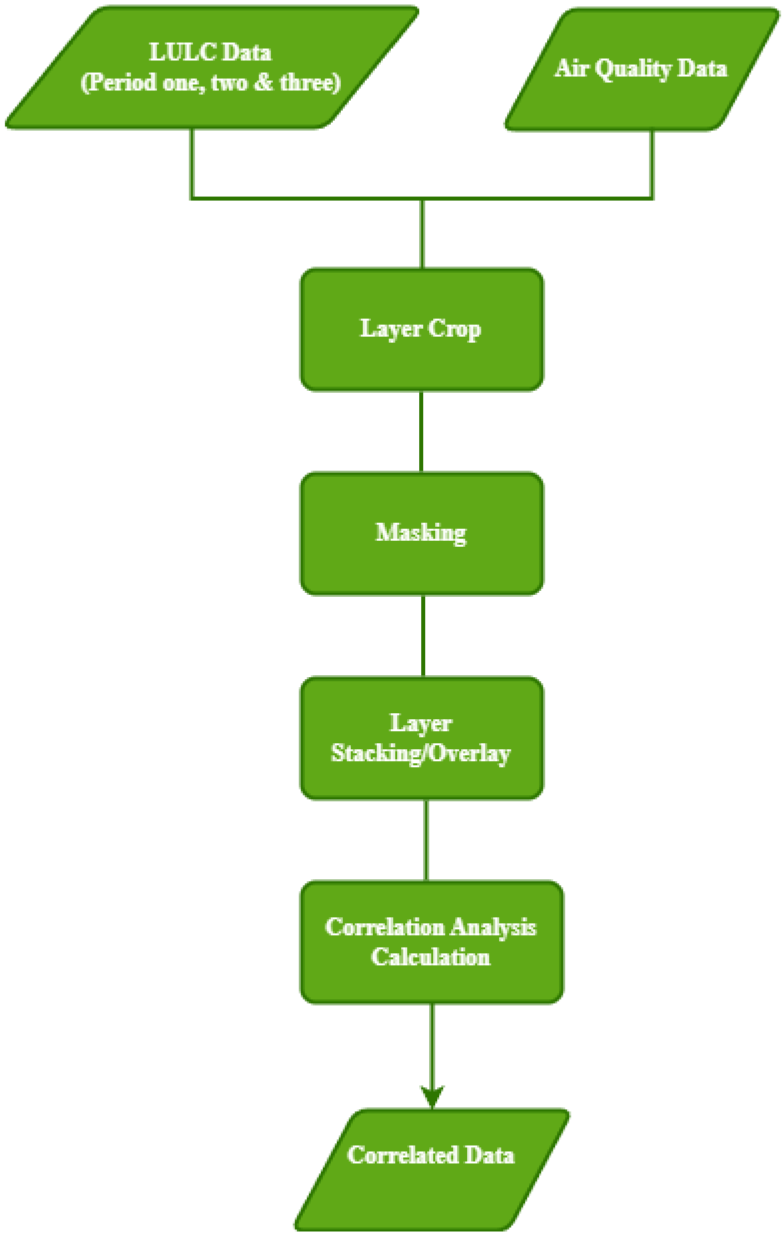

Figure 3-5: Flow chart of point biserial correlation analysis between LULC change and Air pollutants variables.

For the datasets used in this analysis, data description, source and spatial resolution can be found in Table 3-1 & Table 3-2. Using the Giovanni earth data website (see Table 3-2) a seven years' time-series air pollution datasets were downloaded for the different pollutants as identified above. The seven years' time-series air pollutants variables were used to match the same period in section 3.6 (last paragraph page 41). This was done to match the LULC change period with the air pollution concentration period. Regarding the point biserial correlation analysis the datasets (LULC and air pollution) were first projected using the Universal Transverse Mercator system. The projection transforms the data from spherical coordinate to planar coordinate system. It also helps to minimize distortion, allows for accurate angles and distance measurement to be computed easily.

As explained in section 1.5, R-studio was used for processing whereby the datasets were clipped/cropped to the processing extent of the study area (to assign the same extent, rows, and column to all the datasets used in the calculation to avoid processing error, and also reduce processing time). Following the clipping method, the masking function was used to remove areas with no values in the two datasets to mitigate misinterpretations of results. Additionally, the LULC classes in the region were separately masked to enable the correlation calculation of one specific LULC class to a specific air pollutant variable in the entire area. The LULC change period were obtained from the LULC change detection analysis as explained in section 3.7, after which the class values of each LULC class change in the detection analysis were identified. Followed by creating a mask to exclude other LULC classes in the analysis (see in the R-Studio script in the appendix section). This was to examine the effect of a specific LULC class to a given air pollutant over time rather than grouping all the LULC classes and calculating their correlation to the given air pollutants. Using the stacking/overlay function, the datasets were matched together by resampling the air pollution datasets to the LULC data (respectively) to have the same cell size and coverage area using the nearest neighbour method. The datasets were then overlayed using the raster stack function to create a new raster dataset containing the two datasets, after which the point biserial correlation function was applied to the datasets to test for correlation between a specific LULC class and air pollutant variable in the study area. The R-studio script used for the analysis can be found in the appendix section.

3.9 Modelling Land Cover Change to Predict Potential Outcome of the CSB Forest Region Without Interventions

This section will be based on fulfilling objective three and research questions 3.1 and 3.2. The characteristics of LULC change rates and intensities are fluctuating due to their high association with over exploitation of the natural resources present in the areas. Though natural variables such as soil condition, weather and terrain characteristics have accounted for some change, most of the changes have been associated with anthropogenic factors (Serra et al., 2008). For a proper development to support decision-making and strategic planning, an understanding of the dynamics and drivers of LULC change is important. The driver of change may be direct factors caused by natural occurrence or indirect factors which are caused as a result of human activities on the environment (Behera et al., 2012). The assessment and prediction of future forest change status is expected to play an important role in planning and management of forest resources. Hence, the use of historical satellite data is necessary for monitoring and analysing the change (Yirsaw et al., 2017).

The forest forecasting model in this section will be based on the Multi-Layer Perceptron Neural Network (MLPNN) and CA Markov Chain (CA-MC). The model works by identifying the transition potential of pixel classification classes to change into another class by analysing the Multi-Layer Perceptron drivers associated with change see section 2.6.1 for a detail explanation of Markov chain model (Mas et al., 2014). The application of the Markov chain (stochastic algorithm) to forest cover change forecasting is dependent on the LULC classification image (past and present) to provide the transition potential into the future prediction which is based on historical change data (Shooshtari and Gholamalifard, 2015). The blend of MLPNN and CA-MC can simulate spatiotemporal forest cover change dynamics. The accuracy assessment of the prediction is validated via assessing the prediction made between the predicted and observed LULC map (Li et al., 2015).

Land cover change modelling tools are useful for environmental monitoring and the models can assess forest cover for either changes occurring in the same location or changes that affect multiple regions (Zadbagher et al., 2018a). The MLPNN and Markov chain models were used because of their strong proficiency in projecting dynamic changes, capability of simulating different categories of environmental land cover types, and the suitability of their calibration to the required variables (Regmi et al., 2017). The MLP-Markov chain modelling is included in the TerrSet software's Land Change Modeler (LCM) module which works by furcating forest or LULC change based on categorized LULC map of an area. LCM methods for assessing and forecasting land cover change and its consequences are arranged around four key job areas:

1. Change analysis between an earlier and later land cover,
2. Transition potentials (modelling the potential for land transitions),
3. Change prediction (predicting the direction of change into the future change prediction),
4. Planning interventions.

For this study, only the first three sections are used as the aim is to forecast the future of the forest. The full LCM workflow process is described below.

3.9.1 Transition Potential Modelling

The first step to creating a land cover prediction model is the change analysis step of which the methodology has already been addressed in sections 3.6 and 3.7. This entails evaluating gain or loss by category and producing a categorical change prediction map which highlights the transition of the different LULC classes. The second stage in the prediction is the LULC classes transition potential change modelling. After the transition change calculations of the different LULC classes, the transition change classes are evaluated by grouping all the classes into sub-model named according to the different factors accounting for the transition change. Examples of transition change include disturbance from logging or agriculture.

The next step is defining the transition sub-model structure. This is based on providing the regional deforestation drivers and variables that are contributing to forest loss in the area, as shown in Table 3-3 below, which is based on the sub-model names that were created in the transition sub-model step above. In the transition sub-model structure pane, the deforestation drivers and variables were set at static (for transitions that remain the same over time) and dynamic (for transitions that are time dependent). Creating a transition potential model for LULC forecasting is only possible if the predicted deforestation variables have been selected. The variables are selected based on adequately representing the environmental and socio-economic/human factors that are responsible for promoting deforestation. The selections are based on the following assumptions.

- Topography: High risk change areas are at low altitudes while low risk change areas are at higher altitudes.
- Consideration of areas with past forest loss.
- Areas with high population density influence high consumption of resources.
- The distance from important features influences changes in land cover.
- Soil types: fertile soil is better suited to agriculture (Cushman et al., 2017).

The table below identifies the deforestation variables used in the transition modelling.

Table 3-3: Deforestation driving variables used in the transition potential process.

Environmental	**Proximity**	**Social & Economic**
Elevation	Distance from roads	Agricultural output
Slope	Distance from rivers	Growth rate
Surface Temperature	Distance from built-up areas	Industrial output
Precipitation		Protected areas
Soil		

Table 3-3 lists several variables that were used to model the transition potential of the predicted LULC. Introducing these variables in the modelling helps to contribute to a better understanding of the factors shaping LULC dynamics and can inform land management and planning efforts (Khoi and Murayama, 2010).

The last step in the transition potential change modelling is the implementation of the transition sub-model using the appropriate machine learning model. The LCM is equipped with six machine learning methodologies for modelling/predicting change. These are: multi-layer perceptron neural network model, decision forest, logistic regression, weighted normalize likelihood, support vector machine, and similarity-weighted instance-based machine learning. The implementation of the transition sub-models was performed using the MLPNN which is the best for working with complex and non-linear relationships (Eastman, 2020). The sample size per class value for training was set at 10 000 which is equal to the least number of pixels that have transitioned from one class to another. From the sample, 50% is trained while the rest is tested on the prediction.

The next section in implementing the transition sub-model is based on setting the MLPNN parameters such as the start and end learning rate, and hidden layer nodes. Hidden layer nodes are the computational units located between the input layer and the output layer. Neural networks consist of multiple layers of interconnected nodes, and the hidden layer nodes play a crucial role in the network's ability to learn and generalize from data. The hidden nodes are controlled by an algorithm that automatically sets the hidden layers based on the parameters needed for prediction. In this study, the hidden layer nodes were set at 12 because it was the optimal number of nodes that produced the highest percentage of accuracy rate and skill measure. For the learning rate, its parameters are also automatically based on the training, testing rate, and accuracy rate of the error graph. After setting the parameters, the sub-model is executed to create a transition potential of all the LULC classes. If the accuracy rate of the model is below 70% the model is retrained followed by adjusting the hidden layer nodes and potential driven factors (Eastman, 2020). Figure 3-6 below shows a screen grab of the transition potential modelling.

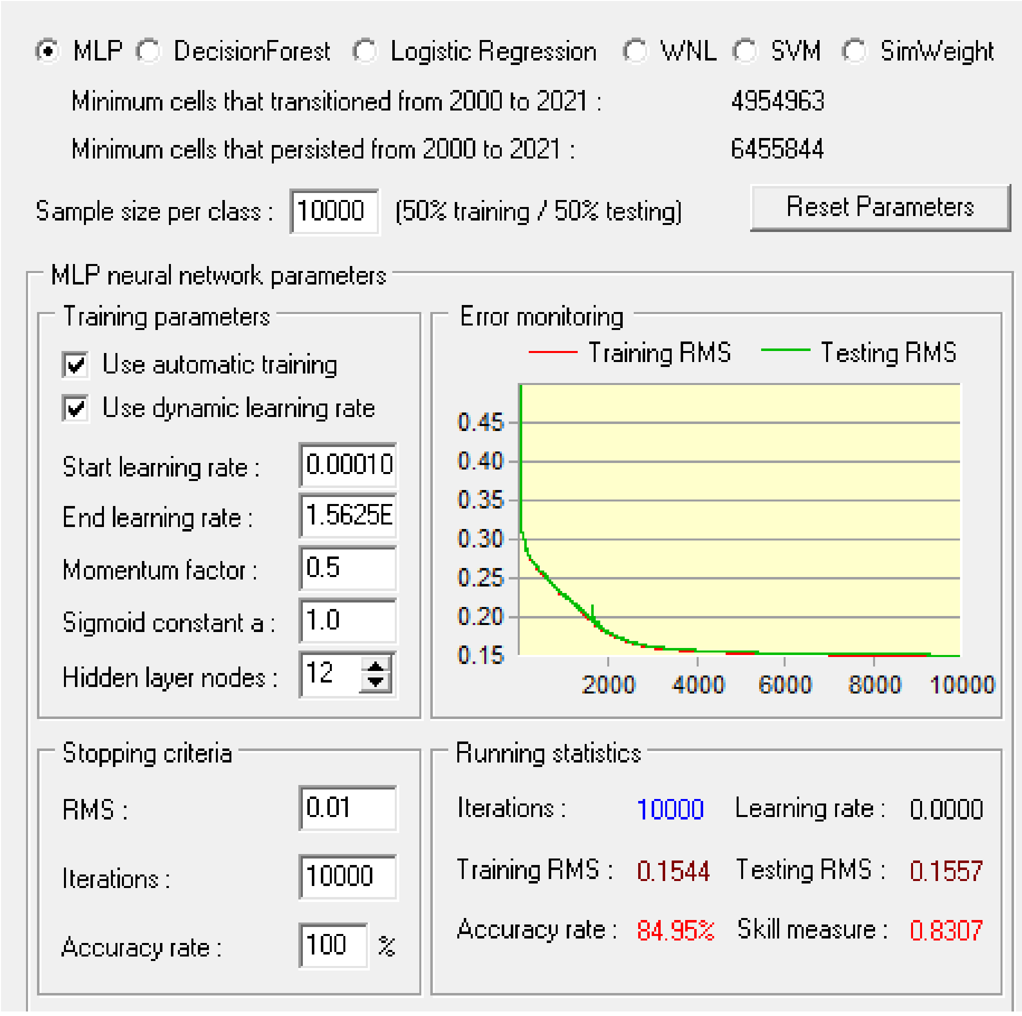

Figure 3-6: Screen grab of transition potential modelling in TerrSet.

Figure 3-7 below depicts the steps used in creating a transition potential model.

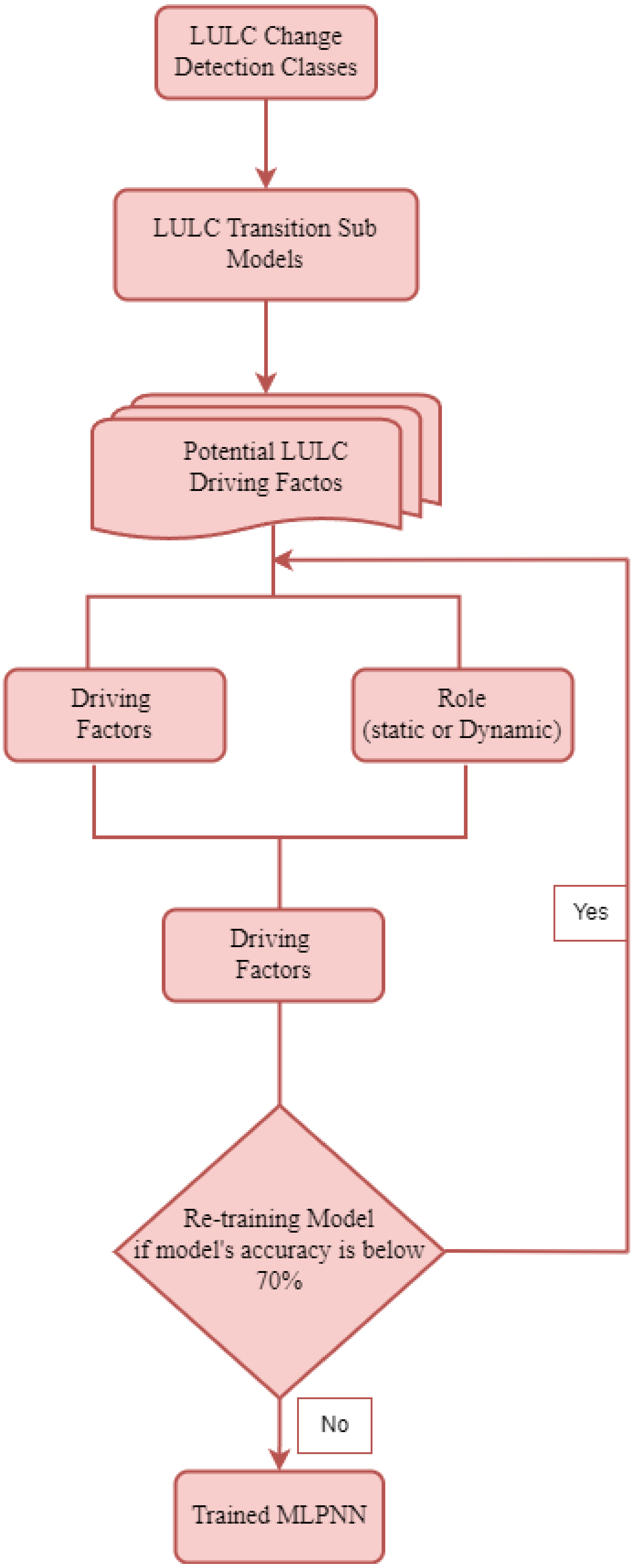

Figure 3-7: Transition potential Modelling of the LULC classes with respect to the potential LULC driving factors.

3.9.2 Change Prediction

The last process required for forest prediction is the change prediction step which comprises of change prediction modelling. This computes the change that may occur in the future for the study area. The Markov chain model analyses the two sets of LULC cover images and produces a transition probability and a conditional matrix of LULC classes to change from each other. The predicted year was set at 2063 (in line with goal 7 of the African Union agenda 2063 for promoting sustainable forest development across Africa). The output produces a soft prediction which is a continuous map of vulnerability to change and a hard prediction which calculates the transition potential of each class then aggregates the classes to produce the predicted output. The resulting output image is a predicted 2063 land cover map of the CSB region indicating the different LULC classes. This prediction is based on the spatial structure of the various LULC categories and scenarios on the transition potential model (Eastman., 2020).

The Markov matrix model relies on the Bayes equations below to predict LULC change by comparing the past (time 1) and present land cover (time 2) (Eastman., 2020).

$$S_{[t+1]} = P_{ij} * S_{(t)} \qquad \textit{Equation 3-7}$$

$$Pij = \begin{bmatrix} P11 & P12 \ldots \ldots & P1n \\ P21 & P22 \ldots \ldots & P2n \\ \ldots & \ldots \ldots \ldots & \ldots \\ Pn1 & Pn2 \ldots \ldots & Pnn \end{bmatrix} \qquad \textit{Equation 3-8}$$

Where S(t) and S(t+1) are the system status at times t and t + 1, respectively. $0 \leq pij < 1$ and $\sum_{j=1}^{n} Pij = 1, (i, j = 1, 2, \ldots . n)$ is the transition probability matrix.

3.9.3 Model Validation

Validation is an essential process to evaluate the accuracy and quality of a predicted LULC map against a reference map (Wang et al., 2016). Validation involves a three-way comparison between the predicted LULC map (2063), the reference map (2021), and the previous land cover map (2000). A cross-tabulation was performed to assess the agreement between these maps which reveals the following scenarios:

- Hits: Areas where the model correctly predicted the LULC changes.
- False Alarms: Areas where the model predicted changes, but no changes occurred.
- Misses: Occasions where the model failed to predict changes, but changes occurred (Eastman., 2020).

Prior to the actual 2063 land cover prediction, a predicted LULC map of 2021 was first developed between the 2000 and 2014 classified LULC maps of the region to simulate the classified 2021 LULC map. The simulated map was then compared to the actual classified LULC map of 2021. The validation process ensures that the models prediction capacity was verified between the 2000 and 2014 periods before projecting the LULC maps for 2063 using the 2000 and 2021 classified maps (Eastman., 2020). The validate module/tool gives a comprehensive statistical analysis that simultaneously answers two questions.

- How well do two maps agree in terms of cell quantity in each category?
- How well do two maps agree in terms of cell location of each category?

The question is simultaneously answered by calculating the various Kappa indices and related statistics. The Kappa coefficient/indices assess the agreement between the predicted map (2021) and the actual land use map (2021). However, to provide a more comprehensive evaluation, cause-dependent Kappa indices were calculated, including Kappa for no information (K-no), Kappa for location (K-location), Kappa for standard (K-standard), and Kappa for stratum-level location (K-location-strata). These indices help differentiate between quantification and location errors, enhancing the expressiveness of the evaluation (Mosammam et al., 2017). Figure 3-8 below highlights the flowchart and steps used for predicting land cover change.

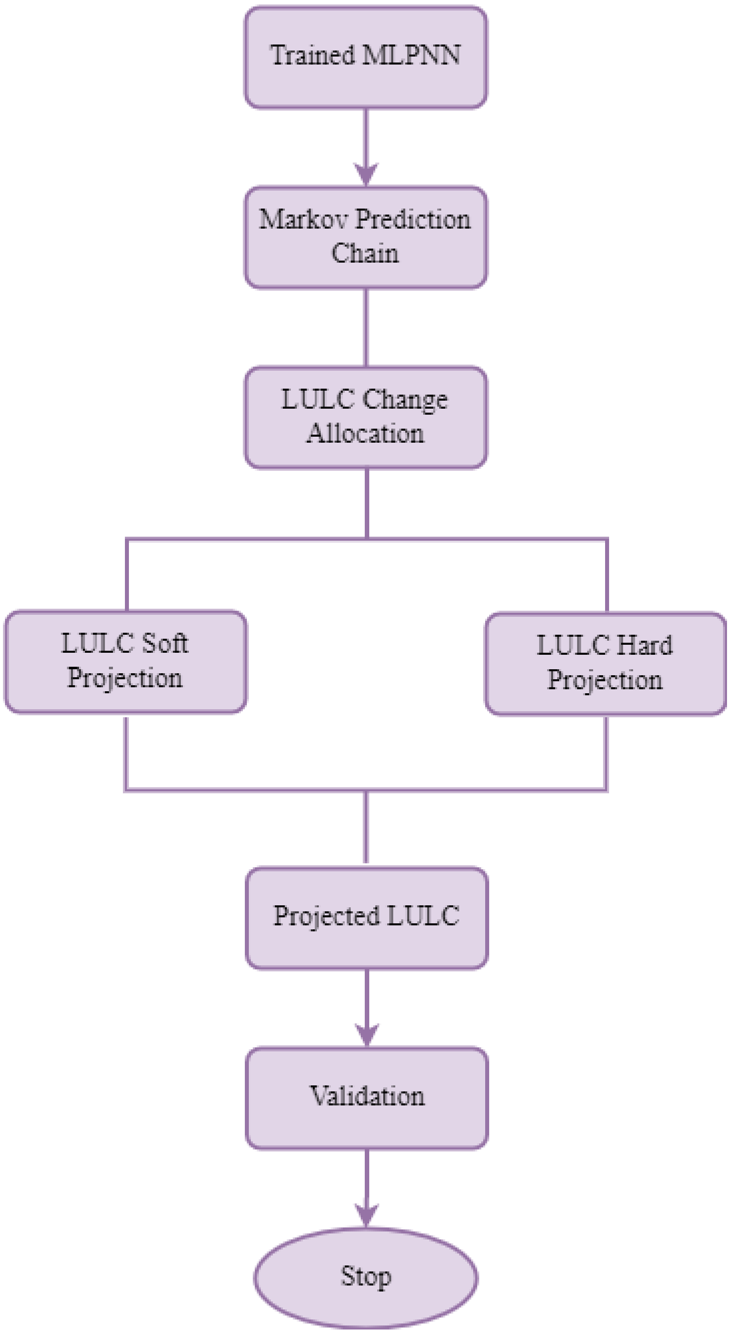

Figure 3-8: Change prediction flow chart depicting the main steps in forecasting LULC change using Markov Chain.

3.10 Summary

In this chapter, the methodology that has been explained is in line with the research questions above (see section 1.4.2). Forecasting of environmental change in recent years has been an important phenomenon which has been helping land authorities to allocate resources appropriately and preserve the environment. The datasets utilized in this study originated from a wide variety of sources as described in Table 3-1. Each dataset was prepared per the requirements of the different methodologies.

Analysing geo-spatial data for expected results can only be attained using the appropriate methodology. Analysis can only be feasible if data is present and with the advancement of geo-spatial data, many sensors have been developed such as Landsat and Sentinel, for monitoring of environmental change. Environmental monitoring such as land cover changes can be performed in various ways such as post classification change detection approach, which reveals the categorical changes of an area from satellite images collected at two periods in time. Apart from performing environmental monitoring to estimate land cover change, complex relationship patterns between different factors such as temperature and air pollution affecting the environment can be estimated. The relationship between LULC change and air pollutants was tested using the point biserial correlation analysis method. Advances in computational capabilities have given rise to environmental simulations such as land cover forecasting which was used to predict future LULC outcomes in the CSB forest region.

4. ANALYSIS and RESULTS

4.1 Overview

The preceding chapters have been used to lay the groundwork for the analysis and results as presented in this chapter. Data manipulation and pre-processing were identified, assembled, and prepared in the previous chapter. Following the compilation, the completion of each process was based on adopting a logical and workable methodology used by other researchers as described in chapter three. The focus here is on accounting for the historical state of the LULC classes followed by performing a correlation analysis to test for the strength of association between land cover change and air pollution. Following the historical change of the different LULC classes and strength of association between land cover change and air pollutants change, a 2063 land cover change forecast model was developed for the CSB region. Based on the approach that has been explained in chapter 3, this chapter contains an in-depth, comprehensive analysis of the data in the research. The findings of each process are based on maps highlighting the different activities present in the area. The results presented in this chapter are based on the order of the objectives and research questions listed in chapter one.

4.2 Past and Present States of the LULC in the CSB Forest Region

As discussed in paragraph one of section 3.6 above, the focus on the state of the forest region is not based only on forest change or loss but also on the different LULC classes in the entire forest region. The result presented in this section will be addressing objective one and its research questions as seen in 1.4.2 above. A classified LULC map of the forest was created using GEE as described in section 3.6. Performing the CART classification on the different images revealed the distribution of the different LULC classes in the region for the years 2000, 2007, 2014, and 2021. The Kappa statistics and overall accuracy of the classified images are 91.43%, 87.59%, 89.71%, and 90.12% respectively, and the classification accuracy is 0.93, 0.90, 0.89 and 0.88 respectively. The Figure 4-1 and Figure 4-2 below illustrates the LULC classified images in the CSB region.

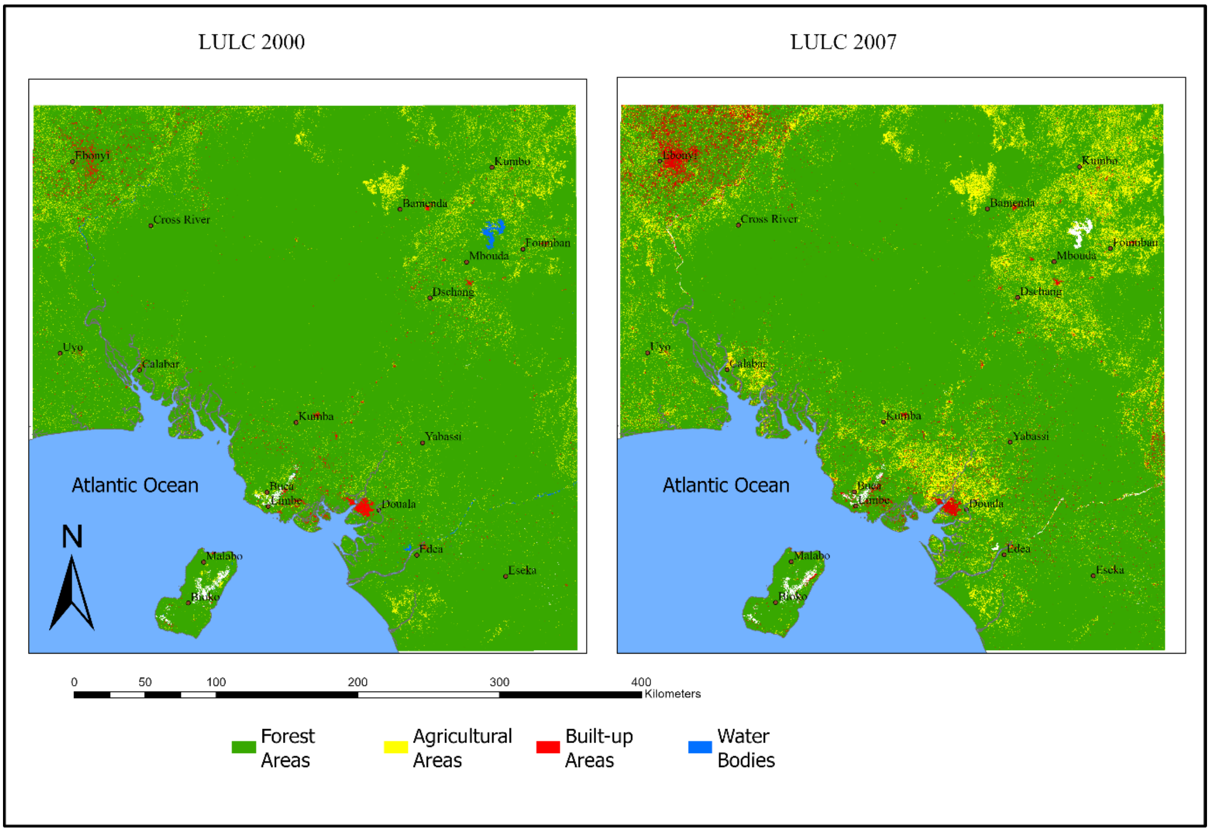

Figure 4-1: Distribution of LULC classes in the CSB forest region at different periods 2000 and 2007

With reference to Figure 4-1 above, in the year 2000, most of the LULC class was made up of forest areas with a few areas occupied by agricultural areas (the north-western part, south-western and a few sections in the eastern part of the map). The built-up areas were mostly in the southern and the north-western part of the CSB region. Going forward to the year 2007, agricultural areas had encroached into the forest areas in most parts of the north-western sections of the CSB region. Built-up areas had increased in the centre of the CSB region and the north-western part of the map.

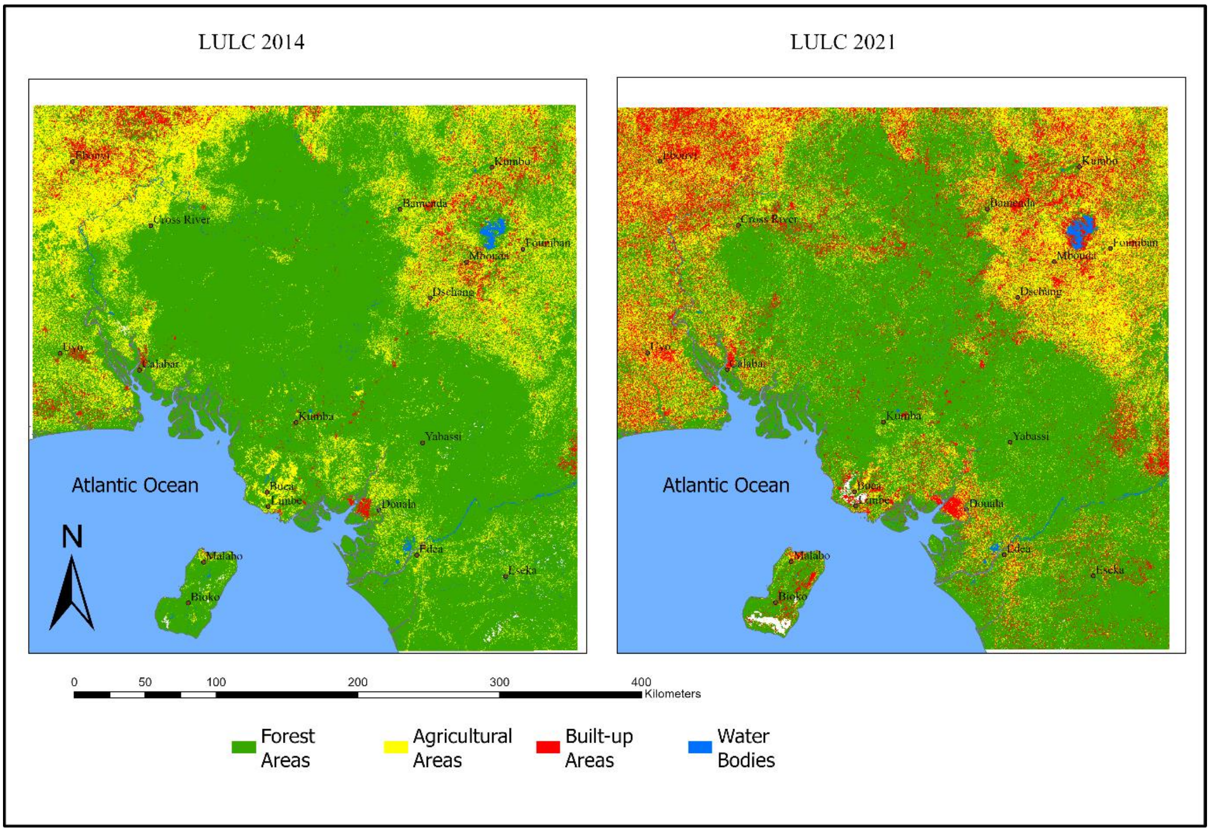

Figure 4-2: Distribution of LULC classes in the CSB forest region at different periods 2014 and 2021

For the year 2014 as seen in Figure 4-2 above, agricultural areas had covered most of the north-western and north-eastern parts of the CSB region. Built up-areas have increased in the western, southern and a few sections of the north-eastern parts of the CSB region. For 2021, the area covered by agricultural and built-up areas has also increased. The distribution also indicated that forest areas in both years had reduced due to encroachment from agriculture and built-up areas. Furthermore, the changes indicated in the classified LULC classes (forest, agricultural, and built-up areas) can also be backed by data from the world bank data catalogue as seen in Table 4-1 below. The table indicates the percentage change of forest, agricultural and built-up areas in the CSB region between the years 2000, 2007, 2014, and 2021. (World Bank Data, 2022).

Table 4-1: Forest, Agricultural, and built-up areas trends of countries in the CSB region (source: world bank data 2022)

		Years			
Country	**Indicator (% of total land area)**	**2000**	**2007**	**2014**	**2021**
Cameroon	Forest Area	45.7	44.7	43.7	43
	Agricultural Area	19.4	19.5	20.6	20.6
	Built-up Area	46	50	54	59
Equatorial Guinea	Forest Area	93.2	91.2	89.1	87.3
	Agricultural Area	7.6	6.9	6.9	6.7
	Built-up Area	49	61	70	74
Nigeria	Forest Area	27.3	26.1	24.8	23.7
	Agricultural Area	72.7	73.9	75.2	76.3
	Built-up Area	35	41	47	55

According to the (World Bank Data, 2022) data, the percentage of total land area for forest, agricultural and urban areas has been experiencing the same changes as seen in Figure 4-1 and Figure 4-2 above. The Figure 4-3 below shows the land cover change area in the CSB region between the years 2000, 2007, 2014, and 2021.

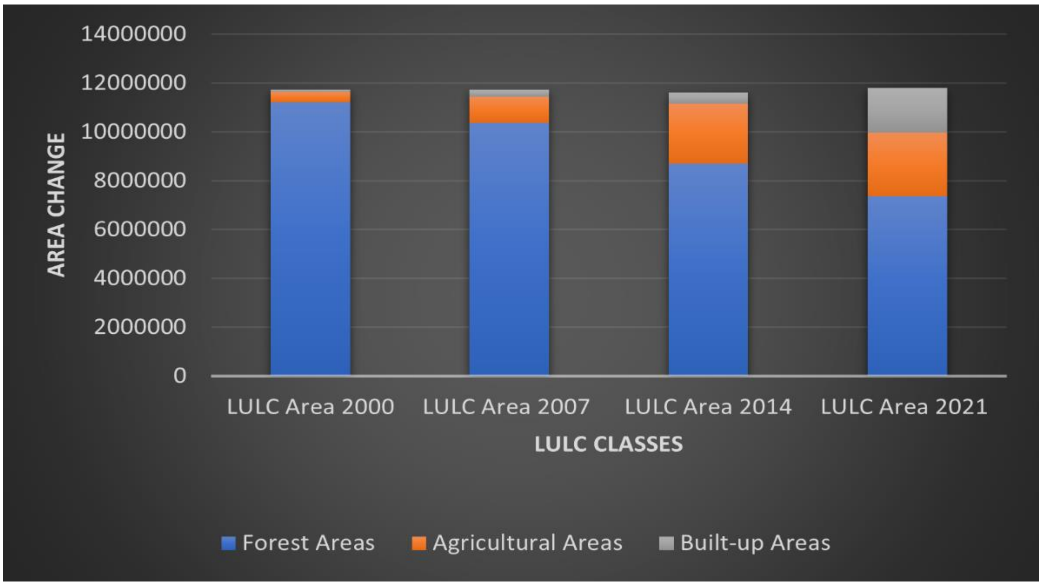

Figure 4-3: Past and present state of the forest indicating the variation of change in the different LULC classes.

Extracting the LULC class areas in the region showed how each LULC class has been changing from the start of the study year to the end (2000 to 2021), based on Equation 3-3 in section 3.6 page 41 the rate of change of the various LULC classes was obtained. The Figure 4-3 (stacked chart) above indicates that from year 2000 to 2021 the forest areas have reduced from 11

199 840.12 hectares to 7 347 636.99 hectares. The rate of forest area change average is 6 162 114.75 hectares over seven years. For agricultural and built-up areas in the CSB region, the area change has been increasing from 2000 to 2021. The change for agricultural areas has been 441 719.01 to 2 624 826.15 hectares accounting to an average change of 1 865 018.186 hectares over seven years. For built-up areas, the land cover has changed from 97 350.93 hectares to 1 838 736.63 hectares with an average rate over seven years of 820 262.94 hectares. Regarding the past and present state of the LULC classes, the year 2021 accounted for the most changes in the land cover areas followed by the year 2014 in second spot while the third spot was the year 2007.

4.3 Identifying changes in LULC in the CSB Region Over Time

The result from this section will focus on addressing the research question 1.2 of object one (see section 1.4.2 above). Using Equation 3-1 and Equation 3-2, the area change of the various LULC classes in the region was obtained for the different periods as explained in the last paragraph of section 3.6. The results are presented in the column charts below indicating the percentage area change of the different LULC classes in the region.

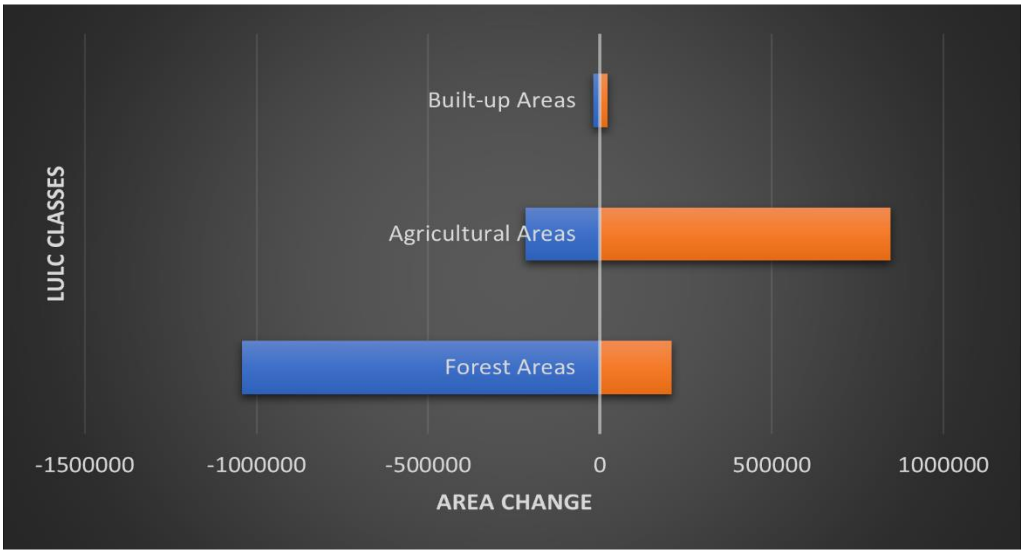

Figure 4-4: Gain and Loss percentage of area change of the different LULC classed by category for period one.

The gain and loss change by category for the different LULC classes for period one (see Figure 4-4) indicated that forest areas had a 6.64% decrease in area that contributed to 1 041 629 hectares loss. There was also a 1.33% increase in area leading to 208 476 hectares gain in forest area. The loss in forest areas might have contributed to the 5.4% increase in agricultural areas corresponding to 846 278 hectares gain in that period. Furthermore, agricultural areas had a

1.32% decrease in areas leading to 216 196 hectares loss. Additionally, built-up areas had a 0.13% decrease which accounted for a 20 261 hectares loss and a 1.42% increase in area which further accounted for 22 332 hectares increase in areas for period one respectively.

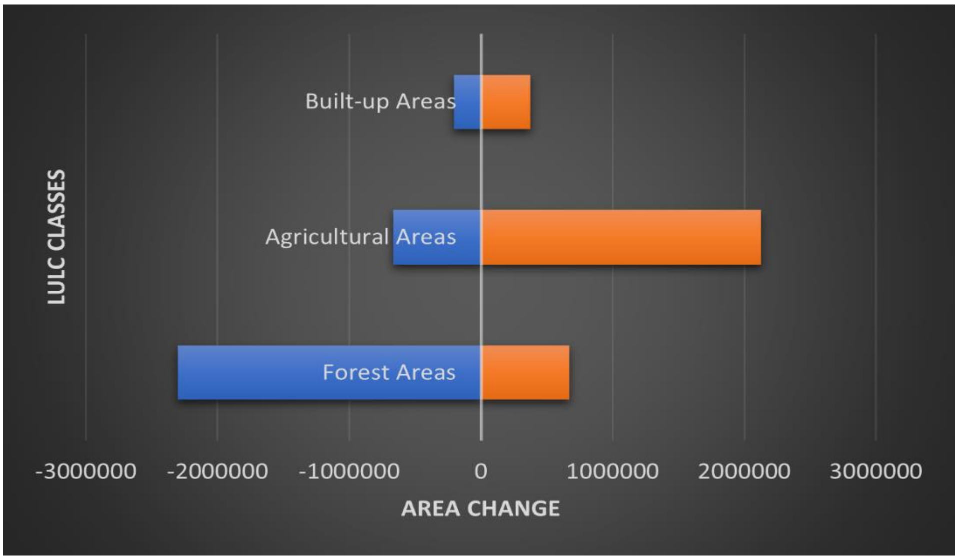

Figure 4-5: Gain and Loss percentage of area change of the different LULC classed by category for period two.

As seen in Figure 4-5 above, there was a continual decrease in forest areas from period one to period two accounting for a 14.69% decrease in area making up 2 303 416 hectares loss in area. Though there was a 14.69% loss the class also recorded a 4.29% increase in area which made up 672 956 hectares gain in period two. While there was a decrease in forest areas, agricultural areas had a 13.55% increase in area which accounted for 2 124 635 hectares gain and a 4.25% decrease making up 665 593 hectares loss for agricultural areas. Furthermore, built-up areas had a 1.3% decrease in area accounting for 203 897 hectares loss and a 2.39% increase in area which also accounted for 375 315 hectares gain in area for period two respectively.

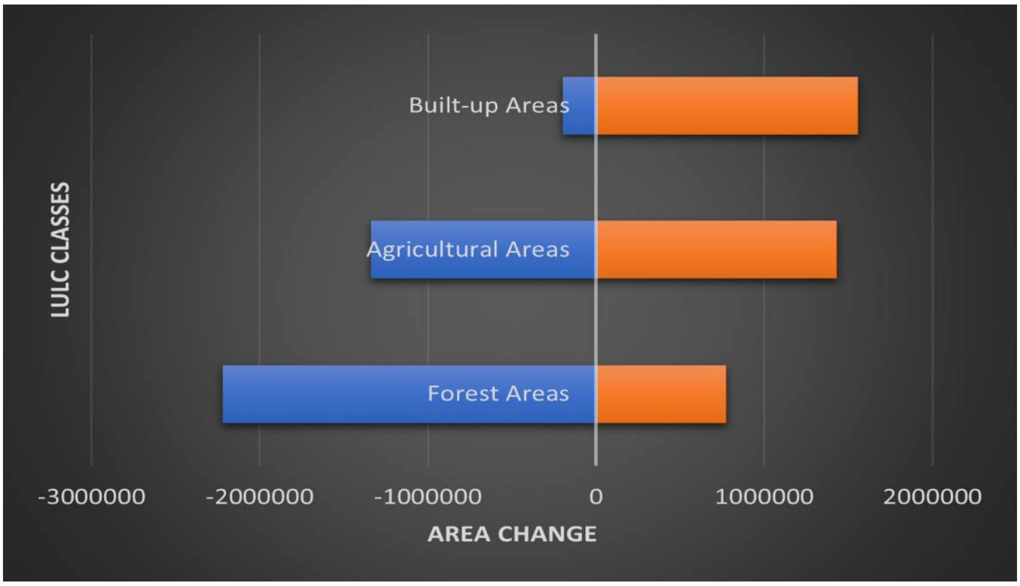

Figure 4-6: Gain and Loss percentage of area change of the different LULC classed by category for period three.

Figure 4-6 above indicated that the loss in forest areas continued to period three which had a 14.17% decrease in area accounting for 2 221 412 hectares loss. There was also a gain in area of 4.93% for forest areas which accounted for 772 493 hectares. Regarding agricultural areas there was an 8.54% decrease in areas resulting to 1 338 246 hectares loss followed by a 9.13% increase in areas resulting to 1 431 134 hectares gain in area. The last of the LULC classes, built-up areas, accounted for a 9.92% increase which made up 1 555 618 hectares which might have been a result the decrease in agricultural areas. Additionally, there was also a 1.27% decrease in built-up areas accounting for 199 587 hectares loss.

Though there was a substantial loss in forest areas such as period two which accounted for the most loss, the LULC class (forest) also accounted for gain in area such as in period three which had the highest gain in forest areas with a percentage of 4.93% amongst the three periods. With regards to agricultural areas, the highest gain was recorded in period two with a percentage of 13.55. Additionally agricultural areas also recorded a period of highest loss (period three) of 8.54%. The loss in agricultural areas might be attributed to the increase in built-up areas with a percentage of 9.92 in built-up areas in period three.

4.4 Assessing the Direction of Change in the different LULC Classes in the CSB Region

This subheading is based on the continuation of research question 1.2 of objective one as seen in section 1.4.2 above. Assessing the direction of change in the different LULC classes in the CSB region was made possible using the post-classification change detection method as explained in section 3.7. The change detection method revealed the change in area from one

LULC class to another. In terms of the post classification method, the detection is measured between two time periods. So, for easy post-classification change detection analysis the change detection was done in three separate periods as before. Figure 4-7 below illustrates the results of the area change of the change detection analysis.

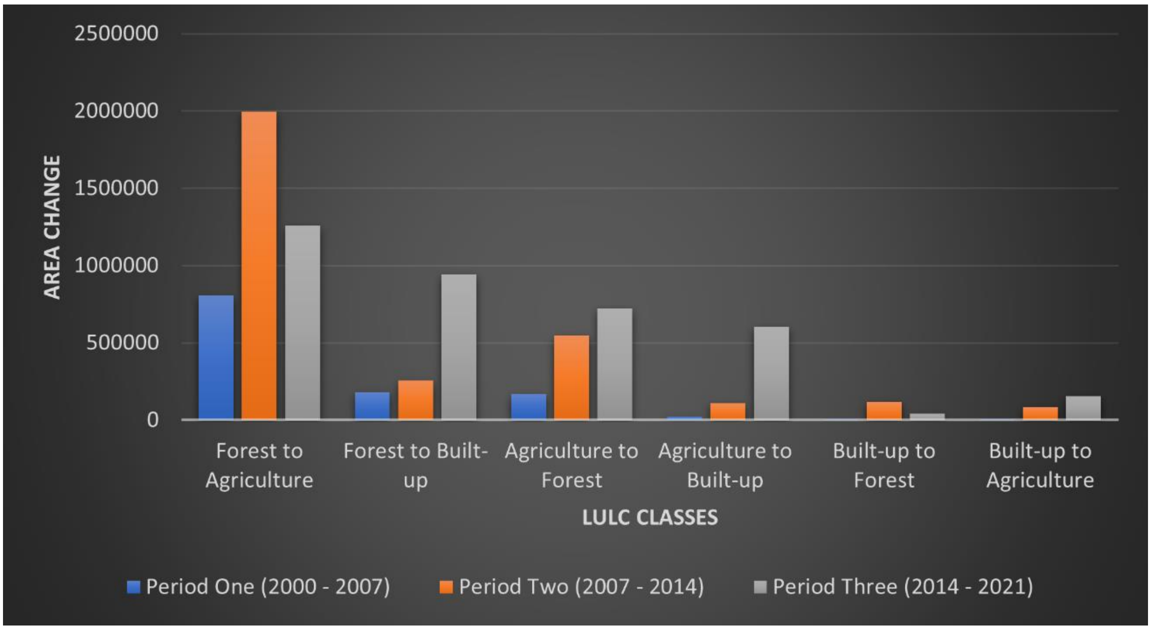

Figure 4-7: Change detection chart of the LULC classes of the CSB region showing From and To changes between the different LULC classes in the region.

The change in areas from forest to agriculture in Figure 4-7 above indicated that period two accounted for the most area change of 1 996 557.4 hectares followed by period three with an area change of 1 259 155.91 hectares and lastly period one accounted for the least area change of 804 816.01 hectares. With regards to the change from forest to built-up areas the most change was experienced in period three (941 886.12 hectares), the next was period two with an area change of 256 340.85 hectares. The third period had an area change of 179 004.26 hectares. Based on the change from forest to agriculture and built-up areas, forest to agricultural areas was the highest change recorded in the CSB region for all three time periods which is in line with what the Food and Agriculture Organization indicated (2018). They explained that land conversion for large-scale agricultural production is the leading cause of tropical deforestation, accounting for about 80% of forest loss. Furthermore, the results of the change from forest to built-up are also in line with the data obtained from the World Bank for the years 2000, 2007, 2014, and 2021 (see Table 4-1) catalogue which shows how built-up areas have been increasing over the years.

The change from agricultural areas to forest likely indicates forest conservation where agricultural areas are turned back into forest areas. Period three had the highest area change from agriculture to forest (721 394.8 hectares). Next in line was period two with an area change of 547 005.95 hectares and finally period one had the least change 167 795.56 hectares. Regarding the change from agricultural areas to built-up areas as indicated in Figure 4-7 above the highest change was recorded in the third period accounting to an area change of 601 643.53 hectares. The second period accounted for a change of 107 061.15 hectares and lastly period one with 212 94.71 hectares change. The Figure 4-8 below shows the change map of the different LULC classes for period one and two.

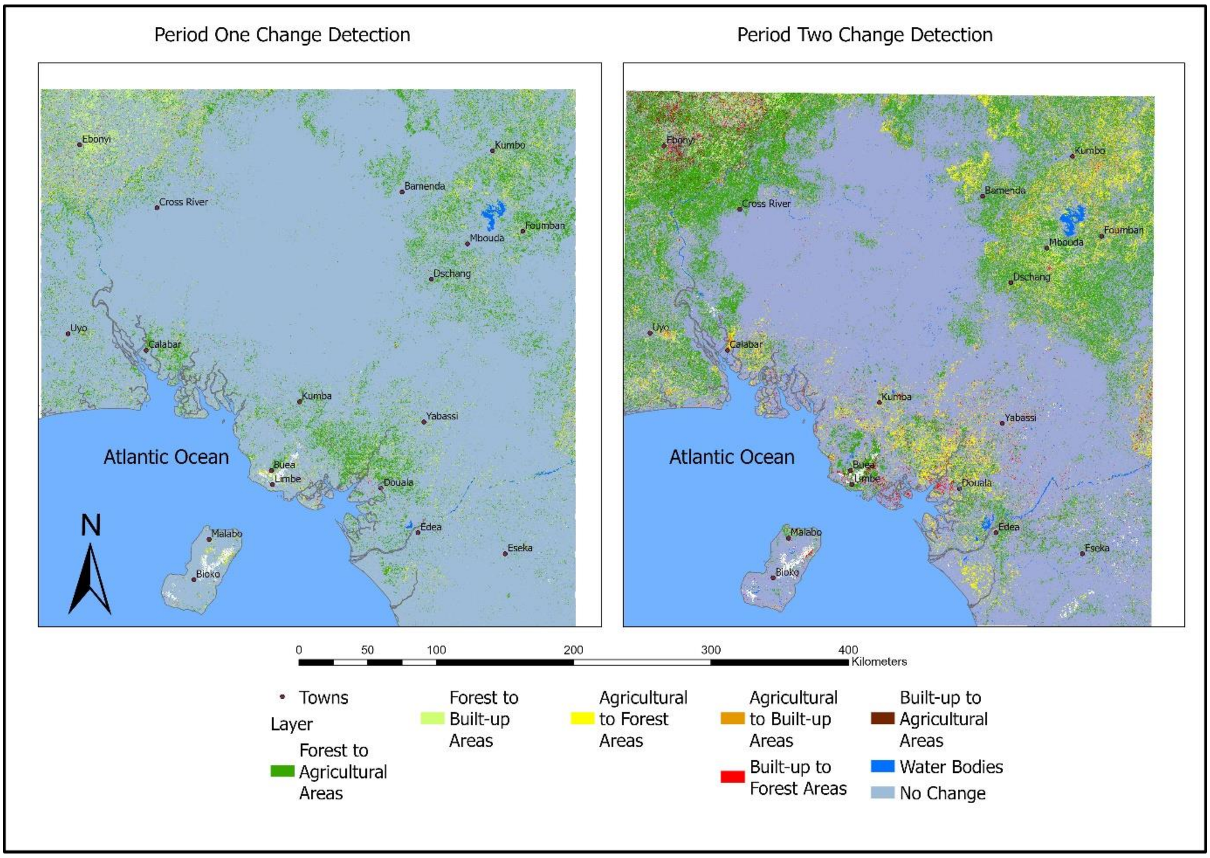

Figure 4-8: Change detection map of the different LULC classes in the CSB region for period one and two (the white areas around Bioko, Limbe and Buea are because of cloud masking that resulted to missing data).

The Figure 4-8 above indicates that areas with green and lemon green represents a change from forest to agricultural and built-up areas for both periods. Yellow and gold regions represent a change from agriculture to forest and built-up areas followed by the areas with red and brown areas which stands for a change from built-up areas to forest and agricultural areas. The reason the colour change (red) from build-up areas to forest and agricultural areas in period one does not appear on the map is because the area of change is very small. It is mostly found scattered in the northwest, northeast and southern parts of the map in areas like Calabar, Douala, and Buea and not as concentrated as seen in period two change detection map. The no change are areas where no change occurred during that period.

Last of the LULC classes to undergo change detection was from built-up areas to forest and agricultural areas. The results in Figure 4-7 indicated that the change from built-up to forest areas had the highest change in the second period amounting to 116 045.15 hectares followed by period three with a change of 407 49.44 hectares. The period with least change was the first period which had an area change of 580.21 hectares. Built-up area to agricultural areas had the highest change in the third period with an area of 154 882.7 hectares followed by the second period 821 87.5 hectares. Last of the change was the first period having an area of 3 660.90 hectares.

The change of built-up areas to forest region in the CSB region might be as a result of the implementation of forest landscape restoration (FLR) initiatives in countries like Cameroon. This initiative employs techniques like afforestation, natural expansion, agroforestry, green infrastructure development, urban woodlots and ecosystem-based adaptations, supported by significant funding and high-level political support. As a result, built-up areas are being converted back to forested landscapes, contributing to climate change mitigation, biodiversity conservation, and improved livelihoods for local communities (Food and Agriculture Organization, 2021). The Figure 4-9 below shows the change detected from the different classes for period three.

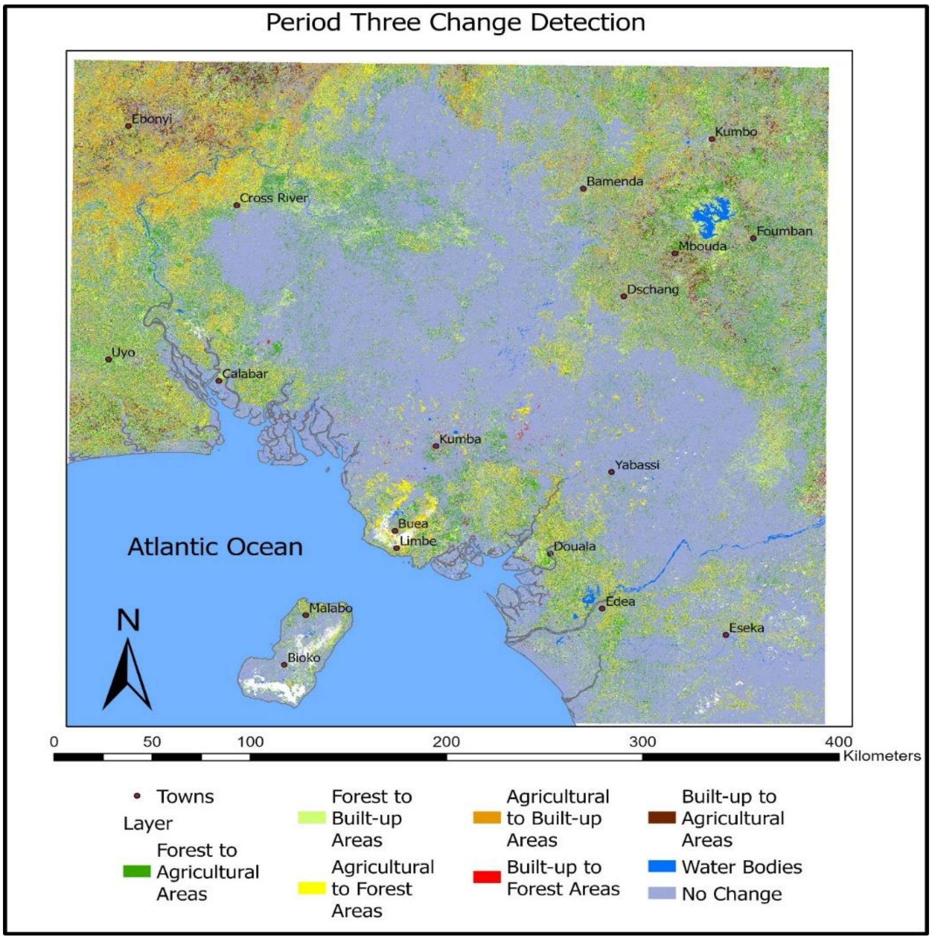

Figure 4-9: Change detection map of the different LULC classes in the CSB region for period three (the white areas around Bioko Limbe and Buea are because of cloud masking that resulted to missing data).

The green and lemon green regions as seen in Figure 4-9 above indicates areas that changed from forest to agriculture and built-up areas in the map. For the change from agriculture to forest and built-up areas the regions are represented with yellow and gold respectively. The red and brown region identifies areas that underwent a change from built-up areas to forest and agricultural areas respectively. The no change are areas where no change occurred during that period.

4.5 Correlation between LULC Change and Air Pollution in the CSB Forest Region

4.5.1 Descriptive Statistics

Addressing this section will be based on objective two and its research questions as seen in section 1.4.2 above. The air pollutants examined in the CSB forest region consist of annual mean values of carbon monoxide (CO), nitrogen dioxide (NO_2), ozone (O_3), particulate matter 2.5 and sulphur dioxide (SO_2) as explained in section 3.8.1. The basis for comparing the mean pollutant values of the CSB region was based on the (World Health Organization, 2021b) yearly air pollutants emission guidelines. Figure 4-10 below highlights the values of the air pollutants form the descriptive statistics.

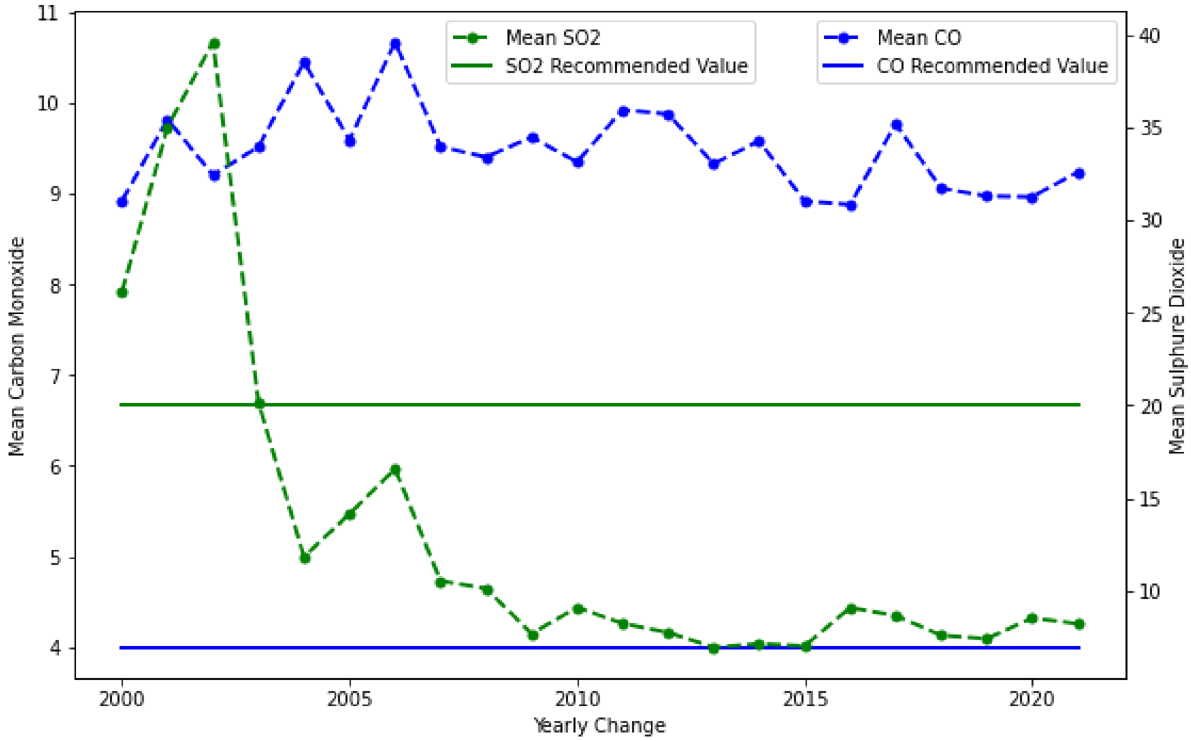

Figure 4-10: Mean annual distribution of Sulphur Dioxide and Carbon Monoxide in the CSB forest region over the study period (source: NASA Earth Explorer).

The recommended WHO guidelines for SO_2 and CO (World Health Organization, 2021b) are 20 and 4 micrograms per cubic meter (µg/m³) respectively. Figure 4-10 shows that the distribution of SO_2 and CO has been changing across the study period with maximum values of SO_2 (39.6 µg/m³) and CO (10.6 µg/m³) occurring in 2002 and 2006 respectively. For the years 2000 to 2003, the mean SO_2 values exceeded the recommended guidelines, whereas the mean CO exceeded the WHO recommended guidelines for the entirety of the study period.

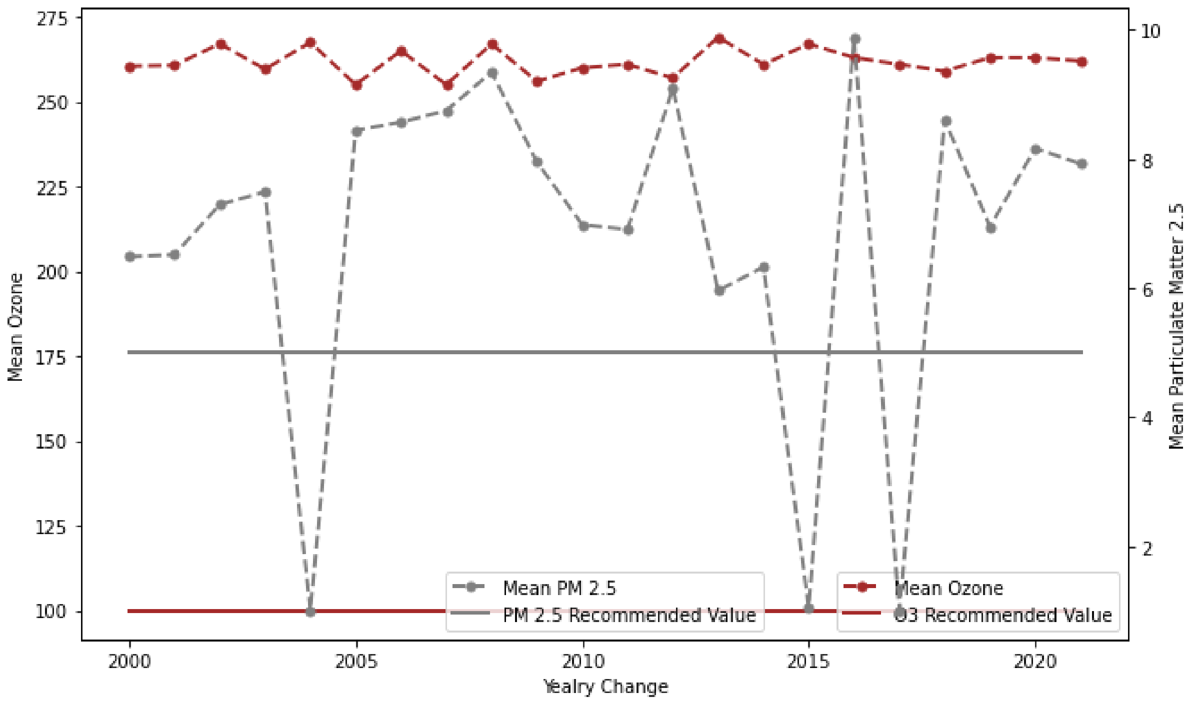

Figure 4-11: Mean annual distribution Particulate Matter 2.5 and Ozone in the CSB region.

For Figure 4-11 the WHO guideline for pm 2.5 emission is 5 µg/m³ annually. The results from the analysis indicated that the emissions have exceeded the above-mentioned guideline except the years 2004, 2015 and 2017. The year 2016 recorded a maximum annual value of 9.8 µg/m³. The WHO recommended mean annual O_3 emission is 100 µg/m³ (World Health Organization, 2021a). As seen in Figure 4-12, the emitted pollutants were above the recommended standard with a maximum value of 268.63 µg/m³ recorded in the year 2013.

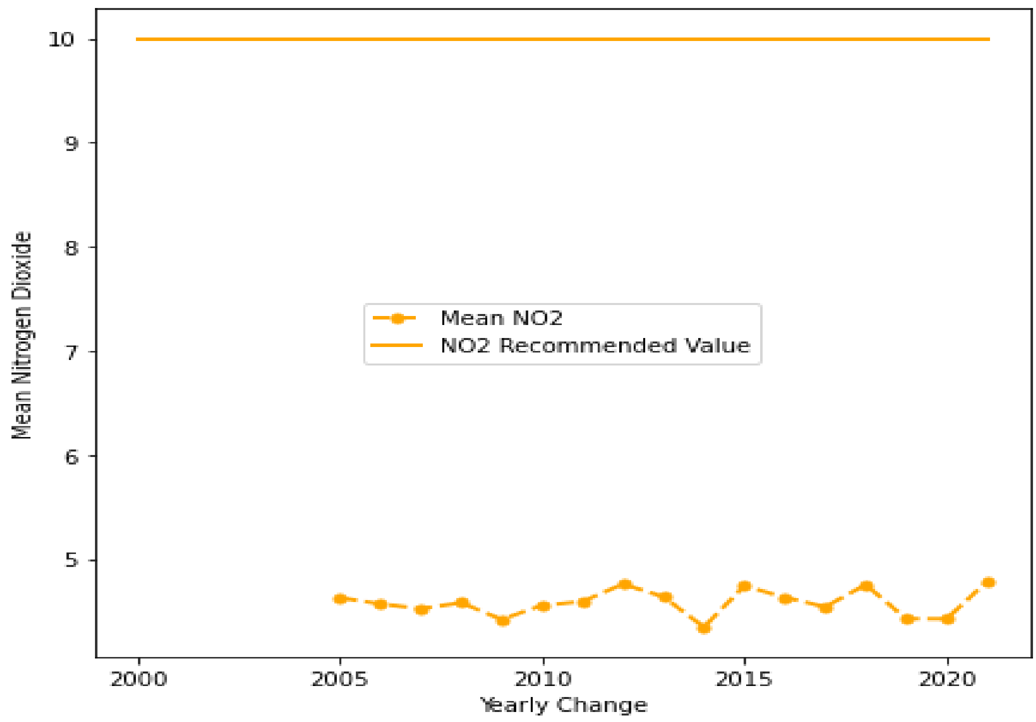

Figure 4-12: Mean annual distribution of Nitrogen Dioxide in the CSB forest region across the study period.

For NO_2, the Figure 4-12 above shows that from the year 2000 to 2004 there was no data because the sensors only became operational in 2005. From 2005 onwards, the annual value has been below the recommended guideline of 10 µg/m^3.

As seen from the results of the descriptive statistics, the mean annual values of the pollutants (carbon monoxide, ozone, pm 2.5 and sulphur dioxide) in the CSB region have generally exceeded the recommended air quality guidelines set by the WHO. Nitrogen dioxide has been the exception, with a mean annual value below the recommended air quality guideline set by the WHO (World Health Organization, 2021a).

4.5.2 Spatial Cross Correlation (Point Biserial Correlation)

The correlation test was based on land cover classes (forest, agricultural, and built-up areas) and air pollution variables. This section was based on the evaluation of point biserial correlation analysis to determine the relationships or the strength of association between land cover and air pollution. The same time periods were used as in section 3.6 page 41 (period one 2000-2007, period two 2007-2014, and period three 2014-2021) to evaluate the correlation throughout the study time. The air pollutant data was divided into 3 periods as seen in Table 4-2 below where the strength of association between the variables and their correlation coefficients is listed.

Table 4-2: Point biserial correlation analysis between land cover classes and air pollutant variables in the CSB forest region. Red = Positive Correlation, Blue = Negative Correlation, Green = No Correlation.

LULC Categories	Carbon Monoxide	Nitrogen Dioxide	Ozone	Particulate Matter 2.5	Sulphur Dioxide
	Period One (2000 - 2007)				
	Correlation Coefficients				
Forest Areas	-0.051	0.225	0.003	0.082	0.005
Agricultural Areas	-0.505	0.49	-0.381	0.189	-0.263
Built-up Areas	-0.18	0.356	0.005	0.24	-0.15
	Period Two (2007 - 2014)				
Forest Areas	0.114	0.072	0.148	0.132	0.105
Agricultural Areas	-0.052	0.236	0.055	0.104	0.135
Built-up Areas	-0.301	0.323	-0.07	0.119	0.032
	Period Three (2014 - 2021)				
Forest Areas	0.142	0.195	0.181	0.111	0.217
Agricultural Areas	-0.285	0.365	-0.15	0.137	0.032
Built-up Areas	-0.167	0.108	-0.095	0.047	-0.024

According to (Ratner, 2009) the correlation values listed in Table 4-2 depict the strength of relationship or association.

Table 4-3: Strength of association between variables and their correlation coefficients, where 0 indicates no relationship.

Positive Correlation Coefficient	Description	Negative Correlation Coefficient	Description
0 to 0.3	Weak Positive	0 to -0.3	Weak Negative
0.4 to 0.7	Moderate Positive	-0.4 to -0.7	Moderate Negative
0.8 to 1	Strong Positive	-0.8 to -1	Strong Negative

With reference to Table 4-2, in period one there was no relationship between forest areas, CO, O_3, pm 2.5 and SO_2. Regarding forest areas and NO_2, there was a weak positive relationship with a correlation coefficient value of 0.225. Based on the results from period two, the relationship between forest areas and the pollutants was weakly positive for CO, O_3, pm 2.5 and SO_2. Additionally, there was no relationship between forest areas and NO_2. For the last period, forest areas had a weak positive relationship with all the pollutants.

Agricultural areas for period one had a moderate negative relationship with CO and a weak negative relationship with O_3 and SO_2. The relationship with NO_2 was moderate positive and that of pm 2.5 was weak positive. For period two, there was a weak positive relationship between agricultural areas and NO_2, pm 2.5 and SO_2, while CO and O_3 had no relationship with agricultural areas. In the last period, agricultural areas had a weak negative relationship with CO and O_3. The relationship with NO_2 and pm 2.5 was a weak positive while that of SO_2 indicated no relationship with agricultural areas.

Finally, for built-up areas, for period one there was a weak negative relationship with CO and SO_2, followed by a weak positive relationship with NO_2 and pm 2.5 while with O_3 there was no relationship with built-up areas. For period two, O_3 and SO_2 had no relationship with built-up areas while NO_2 and pm 2.5 had a weak positive relationship. With regards to CO, there was a weak negative relationship with built-up areas. For the last period, built-up areas had a weak negative relationship with CO and a weak positive relationship with NO_2 while O_3, pm 2.5 and SO_2 had no relationship with built-up areas.

The positive correlation relationship examined in the correlation analysis between the variables (LULC and air pollutant data) revealed a statistical relationship where an increase in LULC areas in the region might be associated with an increase in air pollutants variables in the region. For example, the highest correlation coefficient value recorded in the correlation analysis was between agricultural areas and NO_2 with a value of 0.49 in period one (2000 – 2007). In other words, as agricultural areas were changing, the concentration of NO_2 in the atmosphere tends to rise as well. This type of correlation implies that there might be a tendency for these two variables to move together in a specific direction.

For the negative correlation relationship examined in the analysis, the results revealed a statistical relationship where an increase in LULC areas in the region might be associated with a decrease in air pollutants variables in the region. The highest negative correlation coefficient value recorded in the analysis was between agricultural areas and CO with a value of -0.505 in the period one. This indicated that as agricultural areas were changing in period one, the concentration of CO pollutant was decreasing.

4.6 Modelling LULC Change to Predict Potential Outcome of Forest Region Without Interventions

The modelling of LULC change to predict potential outcome for the CSB forest region was discussed in section 3.9. In that section, the methodology used to model LULC change was identified and implemented. The explanation of results will be based on the different sub-headings identified in that section. The change analysis of this section has already been addressed in section 4.2, 4.3, and 4.4 above. The section will be based on addressing objective three and its research questions as seen in section 1.4.2 above.

4.6.1 Transition Potential Modelling

Using the transition between the different land cover classes, the transition sub-model (which shows the possible changes occurring from one class to another) was created. The deforestation driving factors in Table 3-3 were used to create a transition sub-model structure, after which the model was trained using the MLPNN model as explained in section 3.9.1. The trained model yielded an accuracy rate (the percentage of correct predictions of a dataset) of 84.95% and a skill measure (the difference between the accuracy measurement and the expected accuracy) of 0.83, which is above the recommended accuracy and skill measure values (70) given by (Eastman., 2020). The accuracy rate and skill values from the model predicted the most influential and the least influential driving factors accounting for transition from one class to the other. Table 4-4 below indicates the order of influence of the various variables.

Table 4-4: Transition sub-model results indicating the sensitivity of model to forcing independent variables to be constant.

Variables	**Accuracy (%)**	**Skill measure**	**Influence order**
N/A	**84.95**	**0.83**	**N/A**
Distance to built-up areas	12.18	0.012	1 (most influential)
Elevation	84.51	0.8258	7
Growth rate (population)	83.86	0.8184	4
Precipitation	84.77	0.8286	11
Protected areas	78.07	0.7533	2
Distance to rivers	84.78	0.8288	12 (least influential)
Soil type	84.71	0.828	8
Slope	84.74	0.8284	10
Distance to roads	84.29	0.8232	6
Agricultural output	82.01	0.7977	3
Surface temperature	84.74	0.8283	9
Industrial output (from forestry industry)	84.06	0.8207	5

The transition sub-model results of Table 4-4 above indicates that distance to built-up areas is the most influential variable that will account for the transition of one class to the other. The influence order is obtained by sensitivity analysis by iteratively excluding one input variable at a time and comparing the model's performance which then produces the order of influence for each variable. The second variable to account for transition is distance to protected areas followed by agricultural output. The fourth, fifth and sixth variables likely to account for influence are growth rate, industrial input, and distance from roads. The least influential variable to account for transition is distance from rivers.

The results from the trained transition sub-model variables were then used to create a transition potential map of the different land cover classes in the region. Figure 4-13 below shows the transition potential of forest areas to urban and agricultural areas.

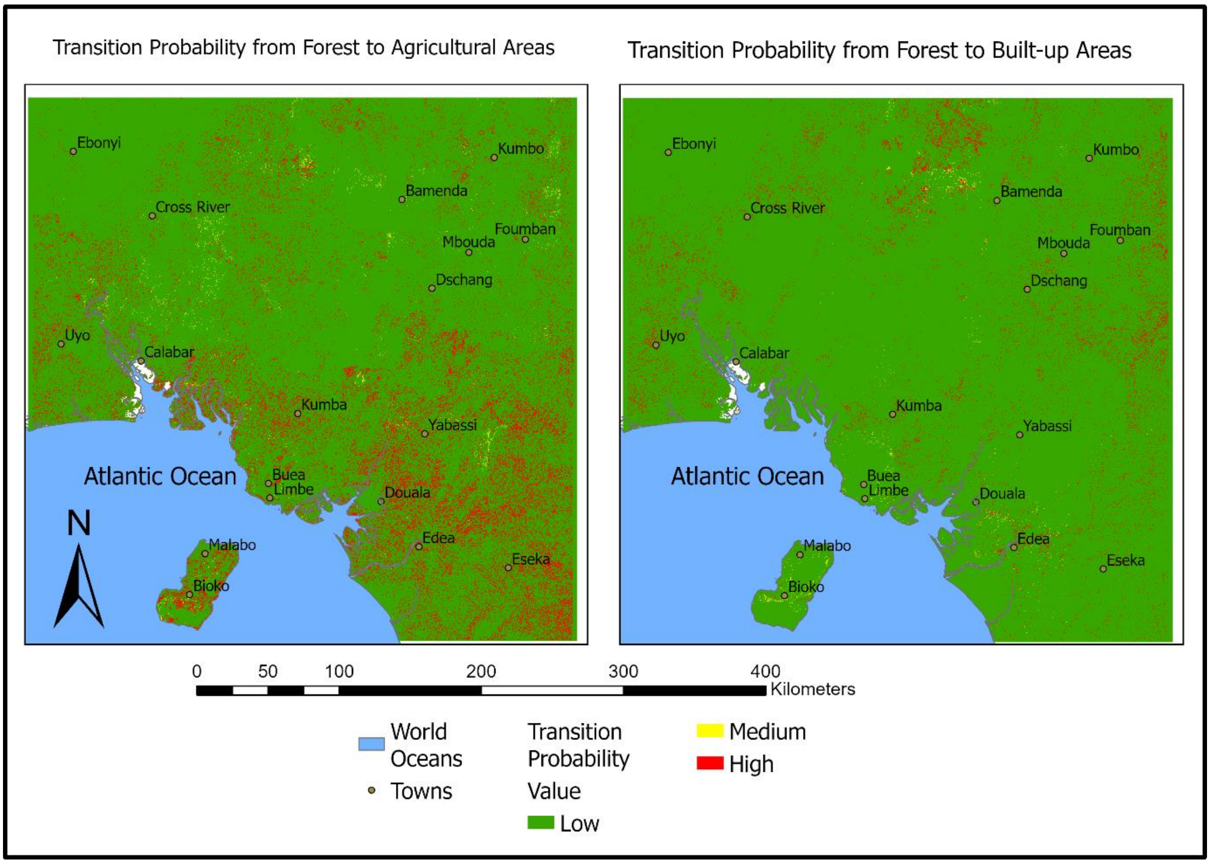

Figure 4-13: Transition potential of projected probability that forest areas will change to urban and agricultural areas in the CSB forest region.

The transition probability of forest to agricultural areas in Figure 4-13 above shows that the red areas found in the western, southern, eastern, and some sections of the centre and northern parts of the map were projected to have a high transition change from forest to agricultural areas. Areas represented with yellow had medium transition change and were in small sections in the region (western, northern, and eastern parts of the map). For the green colour, they were projected to have no transition change between the classes. In addition, the projected transition from forest to built-up areas had a high probability of transitioning (red areas) to built-up areas which were found in the west, east, and northern parts of the region. The yellow areas (small sections in the south and northern areas) and the green areas were projected to have medium and no transition probability respectively. The next figure below indicates the transition potential probability from agriculture to forest and built-up areas.

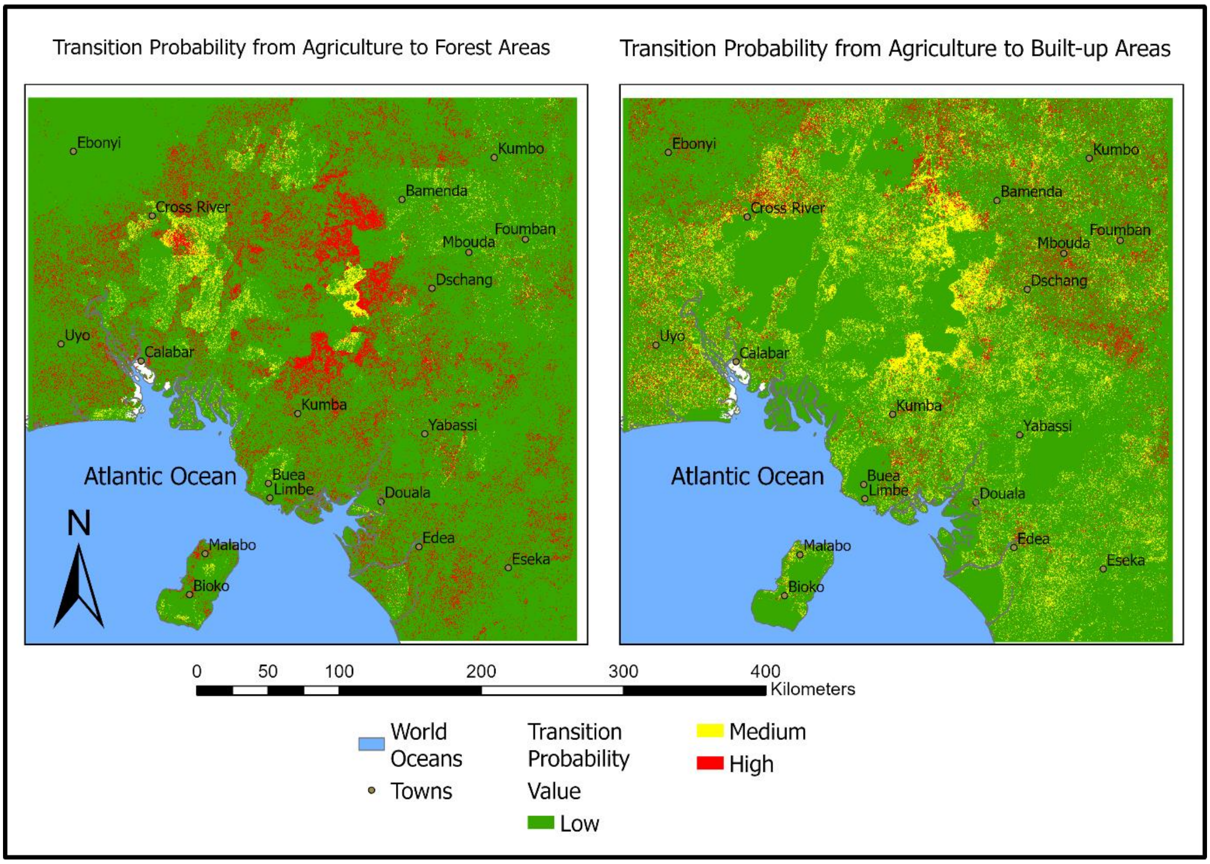

Figure 4-14: Transition potential of projected probability that agricultural areas will change to urban and forest areas in the CSB region.

The transition from agricultural to forest areas is illustrated in Figure 4-14 above. The red areas were projected to have the most transition to forest areas and were found throughout the region, apart from the northwest corner. The areas of medium transition change from agricultural to forest (yellow) were found mostly in the centre of the study region. The green areas were projected to have low probability of change.

The projected probability from agriculture to built-up areas is high in the north-western and north-eastern areas. The centre, west, south, and south-eastern areas were projected to have medium transition change to built-up areas, while the green areas had low probability projection.

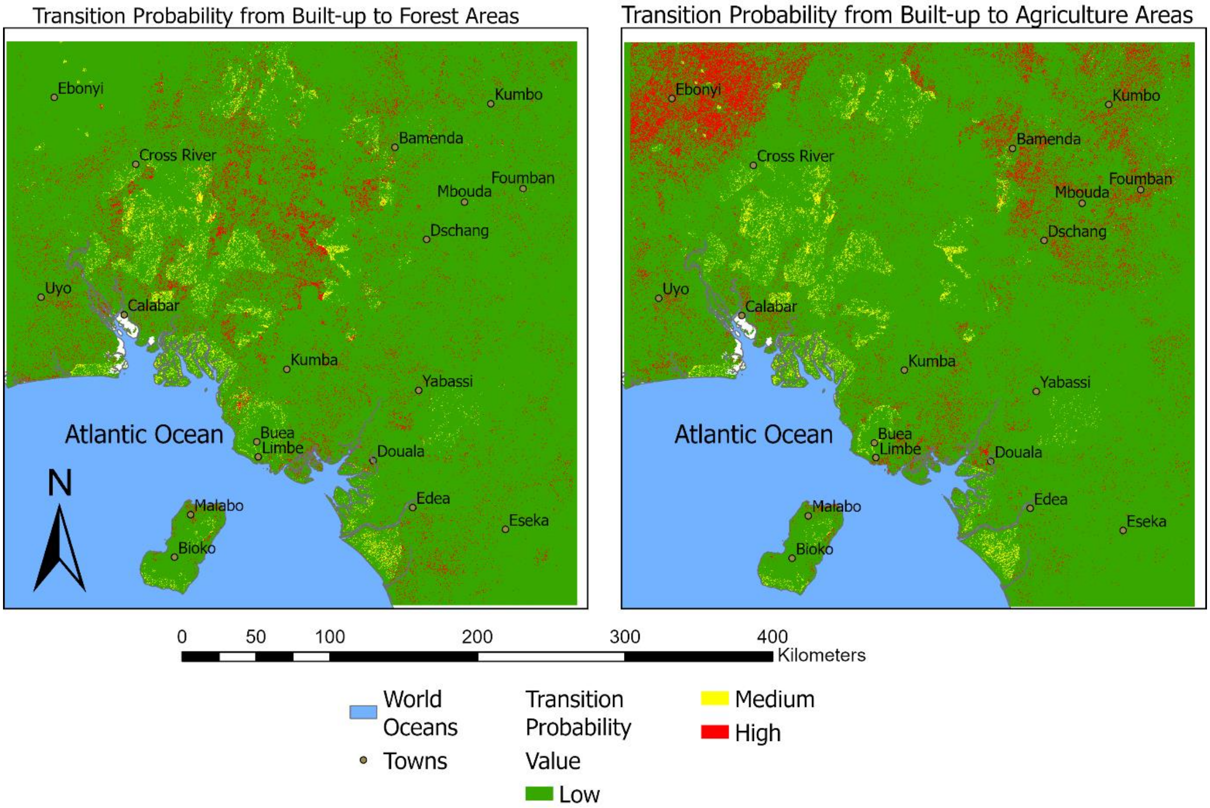

Figure 4-15: Transition potential of projected probability that built-up areas will change to agriculture and forest areas in the CSB region.

Last of the LULC transition probability area of change was built-up areas as seen in the Figure 4-15 above. In the projected transition probability from urban to forest areas, the regions located in the centre, west and scattered throughout the east, south-eastern and north-eastern regions of the map had a high transition projected probability change. The areas located in the west and southern sections of the map had a medium projected transition change to forest areas. In the projected transition from built-up to agriculture areas, the areas located in the west, north (western and eastern regions) and small section of the southwest part of the map had a high projected transition change. The areas which are in the same areas as the transition change from built-up areas to forest had a medium projected transition to agricultural areas.

4.6.2 Change Prediction and Validation

The results from the trained transition sub-model were used to generate a land cover change prediction map for the year 2063. As explained in section 3.9.2, the year was selected to align with the fulfilment of goal 7 (Environmentally sustainable and climate resilient economies and communities) of the African Union agenda. The predicted outcome of the land cover map for the year 2063 is shown in Figure 4-16 below.

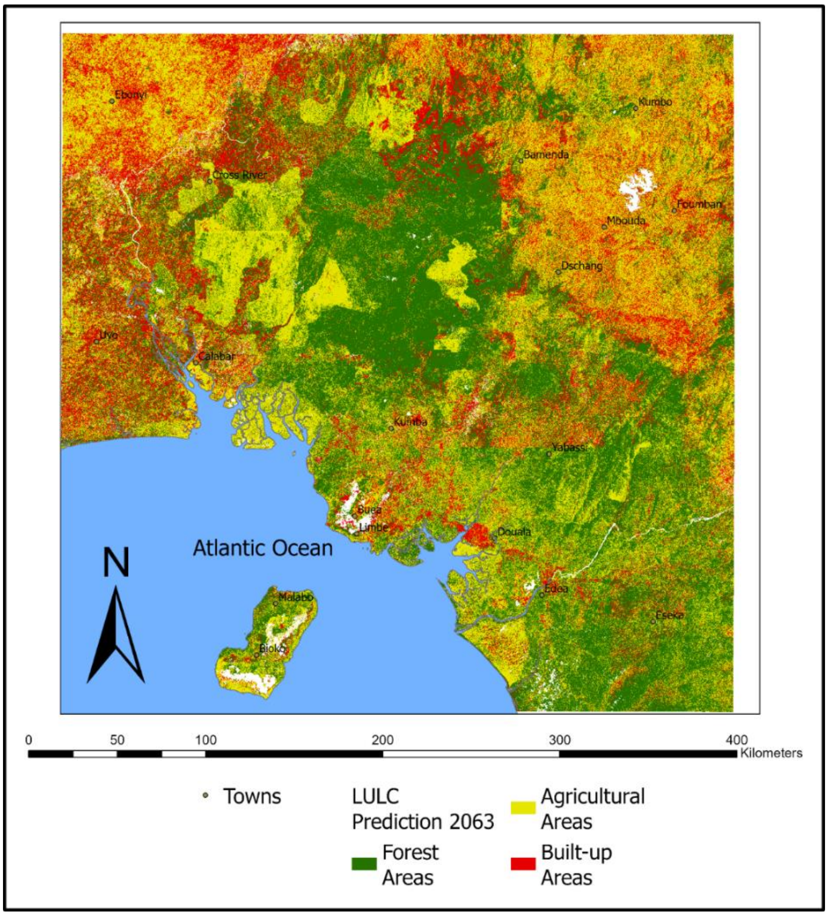

Figure 4-16: Predicted land cover map of the CSB forest region in 2063.

The projected land cover map generated from the trained transition sub-model (Figure 4-16) shows the projected distribution of land cover classes in the CSB forest region in the year 2063. The model suggests that the forest areas will be mostly concentrated in the centre of the region, with a few remnants in the eastern and southwestern areas. For agricultural areas, apart from a few sections in the centre of the region, which is covered by forest areas, agricultural land has spread throughout the CSB forest region. Built-up areas are mostly in the north-western and northern areas, with a few sections in the eastern and southern parts of the map. With the projected results obtained from the analysis as seen in the figure above there is need for promoting forest conservation.

Validating the change prediction map of 2063 is made possible by performing a three-way cross tabulation as explained in section 3.9.3. To begin with, a comparison was made between the actual map of 2021 and a simulated land cover map of 2021 (see Figure 4-17 below) to validate the predicted map of 2063 as described in section 3.9.3. The Figure 4-17 below shows the area change of the different LULC classes of the simulated and classified map of 2021 in the CSB region.

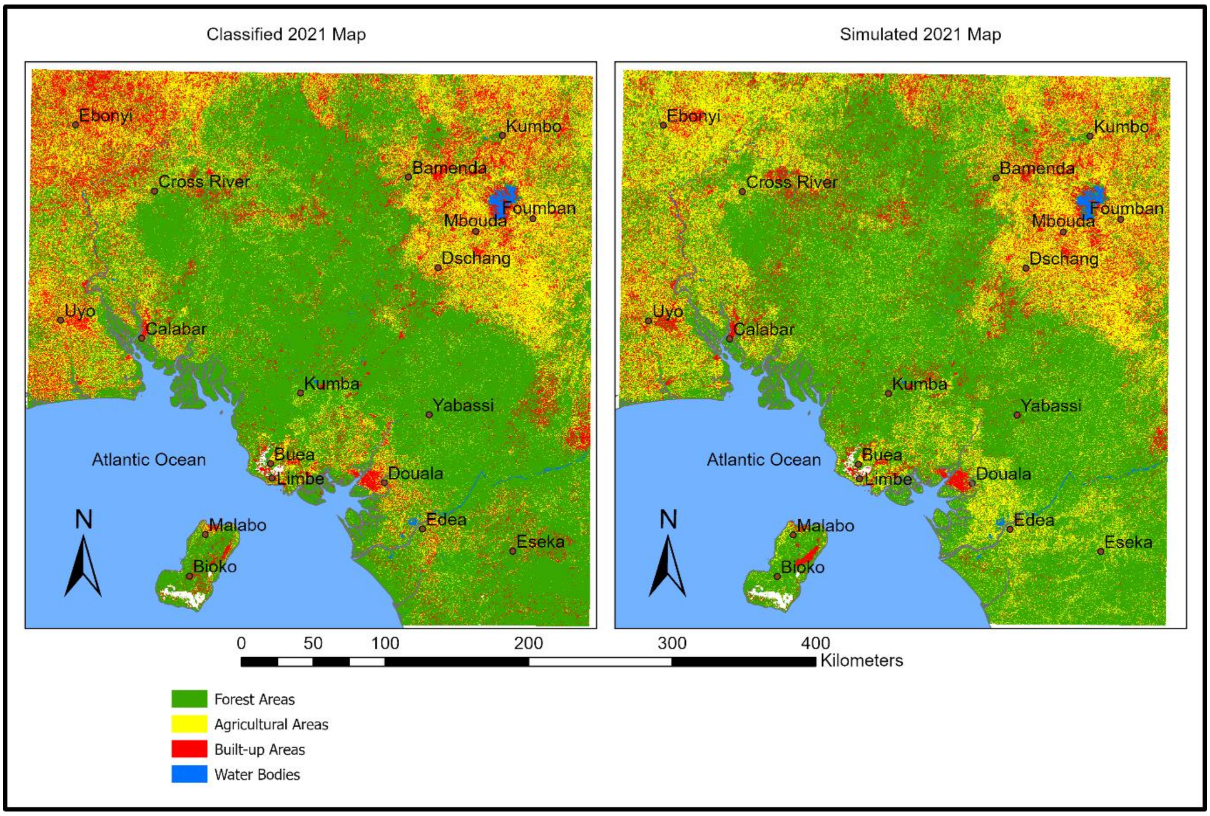

Figure 4-17: Simulated map of the different LULC classes in the region.

The results from the simulated LULC map of 2021 (Figure 4-17 above) indicated a slight reduction forest and built-up areas (north-eastern section of the map for built-up areas) while for agriculture there was a slight increase in area with the actual classified LULC map of 2021. The Figure 4-18 below shows the difference in areas for the classified 2021 map and the simulated map for the CSB region.

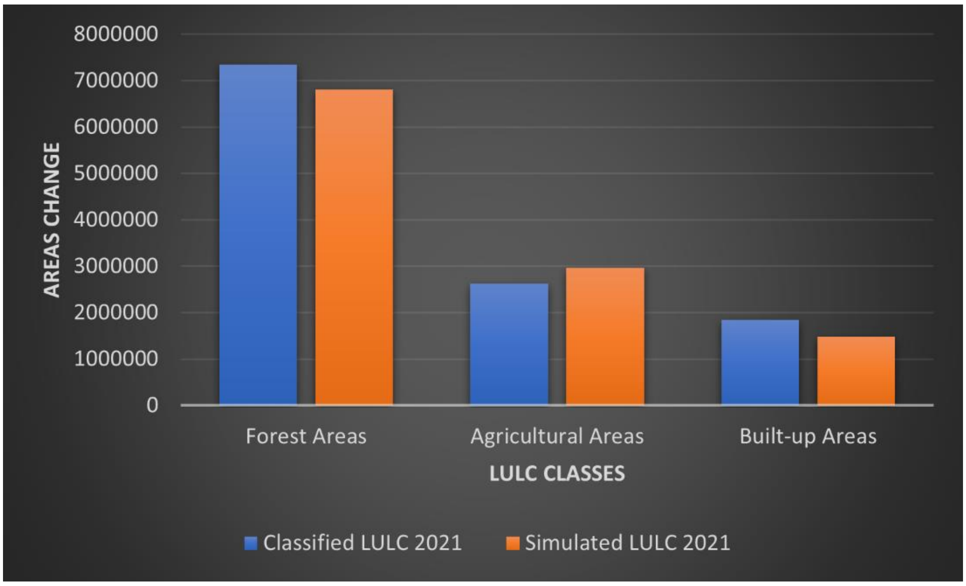

Figure 4-18: Classified and Simulated LULC area of the CSB region.

To check the validity of the simulated map, the validate tool was used as explained in section 3.9.3 of chapter three. The Table 4-5 below shows the outcome of the Kappa indices from the validation tool.

Table 4-5: Kappa Indices values of the simulated 2021 LULC map and classified 2021 LULC map.

Kapp Indices	**Values**
K-no	0.9126
K-location	0.9213
K-locationStrata	0.8936
K-standard	0.8843

A model is good for prediction if the K-standard (overall Kappa) value exceeds 70% (Zadbagher et al., 2018b). In this analysis, the K-standard is 0.8843 (88.43%), indicating that the model showed a good agreement between the 2021 simulated map and the 2021 classified land cover map. This indicated that the simulated map created had an 88.43% accuracy to the actual map.

The next step was to perform the three-way cross-validation on the predicted 2063 land cover map, the reference or classified map (2021), and the previous land cover map (2000). The goal of this process is to test for the quality and accuracy of the predicted map. The result is a validated map of the land cover class prediction for 2063 (see Figure 4-19).

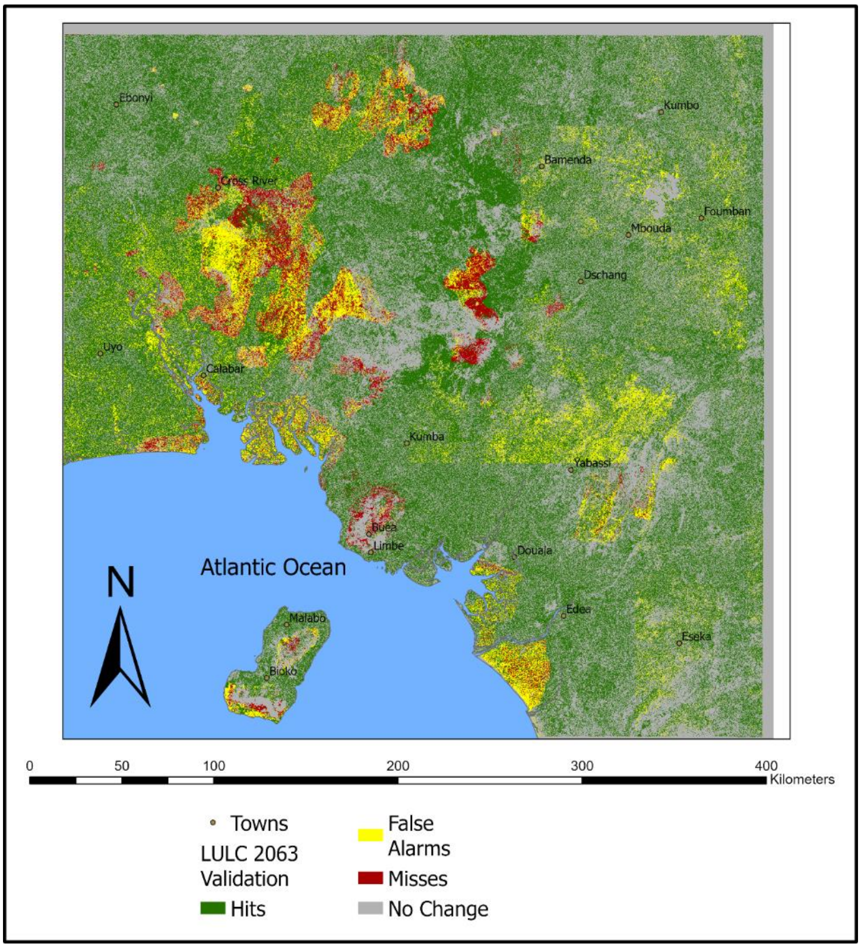

Figure 4-19: Validation map of the 2063 LULC class prediction of CSB forest region.

In the validation model map Figure 4-19 above, green represents areas where the model predicted change correctly (Hits). The yellow areas signify false alarms, where the model predicted change, but it was to an incorrect land cover class. The false alarms areas can be found in some areas of the north, west, south-west, and eastern parts of the region. Misses (in red) are when the model predicted persistence but there was change. These can be found in some areas of the centre, southern and western parts of the map.

Over the past 21 years in the CSB region, based on the land cover areas, forest areas have been decreasing while agricultural and built-up areas have increased (see sections 4.2, 4.3, and 4.4). These changes indicate the presence of deforestation, urbanization, and agricultural expansion. Based on the deforestation driving factors listed in Table 3-3 chapter three page 63, combined with the land cover maps of 2000 and 2021, a land cover forecast map was created for the region (Figure 4-16). The prediction revealed the changes in LULC area that may occur in the land cover classes in the next 42 years. These are quantified in Figure 4-20 below.

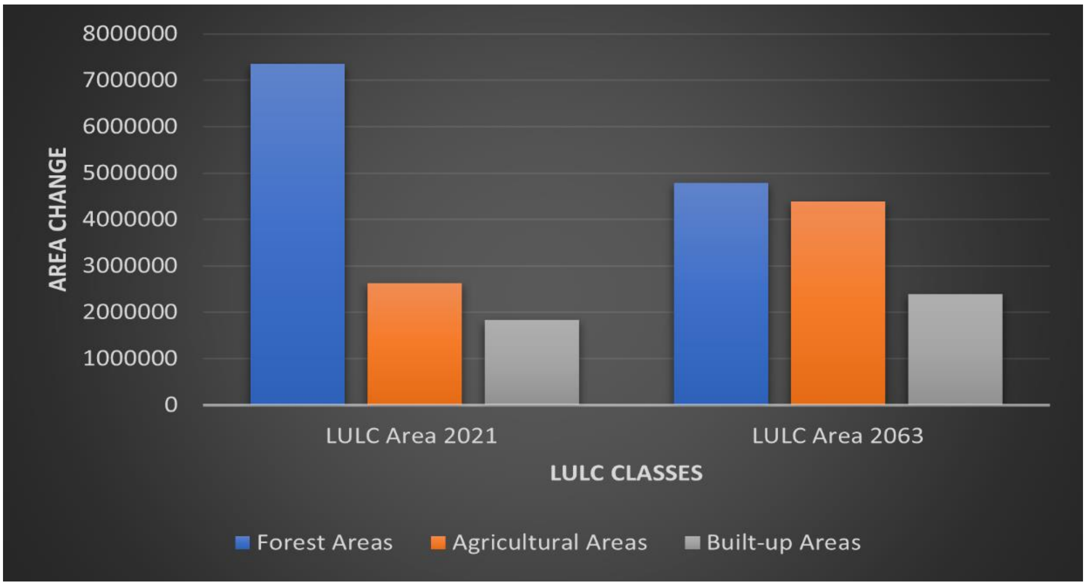

Figure 4-20: LULC area of 2021 and 2063 showing the area change in the various classes in the CSB forest region.

The results from the predicted land cover areas in the CSB forest regions in Figure 4-20 above revealed that from the year 2021 to 2063, there is an expected loss of forest areas of 3 297 198.35 hectares, which equates to a 21.03 % decrease in forest areas in the CSB region. For agricultural areas, there is a projected increase in area of about 3 085 980.72 hectares from 2021 to 2063 amounting to a 19.69 % increase. Built-up areas are projected to increase by 1 706 269.45 hectares from 2021 to 2063, which is a 10.88 % increase. The projected land cover outcome predicted a loss in forest areas and an increase in agricultural and built-up areas as seen above. The variation in the result (increase in loss in forest areas and increase in agricultural and built-up areas) might be from the increase in UN population growth rate of the countries in the region as seen in Table 4-6 below.

Table 4-6: United Nation Projected World Population Growth Rate (Source: United Nations).

Country	**Total Population Growth Rate 2021 - 2063**	**Total Population from 2021 - 2063**
Cameroon	82.64	62.53 million
Equatorial Guinea	66.79	3.21 million
Nigeria	72.45	443.33 million

4.6.3 Summary

The state of land cover change in the CSB region has been in a state of flux with forest areas experiencing a reduction in area while agricultural and built-up areas have been increasing in size, as seen from the analysis in section 4.2 above. Amongst the changes in land cover in the region, agricultural areas have seen a higher gain in size as compared to built-up areas over the last 2 decades. Agricultural expansion accompanied with urbanization, has been the most driving forces of land cover change in the region. The change in land cover areas has also contributed to a change in air pollutants in the region as seen in section 4.5.2 above, leading to a variety of positive (majority) and negative correlation coefficient values in the region. The correlation analysis revealed a statistical relationship between land cover change and air pollution, indicating a cause for concern for air pollution monitoring in the region. This originates from the descriptive analysis which indicated that the yearly emission rate of the air pollutants highlighted above do not follow the WHO recommended guidelines.

The results obtained from section 4.2 and 4.3 aided in understanding factors that have influenced LULC change and identified areas that are at risk of change. Additionally, the analysis revealed a high loss from forest areas to agriculture and built-up areas as seen in Figure 4-4 to Figure 4-6. Though there was a 10.55% gain in total forest areas within the study time, the analysis also revealed a 35.5% loss in total forest areas which indicated that more forest areas were being destroyed than preserved in the region. Furthermore, the analysis of sections 4.4 and 4.6 provided an outcome of land cover change in 42 years. Based on the results obtained in the analysis there is a need for forest conservation practice in the region. To prevent the further loss of forest areas and the increase in agricultural and built-up areas, there, is a need for sustainable forest management which, if practiced, may create a balance between the use of forest resources, urbanization, and agricultural expansion.

5. DISCUSSION of RESULTS and ANALYSIS

5.1 Overview

This section will interpret the meaning of the results and analysis in the previous chapter. It also explains the results and puts them in context, thereby addressing why they matter. The discussion of results and analysis is based on the objectives and research questions presented in section 1.4.2. But first the research questions 2.1 and 4.1 will be addresses prior to discussing the results from the analysis.

5.2 Examining the Causes of LULC Changes in the CSB Forest Region

This section focuses on addressing the research question 2.1 of objective two as seen in section 1.4.2 above. The CSB region, which falls within the broader region of the Congo basin forest, has for several decades been in the spotlight as one of the world's most endangered ecosystems. Regardless of the forest's strategic importance in global biodiversity richness and climate change, the forest has been battling with both contemporary and historical land cover change issues. The causes of deforestation in the CSB region are also closely tied to the important economic development opportunities present in the region. With a better understanding of the causes of deforestation in the region, the creation of a sustainable future for the CSB forest region can be feasible (de Wasseige et al., 2009).

Deforestation is the result of both direct and indirect causes. The direct causes have the greatest impact on the forest and in most cases the causes are almost the same around the world, with agricultural expansion being the leading cause (as seen in Figure 4-7) ((Kissinger, Herold and Veonique, 2012). Indirect causes are due to anthropogenic factors that occurred in the past, such as social and economics causes that promote the behavioral changes of deforestation agents (Food and Agriculture Organization, 2010). Below are some of the causes that have been attributed to changes in LULC based on the above analysis and reviews from other researchers.

5.2.1 Agricultural Expansion and Poor Land Tenure Schemes

One of the main causes of LULC change in the CSB region is expansion of agricultural lands either by small- or large-scale farmland owners (see Figure 4-4 to Figure 4-6). Agriculture expansion has led to the devastation of forest areas/land. This loss in forest areas amounted to about 13.55% increase in agricultural area in the CSB region from the years 2007 to 2014 which was the highest amongst the three periods examined. Also, agricultural areas accounted for a total gain of 28.08% in LULC for the region.

Kissinger, Herold and Veonique, (2012) explained that the loss of forest area to agricultural areas has been because of slash-and-burn, shifting, and mechanized agricultural activities which in turn leads to large scale forest destruction. Slash-and-burn involves clearing a piece of land by cutting down vegetation and then burning it. The ashes from the burned vegetation provide nutrients to the soil, allowing crops to be planted. The process of shifting cultivation refers to a system where farmers rotate the areas they cultivate, moving from one plot to another over time. After using a plot for a few years, it is left fallow to allow the soil to regenerate before being used again. Mechanical agriculture is characterized by the application of mechanical power and advanced equipment in various farming operations, such as ploughing, planting, irrigation, harvesting, and processing. The activities carried out for long period (years) drains nutrients from the soil, leaving the land barren and abandoned.

The need for an effective land use system, property rights, and access rights are vital to aid in the improvement of natural resource management (Megevand and Mosnier, 2013). The improvement of these systems is necessary for helping farmers, landowners, and communities with initiative to provide a long-term investment and protection of land regardless of the type. The practice of recognizing all land tenure systems is lacking in most rural and urban communities in the CSB forest region. Apart from commercial logging laws, forest areas in some communities in the CSB region are considered as freely accessible under state or community ownership. This creates an incentive to convert the forest lands into other land use activities leading to deforestation.

Nevertheless, it is evident that there is a need for responsible and sustainable land management at a community-based level to prevent forest loss, thus relieving the natural forest from unsustainable withdrawals (Global Environemental Facility Small Grants Program, 2012). Organizations like FAO and UN have been the prominent driving forces in promoting responsible and sustainable land management with agreements such as the VGGTs and FLEGT (as seen in section 5.3). Successful sustainable forest management rests on open partnership with the relevant community living in the area, and other stakeholders. Education is necessary to ensure responsible land management is practiced to help prevent deforestation and promote long-term forest sustainability and agroforestry systems (Megevand and Mosnier, 2013).

5.2.2 Urbanization (Accessibility and Infrastructure)

Urbanization (increase in number of people living in cities) is made possible via the expansion of communities into forest and agricultural lands. The need for accessibility to natural resource and infrastructure development projects which leads to urbanization is a worldwide concern not only in the CSB region. Urbanisation leads to the clearing of natural land cover. This puts pressure on local government to develop the infrastructure to support the people moving into the cities, thus changing the land cover. From 2000 to 2021, built-up areas have gained a total area size of 13.73% of land from the loss of both forest and agricultural areas based on the LULC change analysis as seen in Figure 4-3 to Figure 4-6. Some areas, however, have been protected from increased urbanization due to their inaccessibility (difficult terrain and other factors) and forest conservation polices (see section 5.3) (Grimm et al., 2008). However, increases in technological advancement are making it possible for development in previously inaccessible places (Busch and Ferretti-Gallon, 2017).

The need for urbanization compels local communities to expand towns and cities for easy accessibility and infrastructural growth. This increase enables the inhabitants to support their growing population which is accompanied by a change in land use classes, thus transforming the area into an urban location. In the CSB region, the quickest and easiest means of access to land cover is through bridges, rivers and roads which are sometimes created by the local inhabitants of the area or foreign corporations. The Table 5-1 below shows the percentage increase in urban population for the CSB countries.

Table 5-1: Percentage increase of urban population in Cameroon, Equatorial Guinea, and Nigeria

	Urban Population (% of total population)		
	2000 - 2007	**2007 - 2014**	**2014 - 2021**
Cameroon	46 - 50	50 - 54	54 - 58
Equatorial Guinea	49 - 61	61 - 70	70 - 74
Nigeria	35 - 41	41 - 47	47 - 53

The Table 5-1 indicates that there has been an increase in urban population from 2000 to 2021. As recorded in the (United Nations, 2022) data catalogue in Cameroon, Equatorial Guinea, and Nigeria the urban population percentage has been increasing over the different time periods. There is hence an increased need for access and infrastructure in the CSB coastal regions, which causes the inhabitants to explore more uninhabited land areas. Developing the necessary infrastructure to support the growing population leads to an increased rate of change of land cover, threatening forest sustainability (Busch and Ferretti-Gallon, 2017).

5.2.3 Over Population and Poverty

The growth of infrastructural demand in an area opens the region to other developmental opportunities, thus pushing people closer to forest areas which in turn puts pressure on the land for development and settlement. The increase in built-up areas in the CSB forest region is a natural response to the population increase (see Figure 4-3). For example, the population of Cameroon represented in the CSB region has grown from 5 557 315 in 2005 to 8 504 986 in 2021. That of Equatorial Guinea has increased from 260 462 in 2001 to 411 914 in 2021 while that of Nigeria has increased from 2 892 988 in 2001 to 4 175 020 in 2019 (United Nations, 2022). The increase in population in the CSB region has led to an increase in the demand for land leading to changes in LULC. Furthermore, the increase in population has also prompted the inhabitants to depend more on natural resources for their livelihood and sustenance. The continuous growth in population in the areas can result in transition from one LULC class to another. This transition has mostly been seen from forest areas to agriculture and built-up areas, and agriculture to built-up areas, to create farmlands and infrastructure to sustain their growing population. This puts pressure on the land cover classes in that region such as forest and agricultural land.

An increase in population increases the demand for food. The link between over-population and poverty is interrelated in that the occurrence of one (over-population) may lead to the other (poverty) (United Nations Population Fund, 2014). In tropical and coastal forest areas such as the CSB region, pressures from human settlement and population increase creates the need for the exploration of more uninhabited land. This therefore drives people to settle on available land (forest land closer to the urban or agricultural areas) thus leading to LULC changes. The rise in inflation, corruption, terrorism, and national debt in the countries of the CSB region has increased the rate of poverty. The associated economic and political instability has thus caused the percentage of inhabitants of the total population to be dependent on agricultural activities (United Nations, 2022).

5.2.4 Forest Exploitation

The presence of rich and fertile soil for large scale agricultural production of goods and services (rubber, timber, palm oil, banana, and cocoa) and the abundance of mineral resources in the CSB region have given rise to the exploitation of natural resources leading to changes in LULC. As of 2020, Cameroon and Equatorial Guinea were amongst the top 10 countries in Africa exporting timber, the estimated worth of which is between 611.9 – 283.3 million USD (Cameroon Timber Export Sarl, 2021). With the estimated income that timber production brings into the country, many forest areas are being lost. This influx of income promotes logging of timber through illegal and unapproved tactics which in turn destroys forest trees because people are not adhering to the appropriate regulations concerning the harvesting of trees. Regardless of the existing laws governing or prohibiting illegal logging (see section 5.3), many inhabitants of forest communities in the CSB region still engage in the process. The commercialization of trees besides timber for fuelwood and charcoal is common in communities close to the forest, and it is regarded as a method of subsistence economy.

Exploitation does not only destroy the forest environment but also impacts the indigenous people of the region, for example the indigenous people of Ecuador and Costa Rica have both raised concerns about the payment of carbon credits standards (Amanzon Watch, 2023). They say it is non-compliance with the UN declaration on rights of indigenous people, criticising the Architecture for REDD+ Transaction (ART). ART is a global initiative that seeks to incentivize governments to reduce emissions from deforestation and forest degradation (REDD), as well as restore forests and protect intact forests. The complaints mainly focus on the transaction being unable to address the fundamental problems brought up by carbon markets. For example, carbon ownership, non-compliance with land rights and consultation under the principle of free and prior informed consent are crucial for indigenous people.

With regards to goods and services, the production of palm oil in Cameroon, Nigeria, and Equatorial Guinea has grown over the years: from 2000 to 2019, Cameroon produced 10 000 to 70 000 tons, while Nigeria produced 200 000 to 1.6 million tons of palm oil respectively. The increase in production creates the need for more land areas which usually converts large amount of forest areas to agricultural land (Hannah Ritchie and Roser, 2021). The exploration and extraction of mineral resources from the environment has grown from 2% to 12% extraction in Cameroon, 10% to 60% extraction in Equatorial Guinea and 5% to 30% extraction in Nigeria (Hannah Ritchie and Roser, 2021). This increase in demand for more goods and services for exploration places pressure on undeveloped land and may lead to forests being replaced with agriculture or urban areas.

5.3 Forest Protection Measures

This section will address research question 4.1. Forest resources play a crucial role in supporting livelihoods for communities in the CSB region and around the world. Paradoxically, deforestation is still permitted with resultant loss of forest biodiversity. With the changes in forest cover and quality, questions have been raised regarding the effect it has on the environment (Barnett et al., 2008). Though deforestation is a global phenomenon, there exist manageable protocols that have been set in place that if practiced will at a certain level prevent and protect the forest. The various laws governing deforestation implemented by various nations, organizations and agencies have been created to reduce deforestation via economic incentives (Fisher et al., 2009).

Examples of some forest policy structures developed by some governments and private agencies to limit deforestation have been linked with land right laws such as community forest rights, the right to own and use a land, livelihood support, financial support, and payment of ecosystem services (Laurance et al., 2011). Though no single approach is capable to limit or prevent deforestation, integrating the approaches with the consideration of multiple ecological variabilities and geographic scales can limit the process. Implementing the approaches can aid in limiting deforestation and can be done at different stages such as local, regional, national or international levels which requires an understanding of these approaches (Dale et al., 2000).

Assessing the forest change resulting from agriculture and urban increase involves evaluating how forests are being managed to ensure their sustainability, health and productivity. This assessment typically includes a comprehensive analysis of various factors and practices that influence forest management. Such as forest health, forest management practices, regulatory and policy framework, socio-economic factors, monitoring and evaluation, environmental impacts, certification & standards and threats & challenges (International Forest Stewardship Council, 2022). For this study only the forest regulatory and policy framework will be considered as assessment factor. The forest policies in the section below are divided into international and national forest-based policies that have been structured to help promote sustainable forest management. The international forest-based policies are policies that have been adopted by individual governments and global organizations such as FOA and UN of the countries to combat deforestation, while national forest-based policies are laws implemented by individual nations to protect their forest.

5.3.1 International Forest Policies Adopted by the CSB Countries

The focus on governance of international forest regions can be traced back to the late 1980's and early 1990's. This period was coupled with increased awareness of environmental concerns, accelerated global trade, industrialization, and urbanization which led to the loss of forest ecosystems as a result of deforestation (Humphreys, 2006). During the late 1980's, deforestation was one of the main global concerns contributing to loss of forest ecosystem and biodiversity. The release of the Brundtland report in 1987 (section 2.3) on the world commission for sustainable development of forest lands, triggered the need for a sustainable environment, whereafter the global initiative to preserve forests began gaining recognition. International governance of forests was developed to aid in the fight against deforestation and to promote global sustainability (Brundtland, 1987). The points below are examples of international forest policies that the governments of the CSB region (Cameroon, Equatorial Guinea, and Nigeria) have adopted to help mitigate deforestation loss in their countries.

a) The International Tropical Timber Agreement (ITTA)

The ITTA consists of an intergovernmental organization made up of 78 countries (including Cameroon and Nigeria), made up of forest producers (countries producing and exporting timber) and forest consumers (countries buying the exported timber). The continuity of the ITTA was made possible via intergovernmental agreements negotiated under the United Nations. The understanding of this agreement was made between timber producing countries (producer countries) and industrialized countries that need the timber products (consumer countries). The first ITTA was signed in 1983 and later implemented in 1985, followed by the second agreement signed in 1994, and implemented in 1997. The third agreement was signed in 2006 backed by the United Nations Conference on Trade and Development. After the signing of the ITTA agreement, it was implemented in 2011, and had a validity period of 10 years. The administration of the ITTA was done by the international tropical timber organization consisting of a producer and a consumer member nation. The international tropical timber council consisting of different member countries took care of drawing up agreements and decision-making regarding forest production and consumer laws.

The major policy goals of the ITTA are to promote the diversification and expansion of international trade in timber for sustainable management of legally harvested forest resources and to promote the sustainable management of forest within those countries. For these goals to be achievable, a combination of economic and information policies was developed. Amongst the achievable policies were the capacity building demonstration transfer projects, timber trade monitoring, guidance and information, statistics, promotion of tropical timber and non-timber forest programs, and finally the encouragement of non-state market driven forest certification. Furthermore, a tropical forest alliance treaty (public private partnership adopted to reduce tropical deforestation) was adopted in 2020 with key global private conservation organizations which is part of the ITTA agreement (United Nations Conference on Trade and Development., 2006).

b) United Nation Convention on Biological Diversity

The 1992 United Nations Earth Summit Conference in Rio titled the Convention on Biological Diversity (CBD) was implemented in 1993 as an international environmental binding legal treaty. This treaty was under the authorization of the United Nations to help fight the effects of deforestation. After long decades of advocacy from scientists and non-governmental organizations explaining the global crisis related to deforestation and forest degradation, the CBD negotiation talks were initiated. These were held by various international government agencies and nations and the treaty was signed in Rio de Janeiro, in 1992. Though the policy was signed in 1992, the implementation stage of the treaty by most participating nations was official in the year 1993 (Boisvert and Vivien, 2012). The implementation of this policy was made achievable via the help of various international political organizations. Triggered by the Brundtland report (see section 2.3.1), many nations and organizations in the conference developed three legally binding policy goals for the CBD treaty acceptance (United Nations, 1992):

- Conservation of biodiversity
- Sustainable use of the biodiversity components
- Fair and equal distribution of the benefits obtained from the utilization of resources.

The legally binding policy goals pertaining to the CBD were further explained and elaborated in the 2010 United Nations Conference of the parties meeting in Nagoya, Japan. Amongst the goals, the most important was the Forest Aichi Biodiversity Strategic goals and target as stated in the strategic plan for biodiversity 2011 to 2021 as agreed in the conference of parties (United Nations, 2010). The creation of the national biodiversity strategy program and action laid the groundwork on forest biodiversity preservation in the main global forest biodiversity policy tool (Convention on Biological Diversity., 2021). Within the expanded program of work on forest biodiversity, there exist 27 objectives, 12 goals, and 129 policy actions. The policy actions for the United Nation Convention on Biological Diversity are modelled around the 3 key priorities (United Nations Environment Programme/Convention on Biological Diversity, 2002):

- Conservation, sustainable use, access, and benefit sharing
- Socio-economic and institutional enabled governance
- Knowledge assessment and monitoring.

c) United Nation Framework Convention on Climate Change

During the United Nation Rio Earth Summit 1992 Conference, the United Nation Framework Convention on Climate Change (UNFCCC) was agreed upon and later implemented in 1994. The treaty was categorized as a global environmental framework that was approved by many intergovernmental organizations and various countries. The main goal of the UNFCCC was based on the protection of global climate, that is stabilization of greenhouse gas effects which are amongst the causes of deforestation and pollution of the atmosphere at concentrations that are harmful to the environments (Sands, 1992). In addition to the UNFCCC policy, the Kyoto Protocol was adopted in Japan in 1997 and later implemented in 2005 to help strengthen the UNFCCC. Using the Kyoto Protocol, various nations and intergovernmental organizations were committed to reduce the emission of greenhouse gases produced by their countries. The treaty was designed to take place in 2 strategic intervals, from 2008 to 2012, and 2012 to 2020. The different parties involved were required to fight climate change in their different capabilities owing to the difference in economic standards.

As stated in the Kyoto Protocol, forest ecosystems are necessary for the fight and reduction of climate change (Intergovernmental Panel on Climate Change (IPCC), 2007). Amongst the UNFCCC and Kyoto Protocol treaty, different treaties have been implemented to help in the fight against climate change; for example, the Paris Agreement implemented in 2016. It consisted of a multilateral climate policy with legally binding actions on all participating nations tracing back to the UNFCCC treaty to help preserve and protect the environment (United Nations, 2015).

d) International Agreement on Forest

The origin of the International Agreement on Forest (IAF) arose due to the repeated disagreement on the Global Forest Convention before and after the Rio 1992 United Nations Earth Summit. The different parties involved in the conference found a common ground that was suitable for them in the preservation of the global forest biodiversity via the IAF policy. The failure of the global forest convention led to the creation of the IAF which mainly consisted of various sub-policies that were generated on a non-legally binding multilateral agreement. Following the United Nations Conference on Environment and Development earth summit (1992), the different parties involved in the conference adopted two separate policies pertaining to the preservation of the world’s forests. The policies adopted in the conference gave rise to the IAF agreement which was based on sustainable development of all types of forest regions in the world (forest principle). Furthermore, it also aided in a non-legally binding authoritative statement of principle for a global concern on management, conservation, and sustainable development of all types of forest (Bernstein and Cashore, 2012).

The agreement prompted the release of a non-legally binding agreement by the United Nations on all forest types. The agreement led to a standardized definition of sustainable forest management (see section 2.3.2) which was under the context of the United Nations Sustainable Development Goals. The creation of these goals brought about a general understanding of the issue to safeguard the world's forests under the agenda 2020 to 2030. The main objective of the IAF agreement was based on the strengthening of political commitments and actions at all levels to effectively implement sustainable forest management. For a better contribution of forest for sustainable development, the participating parties in the conference developed a strategic plan aided by the United Nations. They formulated six global forest goals, with 26 targets on forest preservation, which must be adhered to by the various parties in order to mitigate the effects of deforestation and promote sustainable forest management (United Nations, 2017).

e) Reducing Emission from Deforestation and Forest Degradation Mechanism (REDD+)

The purpose of REDD+ was aimed at reducing emission from deforestation, forest degradation and promote conservation, sustainable management of forest and enhancement of forest carbon stock in countries around the world. Furthermore, it was a means to create alliance between developing and developed countries in the aspect of environmental conservation. Included in the decision making of the REDD+ treaty were intergovernmental and private organizations (United Nation Framework Convention on Climate Change, 2013). Upon agreement, article five (inviting countries to fight for forest conservation by reducing deforestation to combat greenhouse gas emissions) of the 2015 legally binding Paris Agreement was used. The article was used to create two goals governing the REDD+ treaty (United Nations, 2015):

- Conservation of forest carbon-stock
- Encourage the fight against deforestation by implementing actionable framework for REDD+.

The negotiations of the REDD+ treaty began in 2005, with its main goal to mitigate climate change via decreasing net emission of greenhouse gases through enhancement of forest-carbon stock. By 2013, the key REDD+ decision regarding the treaty was already completed (Mcdermott, 2012). The REDD+ interventions strategies are based on maintaining forest regions (all kinds) economically which is more valuable than converting the forest to other land use activities. Using the strategy, deforestation was discouraged by promoting forest growth via adhering to the proposed rules in the REDD+ rule book (United Nations, 2010).

The adoption of the REDD+ treaty in the CSB forest regions will in a long run reduce large scale forest degradation and deforestation occurring in the region which falls within the broader region of the Congo basin. With regards to the participating membership of the REDD+ treaty, the governments of the CSB region are actively working towards REDD+ at different readiness stages or processes. The REDD+ readiness phase level in the CSB region varies in the different countries. This is because the different nations did not implement the policy at the same time. Nigeria and Cameroon are at readiness phase 2, while Equatorial Guinea is at readiness phase 1 (Mosnier et al., 2014). The readiness phases are described below.

- **Phase 1**: which is regarded as the early readiness phase, consists of protocols whereby the host country is responsible for creating an action plan or a REDD+ strategy. This consists of a national forest monitoring system, forest reference emission, and safeguard information system via capacity building and multi-stakeholder consultations.
- **Phase 2**: advance readiness stage, consists of implementation of strategic plans in phase 1, followed by capacity building projects to reduce emissions.
- **Phase 3:** compensation phase, comprises of a stage where the country has succeeded in applying the REDD+ mechanism and it is functional. They get compensated financially because they have enhanced carbon stock based on the agreed level by the commission (Angelsen et al., 2009).

The implementation of the REDD+ policy enables the participating nation to receive benefits such as technical and priority financial support from the Forest Carbon Partnership Facility, UN REDD, World Bank Investment Program, and African Development Bank.

f) Forest Law Enforcement Governance and Trade (FLEGT)

The improvement of forest governance has to do with strengthening the laws that control forest resources and promoting sustainable balance of demand and supply of forest products. The FLEGT was signed by the governments of the CSB region in 2005 and implemented in 2008 to aid in the prevention of illegal timber trade from timber producing countries to the United States and European markets. This approach is aided by monitoring, enforcement, and tracking technology. The FLEGT has been very active over the last decades in the CSB region with the help of the European Union (EU). Using the Voluntary Partnership Agreement (VPA), which is a key element in the FLEGT approach, a bilateral trade agreement was signed between a timber exporting country outside of EU and within the EU. The agreement aims to safeguard the exportation of timber from the CSB regions to EU countries. Using the VPA, the timber producing countries implemented a verification system for timber which allows for legal and licensed export of timber to EU nations (Saunders, 2009).

Amongst the CSB region, only one country has implemented VPA which is a key element in the FLEGT approach (Cameroon). Other nations are still in the negotiation stages. The implementation of the FLEGT approach provides an ideal opportunity for timber producing nations in the CSB region to help strengthen their forest governance laws thus preserving the forest. The FLEGT approach works by closing the loopholes in forest certification by using the national timber supply approach, thus avoiding black-market sales of timber, and ensuring constant demand from their top consumers group (EU and United States). Since the establishment of the FLEGT initiative, about 124 FLEGT projects (6 projects ongoing as of 2018) have been developed in the forest regions of the Congo basin including the CSB region. The project interest areas have been based on transparency, information sharing, timber legality assurance, monitoring, domestic markets, and legal reform works. The implementation of these projects has brought together stakeholders from various civil society organizations, government agencies, private sectors, and indigenous people to improve forest governance to help achieve sustainable forest development (Ngankam and Tekem, 2020).

g) Voluntary Guidelines on the Responsible Governance of Tenure of Land, Fisheries and Forests (VGGTs)

The voluntary guidelines aim to enhance the management of fisheries, land, and forests tenure, emphasizing the well-being of all, particularly vulnerable and marginalized populations. The ultimate objective is to bolster food security, progressively fulfil the right to adequate food, eradicate poverty, foster rural development, and uphold environmental sustainability and social-economic progress. Since the UN committee on world food security established these principles in 2012, they have been in compliance with international legal norms, including the Universal Declaration of Human Rights and other human rights treaties. The implementation of these voluntary guidelines seeks to achieve several objectives:

- **Enhance Governance:** Offer direction and data on globally recognized methods to strengthen the governance of land tenure, focusing on the rights related to the use, control, and management of land, fisheries, and forest resources.

- **Policy and Legal Development**: Participate in the improvement and creation of organizational, legal, and policy frameworks that control the range of tenure rights connected to these resources.
- **Transparency and Functionality:** To guarantee just and equitable access to and use of land, fisheries, and forests, enhance the transparency and functioning of tenure systems.
- **Capacity Building:** Enhance the abilities and functions of local governments, implementing agencies, judicial authorities, farmers' organizations, small-scale farmers, fishers, and forest users. This entails encouraging collaboration amongst these players and encompasses all parties interested in tenure governance.

It should be noted that these rules are voluntary and should be understood and applied in accordance with national and international legal requirements, as well as voluntary commitments under regional and international institutions. They supplement and assist programs addressing human rights, as well as attempts to ensure tenure rights to land, fisheries, and forests, as well as efforts to enhance governance. VGGTs can be used by a variety of players, including states, judicial authorities, local governments, farmer and fisher organizations, and forest user groups. This will aid in assessing tenure governance, identifying areas for improvement, and putting relevant measures in place. The Guidelines have a worldwide reach and can be used by any country or region at any level of economic growth. They are applicable to all forms of tenure, such as public, private, communal, collective, indigenous, and customary. It is emphasized that the Guidelines should be interpreted and applied within the framework of national legal systems and institutions (United Nations, 2012)

5.3.2 CSB Region Forest Policy Structures

The countries in the CSB have for the past years been faced with the challenge of developing economically by reducing poverty while limiting the effect of over exploitation and deforestation. Due to the growing global recognition of forest governance in the importance of climate change rectification, there is a need for the countries in the CSB region to change their views concerning the over-exploitation of the forest resources by creating forest-based policy to help protect the forest (de Wasseige et al., 2015).

The end of the UNFCCC in 1992 paved the road for a different framework on forest policies. These frameworks were targeted on the reduction of greenhouse gas emissions via deforestation and forest degradation. The implementation was based on reviewing the interested nations' forest policies based on credible data. The intended data was used to accommodate the countries' goals of forest preservation or sustainability. By highlighting the policies to limit deforestation and promote growth (economic) in a sustainable and inclusive way, the country grows economically without harming the environment (Megevand, Carole and Mosnier 2013).

Amongst the different forest policies that have been implemented by the government of the CSB region, most of the policies' goals are to help reduce over-exploitation of forest and help reduce deforestation. The section below outlines forest policies that have been adopted by countries in the CSB region.

a) Forest Policies in Cameroon

The list below consists of forest policies that have been implemented by the government of Cameroon to protect the forest region of the country against deforestation.

- **Forest Stewardship Council of 1993**. This council was established as a follow up of the Rio de Janeiro United Nations Conference on Environmental Development. The goals of this policy were aimed towards the environment, social and economic factors. Using the council, the government could promote environmentally appropriate forest management practices by ensuring the production of timber, non-timber, and ecosystems services to maintain productivity, biodiversity, and ecological processes. For social factors, the local inhabitants and the society at large will enjoy the long-term benefits of the forest by practicing socially beneficial forest management practices. Economic factors provide a viable forest management operation which was sufficiently profitable for both the local community and the ecosystems (Forest Stewardship Council, 2020).
- **National Forest and Wildlife Policy (NFWP) of 1994**. The policy outlines strategies and principles for forest conservation including the creation of protected areas, such as the promotion of community forestry, the adoption of sustainable forest management practices, and the reduction of greenhouse gas emissions from deforestation and forest degradation. The NFWP also recognizes the importance of involving local communities in forest management and decision-making (Ministry of Foresty Cameroon, 1994).
- **The Forest and Wildlife Law of 1994**. This law was based on laying down the groundwork for the regulation of wildlife, forestry, and fishery. The framework was later revised in 2014 to provide for the management and conservation of forest, wildlife,

and fishery resources for sustainable development (Ministry of Foresty Cameroon, 1994).

- **Community Forest Policy of 1994**. This policy was drafted in 1994 and implemented in 1995. The main objective of this policy was based on the protection and preservation of the environment and natural resources by involving local communities in the decision making of forest laws governing their lands to promote conservation and management of forest resources (Luc Moutoni, 2019).

b) Forest Policies in Equatorial Guinea

Below are forest policies in Equatorial Guinea implemented to protect their forest areas.

- **National Environmental Management Plan**. This plan, implemented in the year 2002, establishes the legal framework for forestry management and conservation by outlining the responsibilities of government institutions and forest users. This aided in the management of forest resources and sets out penalties for illegal forest activities in the country (Ministry of Forestry Equatorial Guinea, 2008).
- **National Action Deforestation Program**. This program, implemented in 2015, seeks to achieve the neutrality of national land degradation by preventing deforestation and biodiversity loss and to promote sustainable forest development. The implementation was based on promoting the best practices on conservation and restoration of ecosystems. The aim was to improve living conditions of the population with exclusive dependence on environmental resources. This was followed by establishing a mechanism to strengthen national capacities on the persistent gaps and redefinition of the different sectors to achieve the neutrality of land degradation (National Programme for Forest Action, 2015).
- **Forest and Sustainable Biodiversity Management Policy**. This policy, implemented in 2015, is based on recognizing the forest region in terms of its productivity and conservation. The policy focuses on creating a framework for managing the resources produced by the forest. While managing the forest resources, it gives room for the creation of a national system of protected areas in the country to prevent the loss of the forest (National Programme for Forest Action, 2015).
- **Central African Forest Initiative (Equatorial Guinea)**. The government of Equatorial Guinea entered a partnership with the central African forest initiative in 2016 to support the implementation of sustainable forest management practices in the country

and reduce the emission of greenhouse gases from deforestation and forest degradation (Central African Forest Initiative, 2016).

c) Forest Policies in Nigeria

The points below highlight the various measures that have been taken by the Nigerian government to protect and conserve the forest region for future generations.

- **Community Based Forest Management:** This community-based program was launched in 1992. It was aimed at promoting local community-based forest management by empowering local communities to engage in forest advocacy talks on natural forest resource management. These engagements were via the establishment of community forest management committees in their various communities (Global Environemental Facility Small Grants Program, 2012).
- **Nigeria National Forestry Law:** This law, promulgated in 1988, was created to prevent the further loss of forest areas through deforestation and to help achieve sustainable forest management. The law is aimed at promoting social and economic development while sustainably harvesting forest resources for the present and future generations. The law emphasizes the need to involve local communities in forest governance and decision-making, the promotion of sustainable forest management practices, and the conservation of biodiversity (Federal Ministry of Environment Abuja, 2006a).
- **Community Participation Policy in Forest and Game Reserves:** This participatory program is focused on the collaborative partnership between government and rural communities in protecting the forest. This process, established in 2006, addresses the destructive practices of local communities to open access to forest resources via the development of collaborative forest management practices. The implementation helps define roles, responsibilities, and rights of communities based on sharing the benefits from the forest, thus improving forest management (Federal Ministry of Environment Abuja, 2006b)
- **Forest Management Policy:** The management of forest regions is achieved by the sustainable delivery of goods and services in a manner that will last for a long time. This policy, established in 2006, was guided by the framework of practicing afforestation practices throughout the country. This acts as a supplement for the harvesting of natural forest products for household consumption and export (Federal Ministry of Environment Abuja, 2006a).

- **National Environmental Standards and Regulations Enforcement Agency (NESREA):** The NESREA agency was implemented in 2007. It is aimed at providing a national environmental standards and regulations enforcement agency whose main role is to develop and protect the environment by addressing deforestation and promoting sustainable forest management practices (NESREA, 2007).

5.4 Promoting Sustainable Forest Management

The purpose of this section was used to address research question 4.2 of objective four research questions section 1.4.2 above. With a projected increase in population from 2021 to 2063 for Cameroon, Equatorial Guinea, and Nigeria (see Table 4-6 page 94) (United Nations, 2022) there is an expected increase in the demand for urbanization and agricultural expansion to meet the needs and demands of the inhabitants of the CSB forest region. This increase in demand may lead to a decline in forest areas if measures are not taken to mitigate this. The Figure 5-1 below highlights the change in area for the different LULC classes in the region.

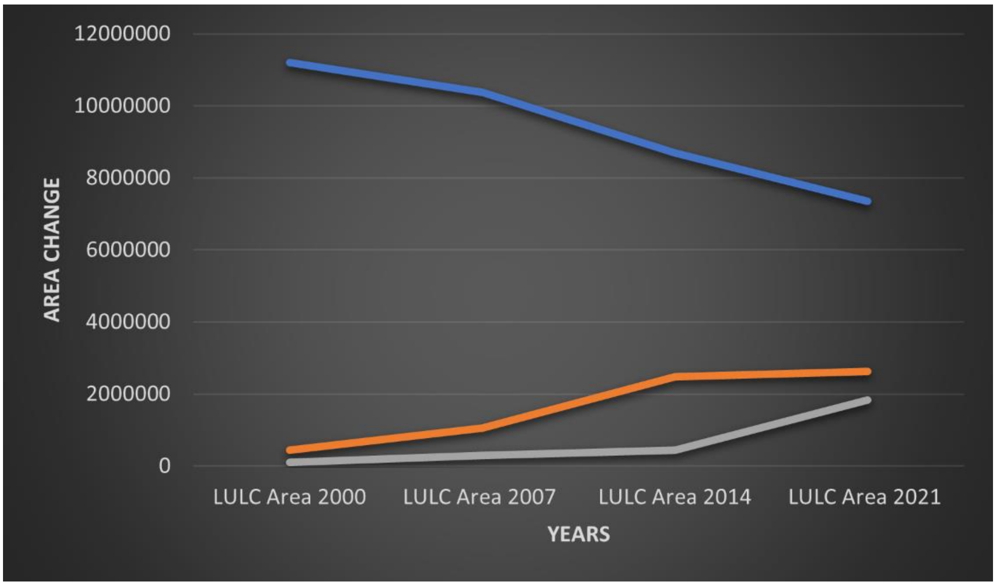

Figure 5-1: LULC Area Change from 2000 to 2021 in the CSB Region.

Figure 5-1 illustrates the land cover area changes from 2000 to 2021. With the projected increase in built-up and agricultural areas and decrease in forest areas in the CSB region (see Figure 4-20), there is a need for a balanced system to account for exploitation and conservation. The section below identifies a few measures that have been highlighted by other research/studies to address the need for a balance between forest conservation, urbanization, and agricultural expansion.

5.4.1 Balancing Forest Conservation and Urbanization

Urbanization is amongst the major drivers of environmental change in the CSB region as seen in Figure 4-3. above. Built up areas have seen a maximum area increase of 9.92 % between the years 2014 to 2021, and it is projected to have a further 10.88 % increase in area from the year 2021 to 2063 in the region. (United Nations Habitat, 2016) maintains that urban conservation strategies play a significant role in balancing forest conservation and urbanization. They call for the establishment of green spaces and species conservation in cities. (For example, Johannesburg, is the largest urban forest in the world (Anise, 2019). The Intergovernmental Panel on Biodiversity and Ecosystem Services suggests that a move towards sustainable cities is required to protect endangered species. The United Nations Framework Convention on Climate Change, the United Nations Convention on Biological Diversity, NFWP of 1994 in Cameroon, the National Action Deforestation Program in Equatorial Guinea and the Nigeria National Forestry Law can achieve the purposes above (Díaz et al., 2019).

The design of urban green spaces offers opportunities for both urbanization and conservation because it creates shared habitats between plants, animals, and people. Examples of such important opportunities include the introduction of biodiversity sensitive environments to manage different land uses in an area (Planchuelo, Lippe and Kowarik, 2019). Smith and Minor, (2019) showed that cemeteries in Chicago, United States, are homes to a considerable number of cavity nesting birds due to the varieties of landscape level features which have caused an increase in the species richness of the birds. They further concluded that more biodiversity friendly cemeteries be created including promoting sympathetic mowing regimes, and planting design such as tree clusters and shrubs to promote different plant and animal species.

The accomplishment of a sustainable environment can be achieved by understanding the intersections between human needs and biodiversity or forest conservation; for example, the REDD+ and International Agreement on Forest. These initiatives can contribute to sustainable urban development by providing financial incentives for countries to protect forests, conserve biodiversity, and enhance ecosystem services, which are crucial for urban areas in terms of clean air, water provision, and climate regulation. Understanding the role urbanization plays in biodiversity creates the pathway for developing methods that can support both systems (Ives and Kendal, 2014). The role of the urban environment in harbouring large areas of important components of biodiversity, such as endangered species, has been proven to be feasible (Planchuelo, Lippe and Kowarik, 2019). However, the habitat characteristics of different urban land use categories differs from one area to another. Therefore, detailed information regarding conservation and associated opportunities in the different urban land cover classes needs to be vetted before policies supporting biodiversity-friendly urban development can proceed.

According to (Apfelbeck et al., 2019), the creation of urban projects offers new opportunities for the integration of biodiversity and urban development at the early stage. Addressing the integration gives the opportunity to identify which plant and animal species will integrate successfully into a unique environment. They developed a conceptual approach to aid in the selection of target species for wildlife-friendly environments using the regional species pool. In the regional species pool, the starting point was to develop a list of local species that could be suited to a local habitat and site given dispersal characteristics. The regional species pool can then enable stakeholders to engage in a participatory approach in creating policies that will be suitable for identifying plant or animal species that will thrive in an urban environment.

Though private gardens are important green spaces in most cities, their ability to support urban biodiversity and provide ecosystem services is often disregarded due to data unavailability (Dewaelheyns et al., 2016). (Schneider et al., 2020) highlighted the importance of geographic information systems (GIS) for urban planning and conservation by modelling a GIS based web application system. This web-based application enabled gardeners to provide valuable information on their management practices and biodiversity related features of their gardens. The gardeners in-turn receive an estimate of the biodiversity friendliness, ecosystem services that their gardens provide, and appropriate management recommendations. The REDD+ agreement, community forest policy of 1994 in Cameroon, the forest and sustainable biodiversity management policy of Equatorial Guinea, and the community participation policy in forest and game reserves of Nigeria, all focus on reducing deforestation and promoting afforestation via the creation of protected areas as seen in section 5.3.

5.4.2 Balancing Forest Conservation and Agricultural Expansion

The increase in demand for agricultural products for fuel, food and other produce puts pressure on the area for forest land. This can be fuelled by increase in the demand for forest land for agricultural uses and thus promoting the conversion of forest land to agricultural land. One of the methods that can bring about the balance of forest conservation and agricultural expansion is agriculture intensification. Agricultural intensification can be brought about through the changes in production system which increases the efficiency of the agricultural land by reducing expansion. Implementing intensification may aid in generating more output in a land area, thereby reducing the rate of forest loss to agricultural land. This may be aided via the use of forest stewardship council agreement, forest and sustainable biodiversity management policy, forest management policy, and FLEGT agreement (section 5.3, sub-section 5.3.1 which all focus on sustainable management and conservation of forest resources thus limiting agricultural expansion. The increase in agricultural production is promoted by the introduction of fertilizers, pesticides, and irrigation to farming practices such as wheat, rice, and maize products. The system generates more output to sustain the demand from the public (though expensive to manage) thereby reducing the need for more agricultural land (Baudron and Giller, 2014).

The process of agricultural intensification can be promoted using several ways such as fertilizers (natural and artificial), seed resistance to environmental change that can produce higher yields, but the most common way is through technology. By introducing agricultural technological practices, labour-intensive practices are replaced by mechanized labour. Nevertheless, to understand the impact of change in forest and agricultural areas, it is important to consider how farmers will adapt to the introduction of novel approaches with regards to conservation and expansion. As explained by (Schultz, 1966), in the presence of unutilized potential agricultural land such as forest areas, there will always be a need for farmers to explore and expand their agricultural lands for economic purposes rather than practicing agricultural intensification.

A sitting tool is used for identifying potential areas for implementing different land development practices for designing an integrated forest conservation and agriculture expansion balance. This tool may assist in the understanding and analysis of key decisions for integrating agricultural expansion with forest conservation. Additionally, this may also help decision makers and other non-governmental organisations reduce the effect of poor decisions on forest and agricultural areas thereby promoting sustainable management practices across different landscapes. The tool allows for social, economic, and environmental concerns about agricultural expansion to be examined. The role of community forest policy for Cameroon, national environmental management plan for Equatorial Guinea forest management policy and NESREA agency for Nigeria can be used in its implementation. These policies and plans aid in promoting protection and conservation practices via the use of local communities, thus allowing the community to be part of the decision making. It identifies which agricultural products are suitable for improved practices in which land cover types these practices should be carried out, and in other cases which practices are not suitable (Mcnally and Enright 2014).

With the growing global commitments to reduce deforestation, it is vital to understand the agriculture-forest linkages and provide the appropriate approach needed to promote a balance between the two systems. Different initiatives have been adopted to protect the conversion of large forest areas for agricultural use such as the production of soy and palm oil. In Netherlands and Belgium there are task forces (Dutch Task Force on sustainable soy and palm production while in Belgium they have an Alliance task force for sustainable palm production) to prevent tropical deforestation. Though the implementation of forest-agricultural policies for example FLEGT is important, it is necessary that in the implementation stage the following elements be considered:

- Covers both forestry and agricultural objectives, variables, and indicators.
- Applicable for a larger area and allows for a wide landscape application.
- Can accommodate changes in landscape.

Understanding the elements above may help bring a balance in forestry and agriculture areas in the aspects of conservation and expansion. This may promote improved agricultural practices, reducing the loss of forest areas (Mcnally and Enright 2014).

Balancing forest conservation and agricultural expansion can also be promoted using land-sharing which involves the integration of agricultural production into nature conservation in a region. This can be done with the aid of the United Nation Convention on Biodiversity and REDD+. The land-sharing approach is based on landscapes that are controlled by agricultural activities linked to agrobiodiversity (which consists of cultivation of planted trees or crop species for shade management). Through this method, accompanied by policies such as the national forest and wildlife (Cameroon), national action deforestation program (Equatorial Guinea), and community participation policy in forest and game reserve in Nigeria, many plant species that are crucial for providing ecosystem services that are important for agricultural production can be maintained and preserved (Cardinale et al., 2012; Leakey, 2014). In terms of agricultural production, two important services accounts for continuity: crop pollination and pest control. The use of chemical pesticides for pest control over time has enabled some plant and animal species to become more resistant to the chemicals. The residuals of the chemical pesticides cause problems to both humans and the environment (Tscharntke et al., 2016b).

An alternative to chemical pest control is the introduction of biological pest control which acts as a natural enemy to the plant and animal species. Integrating wildlife-friendly biodiversity into an agricultural system via land sharing approach not only acts as pest control but also aids in pollination (Naranjo et al., 2015; Pywell et al., 2015). The creation of a diverse landscape that accounts for different biodiversity existence such as land sharing within a heterogenous environment also strengthens outside ecosystems that are not part of the main landscape management process (Bennett, 2017). However, maintenance of these systems is required to avoid overcrowding from one species only. Furthermore, if the approach is practiced properly, it not only contributes to biodiversity conservation, but also enhances the resilience of some ecosystem services in a particular agricultural environment (Lichtenberg et al., 2017).

5.5 Assessment of the LULC Change in the Region Over the Study Period

The results of this section have been addressed in sections 4.2, 4.3, and 4.4 of chapter four. As seen in Figure 4-1, Figure 4-2 and Figure 4-3, forest areas in the CSB region across the study period have been in a trend of reduction, and the magnitude of the reduction varies from approximately 6.64% to 14.69%. This reduction could raise concerns about the future of the forest environment and the loss of natural plant and animal habitats. Nevertheless, there were a few instances where there was a gain in forest areas from the loss of both agriculture and built-up areas and this was recorded in the second and third period of both LULC classes. This increase might have been because of the implementation of sustainable development practices as explained in section 5.3. Additionally, agricultural, and built-up areas have seen consistent expansion in size over the years which may be driven by population increase and changing LULC policies for agricultural practices as explained in section 5.2. There are positive impacts of an increase in these LULC classes, such as an increase in agricultural output, which can help in increasing food security in line with goal two of UN SDGs. Urban growth can signify economic progress; however, the growth has mostly been attributed to an increase in the establishment of slums in most major cities in Africa. The increase in urban growth might also bring about potential environmental degradation and pose threats to the natural ecosystems (African Development Bank Group, 2020).

Comparing the changes between the three different LULC classes in the region allows for a deeper understanding of the evolution of LULC dynamics in the region. Agricultural and built-up areas stand out with increases in areas. These trends might be influenced by socio-economic factors, population growth, and government policies. Furthermore, the significant drop in forest areas (period two and three) and the corresponding increase in built-up and agricultural areas underline the need for robust conservation and sustainable land management strategies. Balancing economic development with ecological preservation is a complex challenge. Effective land use planning, reforestation initiatives, sustainable agriculture practices, and urban planning policies are crucial to mitigate negative environmental impacts as seen in section 5.3 above.

5.6 Causes and Effects of LULC Change in the Region

The changes in LULC areas in the CSB forest regions as seen in sections 4.2, 4.3, and 4.4, have been documented to have negative effects on the environment (see section 2.7). Hence, a correlation analysis was performed in section 4.5 to test for the strength of association between LULC classes and air pollutant variables (see Table 4-2 chapter four page 83) to obtain the correlation coefficient values of the variables. The descriptive statistics indicated a consistent surpassing of recommended air quality guidelines for multiple pollutants in the CSB region except for NO_2. This underscores the urgency of addressing air pollution for the well-being of both humans and the environment.

For the correlation relationship between forest areas and the air pollutants in the analysis (see Table 4-2 the absence of a consistent relationship across all periods for each pollutant suggests the complex and variable nature of pollution dynamics. Factors such as meteorological patterns and local emission sources might lead to fluctuations in these relationships. Forests can function as both sources and sinks for various pollutants. For instance, trees can absorb some pollutants from the atmosphere such as carbon (acting as a sink) while releasing others such as methane from decomposing tress (acting as a source) (Holmberg et al., 2021). These dynamics can influence the observed correlation patterns seen in the results above (Table 4-2). The absence of relationships in some periods and the presence of weak correlations in others highlight the intricate interplay of natural processes, human activities, and atmospheric conditions in shaping pollutant levels. While the relationships may be weak, the findings still underscore the potential influence of forest areas on pollutant concentrations.

Furthermore, the varying relationships between agricultural areas and the air pollutants across all the periods suggest changing emission dynamics, land management practices, and atmospheric conditions that might influence the observed correlations. Factors such as local emission sources, topography, and meteorological conditions might contribute to the observed relationships. Agricultural activities can release pollutants such as ammonia, which can react in the atmosphere to form other pollutants. Similarly, vehicular, and industrial emissions can influence pollutant levels observed in the analysis. Also, the correlation results obtained in the analysis between built-up areas and the air pollutants might be associated with various sources of pollution, including vehicular emissions, industrial activities, and energy consumption.

These sources contribute to the observed correlation patterns in the analysis (see Table 4-2). The varying relationships across all the periods suggest changes in urbanization patterns, technological advancements, and emission control strategies that might have an influence on the results.

In summary, the correlation analysis between the two variables reveals a complex and varying relationship over the study period. These findings emphasize the importance of considering multiple factors in understanding air pollution dynamics and developing effective strategies for pollution control and promoting sustainable environment for the future generation as per the UN and African Union goals.

5.7 Future Land Cover Change

Section 4.6 above describes the projected land cover distribution for the year 2063 in the CSB forest region, generated from a trained transition sub-model. The projection highlights changes in forest, agricultural, and built-up areas. The land cover change projection is validated by comparing classified land cover maps for 2021 and 2000 with the projected land cover map of 2063. The substantial loss of forest areas (see Figure 4-20) highlights the need for effective conservation strategies, sustainable forestry practices, and land-use policies to counteract deforestation and its ecological impacts. Though there are pre-existing forest and environmental policies to mitigate deforestation there needs to be a robust system of forest resource accountability. The projected increase in agricultural and built-up areas emphasizes the importance of balanced urban planning, sustainable agriculture, and considering environmental impacts while managing urban growth as explained in section 5.3 above. Furthermore, the projected land cover changes and their validation will aid in providing valuable insight into the future of the CSB forest region. These insights can inform decisions related to conservation, land use planning, and sustainable development, contributing to the preservation of ecosystems and the well-being of local communities.

5.8 Summary

The concept of urbanization and agricultural expansion is always attributed to the loss or gain of one land cover area to the other. Therefore, the different sections of this chapter explored first the causes of LULC change in the CSB region followed by the balance between forest conservation, urbanization, and agricultural expansion which were structured to answer the research questions 2.1, and 4.1 of objective two and four. The remainder of the sections discussed the outcomes of the results addressed in chapter four from section 4.2 to 4.6.

6. CONCLUSION and RECOMMENDATION

This section provides the research summary, conclusion and suggests recommendations for further studies and policy decision-making where appropriate.

6.1 Research Summary

The objectives of this research included detecting change in LULC in the CSB region from 2000 to 2021 (section 4.2 to 4.4), and identifying causes and effects of land cover change in the CSB forest region (section 4.5). Potential land cover change without any intervention was predicted and the results from the analysis were assessed against sustainable forest policies applicable in the CSB region (section 4.6). Research objectives were further broken down into research questions which made up the different sections within the chapters of the research. Chapters one to three reviewed research relevant to the study to obtain a better understanding of answering the objectives and the research questions. The general conclusion drawn from each objective are listed below.

Chapter one was focused on the background study coupled with motivation, problem statement (addressing why it is important to practice forest conservation), aim, objectives and research questions. Chapter two (literature review) was based on gathering pertinent and up-to-date research related to the topic, integrated into a coherent summary that encompasses the existing knowledge in the field. Literature review is itself an important contribution in the research because it serves as a guide to understanding the past and present states of the methods that have been used by different researchers. It also aids in providing a workflow for present studies depending on the required parameters. The chapter was also used to provide literature which aided in addressing the objectives and research questions of the study. This literature was helpful in identifying methods and techniques suitable to the research.

In chapter three, before the land cover forecast was modelled, the state of the forest region was assessed. Landsat 7 and 8 images were used to create a classified land cover map using a supervised machine learning classification and regression tree algorithm. The classified map aided in the calculation of land cover loss/gain and change detection transition in the CSB forest region over the last 21 years. For a better understanding of the consequences of land cover change on the environment (objective two), the relationships of the land cover classes were tested with air pollution data of the region to examine the distribution and tendencies between the variables. Spatial correlation analysis was performed, specifically point-biserial correlation analysis, which tests for correlation between land cover change and air pollutants (see section 3.8.2). Using MLNN and Markov chain machine learning models, the trend of the forest in the future was forecast by identifying the transition change of the different land cover classes of the region (objective three).

The result and analysis chapter (four) provided an in-depth presentation of the analysis and results of the study covering the research objectives and research questions. The first section was to understand the historical changes (2000 – 2021) of land cover classes in the CSB forest region. The results from the land cover change indicated that over the last 2 decades, forest areas have been constantly decreasing, while agricultural and built-up areas have been increasing. After accounting for loss and gain change in the different land cover classes, the next step was to test if these changes have in any way affected the quality of air in the region. This was accomplished using the point biserial correlation analysis method which tests for the strength of association between the land cover classes and the air pollutant variables. The point biserial correlation analysis in the region revealed that much of the correlation analysis indicated a weak positive relationship. Though there were a few instances of negative and no correlation, the results indicated that there is an overall statically positive relationship between land cover change and air pollutants.

The land cover forecast was based on an integrated approach including remote sensing, GIS, and a MLPNN-based CA-MC model, which was used to understand the spatiotemporal dynamics of land cover prediction in the CSB region. The prediction of change depended upon deforestation drivers that can account for the transition potential change from one land cover class to another. The changes generated from the map showed that the forest areas in the CSB region are still undergoing changes (negative), while the agriculture and built-up areas were predicted to increase in area. Though this is only a possible predicted outcome of the future land cover area in the CSB region, necessary precautions should be taken to avoid the predicted severe loss of forest cover in the region.

Chapter five addressed research question 2.1, 4.1 and 4.2 of objective two and four. This section highlighted some of the factors contributing to forest change in the CSB region based on literature and results from the analysis. It also identified some of the forest policies measures in the region ranging from national to international policies which included community forest engagement, protected areas and international tropical timber agreement. Furthermore, it also identified ways of creating a balance between forest conservation, agriculture expansion and urbanization. Combining the forest policies from each country highlighted in section 5.3, with balancing deforestation and sustainable development the forest areas in the region can be protected and preserve for future generation thus maintaining the ecosystem services and biodiversity of the region.

6.2 Conclusion

This section will provide an overall conclusion based on the each of the objectives addressed in the study. Objective One: To assess the change in the land cover in the CSB region from 2000 to 2021 using time series Landsat 7 and 8 images. The analysis of historical land cover changes in the CSB region from 2000 to 2021 revealed a significant decline in forest areas, coupled with an increase in agricultural and built-up areas. The post-classification change detection method proved effective in capturing these changes, highlighting the trends of deforestation, urbanization, and agricultural expansion. The use of higher spatial resolution images improved classification accuracy, providing a detailed understanding of the extent and nature of land cover change in the CSB region. The consistent expansion of agricultural and built-up areas over the study period is likely driven by population growth. While the increase in agricultural areas can contribute positively to food security, aligning with goal two of the United Nations Sustainable Development Goals (UN SDGs), the expansion of built-up areas often results in the proliferation of slums and associated urban challenges. Urban growth, although indicative of economic progress, can lead to environmental degradation and pose threats to natural ecosystems. These dynamics highlight the complex interplay between socio-economic factors, population growth, and government policies in shaping land use patterns. The comparison of changes between different LULC classes reveals critical insights into the evolution of LULC dynamics in the region. The significant reduction in forest areas during the second and third periods, coupled with the increase in agricultural and built-up areas, emphasizes the urgent need for robust conservation strategies and sustainable land management practices. Balancing economic development with ecological preservation remains a complex challenge that requires effective land use planning, reforestation initiatives, sustainable agriculture practices, and comprehensive urban planning policies

Objective Two: To identify potential causes and effects of LULC change in the CSB forest region using results from objective one: The correlation analysis between land cover change and air pollution indicated a generally weak but positive relationship, suggesting that changes in land use and land cover do impact air quality in the CSB region. Factors such as deforestation, urbanization, and agricultural expansion were identified as major drivers of land cover change, affecting air pollution levels. The spatial and temporal resolution of data played a crucial role in accurately assessing these relationships, underscoring the need for high-quality, detailed data for meaningful analysis. The changes in LULC areas in the CSB region have been documented to have negative environmental effects based on literature (see section 2.7 paragraph 6). The descriptive statistics analysis revealed that air quality consistently exceeded recommended guidelines for multiple pollutants, except for NO2, highlighting the urgent need to address air pollution for both environmental and human health. Though literature on correlation analysis in other studies proved to produce strong correlation analysis between LULC area change and air pollution, the results obtained from this analysis ranged from weak to moderate positive correlation analysis. Nevertheless, the positive correlation coefficient in the analysis indicates the presence of changing emission dynamics and land management in the region. The emissions might be from local emission sources, topography, and meteorological conditions Furthermore, the absence of consistent relationships underscores the intricate interplay of natural processes, human activities, and atmospheric conditions in shaping pollutant levels.

Objective Three: To predict potential land cover change in the CSB forest region without interventions. The land cover forecast model, utilizing a combination of remote sensing, GIS, and MLPNN-based CA-MC model, predicted continued deforestation and an increase in agricultural and built-up areas in the absence of interventions. This forecast underscores the urgent need for proactive measures to prevent severe loss of forest cover. The model demonstrated the potential for using machine learning techniques to predict land cover changes and highlighted the importance of addressing deforestation drivers to mitigate future negative impacts. The projected results obtained from the land cover change (section 4.6) may be reversed if sustainable forest management practices are promoted by the relevant land management authorities as highlighted in section 5.3. These practices such as balancing forest conservation with agriculture and urban expansion as addressed in section 5.3 coupled with the already implemented forest policies in section 5.3 may provide a positive impact in the fight against deforestation.

Objective Four: To view the results from the analysis within the context of sustainable forest policies applicable in the CSB region The review of forest policies from Cameroon, Nigeria, and Equatorial Guinea indicated that efforts have been made to prevent deforestation and promote sustainable forest management. However, the results suggest that these policies need to be strengthened and better enforced to create a balance between forest conservation, agricultural expansion, and urbanization. The study highlights the importance of implementing sustainable development practices and enhancing policy frameworks to achieve a suitable and sustainable environment for humans, animals, and plants.

6.3 Limitation of the Study

Every study has its limitations, and it is from the limitations that the study can be improved. The limitations encountered in this study are presented in terms of the research objectives as seen below.

6.3.1 Assessing the Change in the LULC classes in the CSB Region from 2000 to 2021

This objective was based on identifying the distribution of LULC different LULC classes in the region, followed by understanding the LULC dynamics by performing loss, gain, and change detection analysis of the different LULC classes present in the CSB forest region. The points below identify some of the limitations encountered in this section.

- **Cloud Cover:** The CSB forest region is in the hot and humid equatorial region of Africa, which experiences significant cloud cover all year around. This obscures the earth from optical satellites orbiting above the atmosphere, causing gaps in satellite imagery. The result is a scarcity of suitable imagery in the study area (Przyborski, 2015).
- **Landsat Imagery:** Landsat sensors have the longest history for monitoring the earth's surface from space, and this imagery has mostly been applied to vegetation monitoring at regional scales. The longevity of Landsat imagery spans over different sensors with different spectral characteristics. Examples of some sensors are Landsat 8 OLI/TIRS (Operational Land Imager and Thermal Infrared Sensor), Landsat 7 Enhanced Thematic Mapper (ETM+), and Landsat 4 – 5 Thematic Mapper (TM). The variation in the spectral information means that it is important to correct for spectral reflectance between the images acquired by the different sensors, which is very time consuming. If not corrected, the end product could have errors due to inconsistency when the product is to be used for land cover monitoring (Moran et al., 2001).

6.3.2 Identifying the Causes and Effects of LULC Change in the CSB Region

The goal of this objective was to examine if changes in LULC in the forest region had any relationship to air pollution in the region. The lack of air monitoring stations in the region meant that acquisitions of the air pollutants data were dependent on satellite images. The images have limited spatial and temporal resolution. This limitation makes it difficult to identify local sources of air pollution such as emission from individual components and the time frame of the emission (Kloog et al., 2011).

6.3.3 Predicting Land Cover Change in the CSB Region Without Intervention

This section was based on creating a model for future land cover change prediction in the region without any intervention.

- Both multilayer perceptron and Markov chain models require the selection of several parameters, such as the number of hidden layers in the multilayer perceptron model or the transition probabilities in the Markov chain model (Eastman, 2020).
- The modelling of possible future land cover is based on historical data. With this dependency, if there are inconsistencies or incomplete data, the model may predict an inaccurate future scenario. Furthermore, the model may also not be able to account for unexpected changes in events on the environment (Eastman, 2020).
- Modelling land cover change for forecasting is a time-consuming process and requires high computing processing power, good graphics processing unit and sometimes only proprietary software (that comes at a cost) can perform the modelling. The prices of the software and hardware are often very high, so creating the models without the appropriate requirements is very difficult.

6.4 Recommendation for Future Study

The aim of this study was to assess changes in forest, agriculture and built-up areas in the CSB region from 2000 - 2021, all in the interest of providing reliable information for sustainable forest management. From the first chapter to the fifth chapter there have been a few limitations encountered in the study. So, the following points below are recommended.

- One of the objectives of this study was to understand the historical land cover change in the CSB region by creating a supervised land cover map of the region. Spatial resolution determines the amount of information that can be captured about the objects or features within an image. Lower spatial resolution means that fewer details and features are captured, resulting in a loss of information and a decrease in classification accuracy. Using a higher spatial resolution image can improve classification accuracy by capturing more details and features.
- One of the main challenges of quantitatively modelling the relationships between air pollution and land use is the unavailability of data, be it land cover maps or air quality monitoring sites. In correlation analysis, the spatial resolution of the data can hinder the

accuracy of the analysis if the resolution is too coarse. Furthermore, if the temporal resolution is too low, the temporal variabilities of the pollutants may be missing such as interaction with seasonality, trends, and periodicity. Both spatial and temporal resolution of data can influence correlation analysis. To ensure accurate and meaningful results, it is important to obtain high spatial and the appropriate temporal resolutions for the data. This will help to ensure that the data captures the appropriate level of detail and variability necessary for accurate correlation analysis. Additionally, there is a need to establish more air quality monitoring sites throughout the CSB region to gather comprehensive and accurate data on air pollution levels. This data will aid in modelling the relationship between land use patterns and air pollution more accurately.

- The impact of urban developments and land use patterns on urban air pollution is significant, as they affect both the number of emissions and the ability of the urban ecosystem to remove pollutants from the air. However, accurately modelling the relationship between land use and air pollution is challenging due to the complexity of this relationship. This varies in time and space and is influenced by multiple environmental factors. To address this issue, it is important to obtain more detailed and comprehensive data, particularly ground-level air pollution data and traffic volume data. Implementing the above issues will permit for a better understanding of land cover change and air pollution.
- The modelling of the land cover forecast was based on multilayer perceptron and Markov chain. When using the multilayer perceptron model for creating a transition sub-model potential of the different land cover classes, only a maximum of nine sub-models can be used. So, if the transition sub-model classes are larger than nine, it is recommended that a different model be used. An example of such a model is the weighted normalized likelihood which can perform large transition sub-models.
- Analysis of land cover changes within the CSB region indicates a decline in forest areas, accompanied by a significant increase in built-up and agricultural areas. Predictions also suggest that this trend may continue in the future, leading to loss in biodiversity, climate change, flooding, increased greenhouse gases and soil erosion. Forest policies have been implemented in the region to protect and preserve the forest as seen in section 5.3. Policymakers should reinforce existing forest policies to ensure they are effectively protecting forest areas. Regular monitoring and stricter enforcement of laws are crucial to prevent illegal activities such as logging and encroachment. Encourage the

implementation of sustainable agricultural and urban development practices to balance economic growth with environmental preservation. This includes promoting agroforestry, sustainable farming techniques, and green urban planning.

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Appendix

The code for Supervised LULC Classification on GEE

```
    /**
     * Function to mask clouds based on the pixel_qa band of Landsat 8 SR
data.
     * @param {ee.Image} image input Landsat 8 SR image
     * @return {ee.Image} cloudmasked Landsat 8 image
     */
    function maskL8sr(image) {
        // Bits 3 and 5 are cloud shadow and cloud, respectively.
        var cloudShadowBitMask = (1 << 3);
        var cloudsBitMask = (1 << 5);
        // Get the pixel QA band.
        var qa = image.select('pixel_qa');
        // Both flags should be set to zero, indicating clear conditions.
        var mask = qa.bitwiseAnd(cloudShadowBitMask).eq(0)
                .and(qa.bitwiseAnd(cloudsBitMask).eq(0));
        return image.updateMask(mask);
    }

    var image = ee.ImageCollection('LANDSAT/LC08/C01/T1_SR')
            .filterDate('2020-11-01', '2022-02-31')
            .filterBounds(geometry)
            .map(maskL8sr);



    var final_image = image.median().clip(geometry);

    var visParams = {
            bands: ['B4', 'B3', 'B2'],
        min: 0,
        max: 3000,
        gamma: 1.4,
        };

//Map.addLayer(final_image, visParams)

        Map.addLayer(image.median(), imageVisParam4);

        var bands = ['B11', 'B10', 'B6', 'B5', 'B4', 'B3', 'B2', 'B1'];

//Map.addLayer(image.clip(geometry), viz);

// Loading trining points
        var trainingPoints =
Forest_Lands.merge(Agricultural_Lands).merge(Urban_Lands).merge(Water);

// Storing the land cover properties as consecutive intergers startting
from zero
//var label = "Class";

        var input = final_image.select(bands);

//Overlaying the points on the image to get training samples
        var trainingSamples = input.sampleRegions({
        collection: trainingPoints,
        properties: ['Class'],
        scale: 10
```

```
        });

//print(trainingSamples)

        var trainingData = trainingPoints.randomColumn();
        var trainSet = trainingData.filter(ee.Filter.lessThan('random', 
0.8));
        var testSet = 
trainingData.filter(ee.Filter.greaterThanOrEquals('random', 0.8));


// Filter out null values
        var trainingNoNulls = 
trainingSamples.filter(ee.Filter.notNull(trainingSamples.first().propertyNa
mes()));


// Training a CART classifier with default parameters
        var trained = ee.Classifier.smileCart().train(trainingNoNulls, 
'Class', bands);

//print(trained)

// Classifying the image
        var classified = input.classify(trained);

//print(classified)

// Accuracy Assessment

// confusion matrix
        var sample = trainingSamples.randomColumn('random');
        var train = sample.filter(ee.Filter.lt('random', 0.8));
        var validation = sample.filter(ee.Filter.gte('random', 0.8));

        var classifier = ee.Classifier.smileCart().train({
        features: sample,
        classProperty: 'Class',
        inputProperties: bands
        });

        var confusionMatrix = 
ee.ConfusionMatrix(validation.classify(classifier).errorMatrix({
        actual: 'Class',
        predicted: 'classification',
        }));

        print('Confusion Matrix', confusionMatrix);
        print('Overall Kappa Accuracy', confusionMatrix.accuracy());

// Displaying the inputs and results
        Map.addLayer(input, [{
        bands: ['B4', 'B3', 'B2'],
        max: 4}], 'trainigPoints');
        Map.addLayer(classified, {
        min: 0,
        max: 4,
        palette: [
        '#15b628',
        '#f2ff1c',
        '#c21b14',
```

```
        '#1427ff']},
        'classification');


        Export.image.toDrive({
        image: classified,
        description: 'LULC_21',
        scale: 30,
        maxPixels: 1e10,
        region: geometry
        });


// Calculate Area by Class by creating a 2 band image containg pixel and
landcov
// Using a Grouped Reducer
//Map.addLayer(csb_area, {palette: []}, 'Land Cover 2000');

//var clipArea = classified.clip(geometry);


        var areaImage =
ee.Image.pixelArea().divide(10000).round().addBands(classified);
        var areas = areaImage.reduceRegion({
        reducer: ee.Reducer.sum().group({
        groupField: 1,
        groupName: 'Classification',
        }),
        geometry: geometry,
        scale: 1000,
        tileScale: 4,
        maxPixels: 1e10
        });

        var classAreas = ee.List(areas.get('groups'));
        print(classAreas);

// Potting the land cover classes.
        var areaChart = ui.Chart.image.byClass({
        image: areaImage,
        classBand: 'classification', // Must be the band name of the
classified lulc image.
        region: geometry,
        scale: 1000,
        reducer: ee.Reducer.sum(),
        classLabels: ['forest', 'Forest', 'Agriculture', 'Urban', 'Water']
        }).setOptions({
        hAxis: {title: 'Classes'},
        vAxis: {title: 'Area Km^2'},
        title: 'Area by class',
        series: {
        0: { color: '#15b628' },
        1: { color: '#f2ff1c' },
        2: { color: '#c21b14' },
        3: { color: '#1427ff' }
        }
        });
        print(areaChart);
```

Code for Raster Correlation in R-Studio

```
#Loading packages
library(raster)
library(ggplot2)
library(terra)
library(dplyr)
library(tidyr)
library(sf)
library(rgdal)

# Loading land cover and air pollutant data
land_use <- terra::rast('landcov_01.tif')
air_qual <- terra:: rast('sulphur_01.tif')
#soil <- terra::rast('csb_soil.tif')
#air_rescale <- air_qual / 10**-4

# Masking the different land use land cover categories
forest <- terra::mask(land_use, land_use == 1 | land_use == 2, maskvalue =
FALSE)

agric <- terra::mask(land_use, land_use == 3 | land_use == 4,  maskvalue =
FALSE)

urban <- terra::mask(land_use, land_use == 5 | land_use == 6, maskvalue =
FALSE)

landcov_resam <- resample(forest, air_qual, method = 'ngb')

# Plotting the data
plot(landcov_resam)
plot(air_qual)

# Overlaying the two Raster.
overlay <- c(landcov_resam, air_qual)
plot(overlay)

# correlation test.
cor.test(values(overlay)[,1], values(overlay)[,2],
use = "na.or.complete")
```