NEAR EAST UNIVERSITY

INSTITUTE OF GRADUATE STUDIES

DEPARTMENT OF ENVIRONMENTAL SCIENCES AND ENGINEERING

Quantifying the Impacts of Land Use Changes on Forest Fragmentation in Nimba County, Liberia, Using Remote Sensing and GIS Techniques

M.Sc. THESIS

Emmanuel J. LARMOUTH

Nicosia

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Approval

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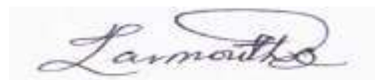
I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conducts, I have fully cited and referenced all material and results that are not original to this work.

Emmanuel J. LARMOUTH



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Emmanuel J. LARMOUTH

Abstract

Quantifying the Impacts of Land Use Changes on Forest Fragmentation in Nimba County, Liberia, Using Remote Sensing and GIS Techniques

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Changes in land use types affect forest resources, especially in today's increasingly industrialized world. Quantifying those changes caused by human activities has become paramount, as it necessitates understanding the status of forest resources. This study aimed to determine the effects of changing land use on forest fragmentation in Sanniquelleh-Mehn District, Nimba County, Liberia, at different epochs (2002, 2012, and 2022). Achieving this involved the application of remote sensing (RS) and geographic information systems (GIS). Images from the Landsat-5 (Thematic Mapper), Landsat-7 (Enhanced Thematic Mapper (ETM+)), and Landsat-9 (Operational Land Imager 2 (OLI-2)) were used in this study from the USGS (U.S. Geological Survey) data source. A supervised classification map shows that the study area has five main land use types. These include waterbodies, bare land, built-up areas, agriculture, and forests. The overall classification accuracy was between 91.79% and 95.42%, while the range for Kappa statistics was between 0.894 and 0.9302. As of 2002, the district's total area (964 km2) was made up of 97.85% forest, with the remaining areas being made up of built-up areas (0.33%), bare land (1.5%), and agriculture (0.3%). But between 2002 and 2022, the area covered by forest decreased from 925.73 km2 (97.85%) to 763.94 km2 (80.75%) and finally to 681.97 km2 (72.09%), resulting in an overall change in forest cover of -26.33% over the 20-year period. The land use change matrix results show that a significant amount of forest cover was converted to agricultural land (75.30 km2), built-up area (74.49 km2), and bare land (9.12 km2) during the 1st period (2002–2012). In the 2nd period (2012–2022), 27.53 km2 of built-up area, 4.61 km2 of bare land, and 50.65 km2 of agricultural land were converted from forest. The percentage change in forest cover from 2002 to 2012 was -17.48%, from 2012 to 2022 was -10.73%, and the overall change from 2002 to 2022 was -26.33%. Generally, the study area continues to experience an increasing trend of built-up area, expansion of agriculture, and large-scale mining activities, resulting in an unending decline of forest cover, which has a tremendous environmental effect.

Keywords: land use, land use change, forest fragmentation, remote sensing, GIS

Özet

Nimba İlçesi'nde Arazi Kullanımı Değişikliklerinin Orman Parçalanması Üzerindeki Etkilerinin Uzaktan Algılama ve CBS Teknikleri Kullanılarak Nicelendirilmesi

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Arazi kullanım amacındaki değişiklikler, özellikle günümüzün giderek endüstrileşen dünyasında ormanlık alanları etkilemektedir. İnsan faaliyetleri tarafından neden olan bu değişikliklerin nitelendirilmesi, orman kaynaklarının durumunu anlamanın gerekliliğinden dolayı son derece önemli hale gelmiştir. Bu çalışma, farklı dönemlerde (2002, 2012 ve 2022) Sanniquelleh-Mehn Bölgesi, Nimba İli, Liberya'da arazi kullanımındaki değişikliklerin orman arazilerindeki üzerindeki etkilerini belirlemeyi amaçlamıştır. Bu amaçla, uzaktan algılama (RS) ve coğrafi bilgi sistemleri (GIS) uygulamalarını kullanılmıştır. Çalışmada, USGS (ABD Jeolojik Araştırma) veri kaynağından alınan Landsat-5 (Tematik Haritalayıcı), Landsat-7 (Geliştirilmiş Tematik Haritalayıcı (ETM+)) ve Landsat-9 (Operasyonel Kara Görüntüleyici 2 (OLI-2)) görüntüleri kullanılmıştır. Denetimli sınıflandırma haritası, çalışma alanının beş ana arazi kullanım tipine sahip olduğunu göstermektedir. Bunlar sulu alanlar, çıplak arazi, yapılaşmış alanlar, tarım ve ormanları içerir. Genel sınıflandırma doğruluğu %91,79 ile %95,42 arasında değişirken, Kappa istatistikleri aralığı 0,894 ile 0,9302 arasında değişmiştir. 2002 yılı itibarıyla, bölgenin toplam alanı (964 km²) %97,85 orman ile kaplıyken, geri kalan alanlar yapılaşmış alanlar (%0,33), çıplak arazi (%1,5) ve tarım (%0,3) oluşturmaktadır. Ancak 2002 ile 2022 yılları arasında, ormanla kaplı alan 925,73 km² (%97,85)'den 763,94 km² (%80,75)'ye ve son olarak 681,97 km² (%72,09)'ye düşmüş, bu da 20 yıllık dönemde orman örtüsünde % -26,33'lük bir genel değişime yol açmıştır. Arazi kullanımı değişiklik matrisi sonuçları, önemli bir miktar orman örtüsünün ilk dönemde (2002–2012) tarım arazisine (75,30 km²), yapılaşmış alana (74,49 km²) ve çıplak araziye (9,12 km²) dönüştürüldüğünü göstermektedir. İkinci

dönemde (2012–2022), 27,53 km² yapılaşmış alan, 4,61 km² çıplak arazi ve 50,65 km² tarım arazisi ormandan dönüştürülmüştür. 2002'den 2012'ye orman örtüsündeki yüzde değişim -17,48%, 2012'den 2022'ye -10,73% ve 2002'den 2022'ye genel değişim % -26,33'tür. Genel olarak, çalışma alanı yapılaşmış alanların artan bir trendini, tarımın genişlemesini ve büyük ölçekli madencilik faaliyetlerini deneyimlemeye devam etmekte, bu da orman örtüsünün sonu gelmeyen azalmaya ve çevresel etkiye yol açmaktadır.

Anahtar Kelimeler: arazi kullanımı, arazi kullanım değişikliği, orman parçalanması, uzaktan algılama, CBS

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List of Abbreviations

ETM+	Enhanced Thematic Mapper Plus
GCP	Ground Control Points
GIS	Geographic Information System
Km	Kilometers
mm	Millimeters
OLI	Operational Land Imager
TM	Thematic Mapper
USGS	U.S. Geological Survey
UTM	Universal Transverse Mercator
WGS	World Geodetic System
WRS	Worldwide Reference System

Chapter One

Introduction

Forests play a vital role in supporting the livelihoods of billions of people globally (Sidiq, 2018). They supply wood fuel, which is utilized for cooking and heating purposes, serve as habitats for various species of wildlife, protect biodiversity, and maintain the overall functionality of ecosystem services (Ochenje et al., 2016). Unfortunately, rapid forest loss has been brought about by the overuse and destruction of forest resources to support economic growth and fulfill the necessities of a growing population, particularly in the tropics where more than two-thirds of the world's biodiversity is located (Asrat & Simane, 2018).

The depletion and deterioration of forests lead to significant declines in biodiversity and contribute to the release of approximately 10% to 25% of the world's carbon emissions. Indeed, from 2014 to 2018, there was an approximate yearly deforestation rate of 26 million hectares (ha), with tropical regions bearing the brunt of this trend. Quick action must be taken to stop or reverse the trend of forest resource loss at all levels to prevent further distraction and its adverse effects on people's lives and economic development (Tesfaye, 2017).

Numerous factors at varying scales contribute to the loss of tropical forests or deforestation (Falaki et al., 2013). According to Woods et al. (2017), the primary causes of deforestation may be sustaining life and commercial farming, followed by the growth of settlements and the construction of infrastructure. Climate change is a substantial ecological problem that affects many nations, endangering forest biodiversity, food production, water accessibility, and the livelihoods of individuals (Sidiq, 2018). Furthermore, there is a common belief that developing nations in tropical regions like sub-Saharan countries have a more severe impact than developed ones (Chen et al., 2018).

Human-caused activities, including mining, agriculture, deforestation, and building, significantly change land use patterns, affecting many current environmental issues. Land use change is becoming more widely acknowledged as a driver of ecological change. Changes in land use are widespread, increasing, and have the potential to harm local, national, and global levels. Using data sensed by remote sensing makes it possible to learn and better understand the variability in land use change and its effects on forest fragmentation in shorter time, at lower prices, and with reasonable precision with GIS participation, which offers a better platform designed for the analysis, updating, and retrieval of data has been transformed by the emergence of high-definition satellite imagery and the advancements in image processing and GIS technology. This transformation has enabled a shift towards more regular and reliable monitoring and modeling of land usage patterns and the fragmentation of forests (Rawat & Kumar, 2015).

Statement of the Problem

"Land use change" describes how human activities like urbanization and agriculture alter the earth's surface. Land use change worldwide is primarily caused by how past and present people have used and managed their land. Changes in land use cause large-scale environmental changes. These changes can affect the earth's biogeochemical cycles, the distribution and abundance of biological resources, the global climate system, the stratosphere's ozone layer, and the quality of the planet's water. Accordingly, changes worldwide are increasingly attributed to land use and land management (Mitsuda and Ito, 2011).

Similarly, land use changes have significantly impacted the forest resources in the study area. Forests have been fragmented due to human activities like iron ore mining by the most prominent company, ArcelorMittal Mining Company in Liberia, tree logging for income generation, the conversion of forests into agricultural areas, suburbanization and encroaching by the towns, and road connectivity. In addition to these significant factors, making charcoal and firewood, among others, is the primary cause of forest fragmentation and loss of species diversity in the study area. As a result, forest fragmentation is occurring at an alarming rate, and this will have a significant impact on the environment at large. The most extensive forests, including the national forest in the area, are being split up into several smaller patches of forest habitat.

Consequently, an evaluation of the effect of a shift in land use on forest fragmentation in the subject location is required. Utilizing multispectral and multitemporal satellite images for precise quantification requires sophisticated equipment such as geographic information systems (GIS) and remote sensing. The utilization of these instruments will furnish precise historical and contemporary data pertaining to the magnitude of habitat loss and forest fragmentation. Considering this, the objective of this research is to quantify the effects of land use changes on forest fragmentation in Nimba County, Liberia, by employing remote sensing and GIS tools.

Objective of the Study

General Objective

The research measures the changes in land use and their effects on forest fragmentation in the Sanniquelleh-Mehn District throughout several time periods from 2002 to 2022. The assessment aims to provide fundamental baseline information needed to have a better understanding of the present state of the forest resources in the region.

Specific Objectives

- Quantifying land use changes in the Sanniquelleh-Mehn District by remote sensing and GIS methods.
- Identify the spatial patterns of forest fragmentation relative to the pattern of land use distribution across selected segments.
- Identify possible land-use changes and their effect on forest fragmentation using 20- year (2002–2022) satellite images and construct the area's updated land-use characterization.

Research Questions

- What is the status of the changes in land use in the study area?
- How are forests fragmented due to land use change in the study area?
- How have forest fragments' spatial and temporal patterns changed over the last 20 years?

Significance of the Study

The current rate of industrialization the world over is alarming. This has necessitated the need for proper planning and environmental management. Therefore, it is essential to carefully choose, organize, and execute land use plans to address the growing demand for human necessities and well-being. These can only be achieved with accurate land use and land cover change data. The data collected from this research will have a substantial impact on decision-making regarding environmental management and the future planning of forest resources in the study region. It will also be vital to sustainably use the forests sometime in the future to analyze the social driving forces of land transformations.

Limitations

By offering a more thorough understanding of the geographic location, combining GIS with remote sensing data can increase the accuracy of spatial analysis. A more comprehensive picture of an area is possible when both technologies are used together, compared to when used separately. However, the temporal and spatial resolutions of remote sensing data are constrained. Because not all remote sensing data is publicly available, and high-quality data can be costly, it is also prone to error, and atmospheric conditions may impact certain data types. Therefore, cloud-free data was carefully evaluated for accuracy before utilizing remote sensing data in a GIS. Another major challenge could be using the two tools ideally because it is difficult to combine GIS and data from remote sensing, as it requires technical know-how.

Definition of Terms

Land Use: The term "land use" pertains to how individuals utilize land, encompassing commercial, industrial, mining, residential, and recreational undertakings within a particular area.

Land Use Change: The term "land use change" refers to the transition between different types of land use, which are typically categorized as crop land, forest, grazing land, and human settlement. Land use changes happen often and on a variety of scales. They can have distinct and combined effects on the quality of the air and water, the functioning of watersheds, the production of waste, the quantity and caliber of wildlife habitat, the climate, and the health of people.

Forest: A place having a high tree density is called a forest. Numerous living things, including plants, animals, and microorganisms, call forests home.

Forest Fragmentation: Large, continuous forests are broken into smaller, isolated forest patches by roads, farms, utility corridors, or other human developments. This process is known as forest fragmentation. It is a subtle but significant factor contributing to ecological disruption and biodiversity loss.

Remote Sensing: The technique of detecting and tracking an area's physical properties from a distance by calculating the radiation it emits and reflects is known as remote sensing (typically from satellite or aircraft). With remote sensing technology, researchers can obtain substantial amounts of data from aerial photographs and satellite images, making it a perfect tool for tracking changes in land cover and use. This method can collect data on changes in land cover, including deforestation, land development, and urbanization.

GIS: The Geographic Information System, or GIS for short, is a potent tool that lets us organize, handle, examine, and display geographical and spatial data. It allows us to recognize trends, relationships, and patterns among various geographic components.

Scope of the Study

The study was carried out in Sanniquelleh-Mehn District, Nimba County, in Northern Liberia, using satellite images for 2002, 2012, and 2022 to determine the changes in the forest concerning land use. Transects were pursued using google earth to check the terrestrial situation surrounding the forest fragmentation.

Organization of this Study

Chapter 1 introduces the research theme, background, and importance/significance of using remote sensing and GIS techniques to detect changes in land uses and their effect on forest fragmentation. The main objectives and sub-objectives that facilitate the tasks of achieving the higher goal are also described in this chapter.

Chapter 2 primarily reviews existing information relevant to land use change and its effect on forest fragmentation in similar areas worldwide, particularly in Liberia and West Africa, while focusing on applying RS and GIS techniques to the process.

Chapter 3 describes the socio-demographic state of the study area. Spatial details ranging from location to the sizes of essential features and the study area's biological, topographical, soil, and climatic attributes were elucidated in the same chapter. It shall describe the major methodologies followed for a detailed discussion of the collection, processing, and achievement of different data sources, such as land use change detection. The general principles and techniques are discussed in this chapter.

Chapter 4 The findings show the works shown on the map, followed by the socio-economic survey conducted at the study location. The findings in this part are presented and explained using a variety of maps, tables, and graphs. It also tried to display the analyzed data of the research to provide interpretable information and results and merge the significant contents and concepts from the previous chapters, leading to a discussion in which the research questions and objectives may be answered. This explains trends in the study's findings. The chapter ends with a summary of the findings obtained from the analysis and contrasts them with previous research (discussion).

Chapter 5 contains a summary, conclusion, and possible recommendations with indications for future research prospects and implementation for decision-makers.

Chapter Two

Literature Review

What is Land Use?

Land is an important natural resource, which has been the basis of human activity since the dawn of time. Thus, humans have modified terrestrial and aquatic systems on land for centuries to satisfy their basic needs. Global land use, atmospheric gas concentrations, and the soil's capacity to hold carbon in the future have all changed (Chaudhary et al., 2008). The characteristics of the biosphere include the local climate, soil types, topography, sedimentary layers with groundwater reserves, surface-level hydrology, plant and animal populations, human settlement patterns, and the physical impacts of human activities. The impacts may include terracing, water retention, changes in land shape, climate, water systems, plant life, animals, and land enhancements such as terraces and drainage systems (Pawar et al., 2020).

Land refers to the Earth's surface that is not submerged in water, along with its biological and physical features that affect its use. Land use pertains to how and why people use land and its resources. These uses include agriculture, urban development, conservation in protected areas, and forestry for wood production. The Food and Agriculture Organization (FAO) has created categories for various land use types to aid in worldwide comprehension and control. The FAO categorizes land use into specific classifications, including agricultural land, forest areas, and built-up areas, to enhance planning and conservation activities (Keenan et al., 2015). These categories aid in understanding the main purposes of land and in making well-informed choices about land management and sustainability.

Forest (Lands): A land area over 0.5 hectares with naturally growing trees that can grow up to 5 meters tall and a canopy cover of over 10 percent. Excluded are lands primarily used for agricultural or urban development.

Other Wooded Land: Other Wooded Land: Land bigger than 0.5 hectares with a canopy cover of 5–10 percent, trees that can naturally reach these thresholds, or a combined cover of more than 10% shrubs, bushes, and trees. Land designated for urban or agricultural use is not included.

Other Land: Area that is not classified as a forest or woodland area is known as other land. It comprises land used for agriculture, pastures and meadows, developed areas (including infrastructure and settlements), arid land, land covered in permanent ice, and other land having trees but not within a forest.

Three additional subcategories are used to classify other land further:

(a) Other Land with Tree Cover:

Land larger than 0.5 hectares with a canopy cover of above 10% or trees capable of reaching a height of 5 meters when completely mature. The land use standard distinguishes between a forest and other forms of land that include tree cover. The term includes groups of trees and single trees located in agricultural areas, parks, gardens, and near buildings, as long as they fulfill certain requirements for size, height, and canopy coverage. This group includes tree stands that are part of agricultural systems, such as fruit tree plantations and agroforestry settings, where crops are grown under the shade of trees (Ravindranath et al., 2014).

Land over 0.05 hectares with trees over 5 meters tall and a canopy cover surpassing 5%, or trees capable of naturally meeting these criteria, or with over 10% of its area covered by both trees and shrubs. The property consists of areas mostly designated for urban or agricultural use, with trees or bushes. It includes a piece of land with trees or bushes that is not primarily utilized for farming or urban development. The size is less than 0.5 hectares, or the breadth is less than 20 meters but more than 3 meters. Instances of this kind of terrain include windbreaks, shelterbelts, and corridors of trees and plants (Nowak & Greenfield, 2012).

(b) Other Land with No TOF:

This category includes land that does not fall under the designation of Other Land with TOF. This may include land with an area smaller than 0.05 hectares, a canopy covers of less than 5% for trees, or less than 10% for a combination of trees, bushes, and shrubs, or dimensions less than 3 meters in width or

25 meters in length for linear structures. Carreiras et al. (2006) list many types of landscapes, such as deserts, peat bogs, inland water bodies, dry terrain, stone outcrops, snow tops, glaciers, treeless meadows, and treeless annual crops.

Land use change

It describes how human activities like urbanization, agriculture, and other practices alter the earth's surface. Land use change worldwide is primarily caused by how past and present people have used and managed their land (Mitsuda & Ito, 2011). Changes in land use cause large-scale environmental changes. These changes can affect the earth's biogeochemical cycles, the distribution and abundance of biological resources, the global climate system, the stratosphere's ozone layer, and the quality of the planet's water. Accordingly, land use and management are becoming the leading causes of global environmental changes (Barnes et al., 2019).

Land use change has occurred since time immemorial, paralleling the rise and fall of human civilizations and changes in global population. Two significant trends in land use change have been observed over the centuries: (i) a dramatic increase in land area dedicated to human uses and (ii) intensification of both land use and control for increased production of goods and services. Land use change may have first occurred to increase the availability of land for wild games by clearing the area through burning; the birth of agriculture hastened the land use change, and industrialization is currently changing the land through urbanization (Lambin & Meyfroidt, 2011). Forests and grasslands, in particular, have undergone significant changes due to changes in land use worldwide. Since the last ice age, humans have cleared or dominated approximately 75% of the world's natural forested areas. The worldwide rate of forest loss is currently 0.6% per year, as reported by Hansen et al. (2010). Forest degradation due to resource extraction and conversion of forest areas to cropland, settlements (urban), and other land use types has resulted in forest fragmentation, decreased productivity, and increased forest isolation.

According to research, naturally occurring old-growth forests may become so severely fragmented due to the lack of management that they cannot maintain viable flora and fauna or their ecological integrity (Smith et al., 2016). The world's tropical regions have seen the fastest rate of change for grasslands and forests. Global land use has changed dramatically over the last few decades due to the enormous rise in human population and food consumption. The world's population has doubled since 1960. Ninety-five percent of people on the planet reside in developing nations. This has numerous ramifications, but the primary one is that increased agricultural output is required to meet fuel, fodder, and food demand. Growing will satisfy this requirement (Lambin and Meyfroidt, 2011).

Global environmental change is a broad problem caused by various social factors defining "land use." Modification and conversion are the two categories of land use changes that can be evaluated using land use. A modification alters a cover form's state (such as switching from unmanaged to regulated water). The process of changing from one type of cover to another, such as from a forest to grassland, is called conversion (Promila et al., 2023). Batar et al. (2017) state that soil is a crucial natural resource on Earth and serves as the primary location for development operations. Therefore, understanding land use is essential to carrying out efficient planning tasks. (David Mayunga, 2018) states that land is a vital natural resource, and knowledge of the spatial distribution of land use is essential to comprehending landscape dynamics. Changes in land use and nature and human adaptations have already brought on deforestation, habitat loss, global warming, and increased natural disasters.

Verheye (2009) asserted that land use and cover are not interchangeable terms. We must, therefore, look at their characteristics to determine how they vary. A "land use transition" is a significant alteration to the earth's surface by humans. The term "land cover" describes a piece of land's natural and artificial covering, including trees, water, bare earth, or man-made buildings.

Land use encompasses the purpose for which the land is used and how its biophysical characteristics are managed (Christensen & Jokar Arsanjani, 2020). It also includes the objective that guides this management. Land use is the principal use of land types like grassland for agricultural production, residential areas, and livestock grazing, and land cover is anything visible, like grass or a building (Briassoulis, 2009).

According to Olorunfemi et al. (2018) land use transformation is pivotal in global environmental alteration because of its intricate connections with climate, ecosystems, biodiversity, and human activities. Additionally, it holds a critical position in resource management and land planning.

The advent of remote sensing and GIS technologies in land analysis during the late 1980s has significantly propelled global monitoring of regional land-use dynamics changes. This progress is evident in various regions, such as the tropical rainforests in the Brazilian Amazon Basin, Africa, and South America, as demonstrated by Yengoh et al. (2016). The International Geosphere-Biosphere Program (IGBP) and the International Human Dimensions Program (IHDP) jointly developed a strategy in 1995 called "Land Use Change," which highlighted land use change as a significant global issue. It highlighted the need to improve our capacity to forecast alterations in land use at various geographical levels, as stressed by Verburg et al. (2013). Land use change is recognized as a key factor in global environmental transformation because of its complex relationship with ecosystems, biodiversity, climate, and human activities. Furthermore, it plays a crucial role in resource management and land-use planning.

Factors Contributing to Changes in Land Use

Changes in land usage are so widespread that they significantly impact essential facets of the functioning of the Earth System when taken on a global scale. They are the leading cause of soil degradation, directly impacting biotic diversity globally, altering ecosystem services, and altering local and regional climate change and global warming. They also impact biological systems' ability to meet human needs.
These alterations also determine how vulnerable individuals and locations are to social, cultural, or environmental upheavals (Pielke Sr, R.A., 2005).

Land use changes are essential to identify environmental change. Land changes have complex political, economic, social, demographic, cultural, technical, and biophysical influences. One must consider local or direct causes and regional or global decisions to understand these influences. Land cover changes are more often brought about by human activity than natural processes, according to Frimpong and Molkenthin (2021). It may be necessary to alter land use and cover due to human activity's direct and indirect effects to safeguard vital resources. McKee et al. (2017) speculate that this phenomenon might be attributed to the prevalence of fires initiated around the same period as the commencement of agriculture. This resulted in extensive clearing, including deforestation and surface management, which continues today. McKee et al. (2017) state that the primary causes include limits on globalization, a thriving informal sector, low economic growth and poverty, population migration and demographic shifts, continuous conflict and war, debt, and reliance on development assistance.

Forest Fragmentation

The leading factor responsible for the worldwide reduction and depletion of species diversity has been forest fragmentation, driven by human actions such as logging, the transformation of forests into agricultural zones, and urban sprawl. Forest fragmentation occurs when a substantial forested region is divided into several smaller patches of forested habitats, as highlighted in the study by Bogaert et al. (2011). This process gives rise to what is termed a "binary landscape," signifying that the landscape is perceived as comprising isolated forest fragments scattered across a non-forested matrix that separates them (Bogaert et al., 2011).

Forest fragmentation may result from human activities or natural occurrences. However, human action is more responsible for causing it than natural phenomena. Lindenmayer & Fischer (2013), state that land cover transition may happen via conversion (e.g., from forest to grassland) or modification (e.g., from dense forest to open forest) of land cover categories. Lindenmayer & Fischer (2013) demonstrated that landscapes respond differently to natural disturbances compared to man-made disturbances, with natural disturbances increasing the complexity of the landscape.

Among the natural causes are landslides, flooding, pests, newly emerging plant diseases, and burning, which occurs most frequently in most areas. Changes in land cover result from humans using nature more often to meet their diverse needs for survival and development. Land cover change can be broadly attributed to four factors:

technological capability, socioeconomic organization, degree of development, and culture. Moreover, most studies on land-cover change recognize that the growing human population has a detrimental effect on the demand for land resources (Briassoulis, 2009).

Utilization of Remote Sensing for Monitoring Changes in Land Usage

The study objective also affects the applicability of the various sensor instruments, as does their capacity and wealth of information. Satellite images created by different sensor instrument models frequently differ significantly in spectral and spatial characteristics. More profound knowledge of land resources is made possible by continuously improving image radiometric and spectral properties, as demonstrated by

Landsat instruments. Since 1972, Landsat satellites have consistently provided high- resolution multispectral imagery coverage worldwide. Because of their dependability and long-established track record, they are extensively used for documenting changes in land cover and usage throughout time (Ramankutty et al., 2006). The US government's introduction of Landsat 7 in 1999 represents another technological leap.

Remote Sensing Fundamentals

Spectral resolution refers to the system's capacity to identify the size and number of wavelengths, intervals, or spectrum divisions. The resolution of an extensive range of wavelengths with comparable sizes and the identification of radiation from different parts of the spectrum are typically made possible by acceptable spectral resolution. Similar to grayscale images, color composites have low reflectivity in dark areas and high reflectivity in bright areas. But comprehension gets trickier when we blend different data bands to create fake composites (Arowolo et al., 2018) Nonetheless, this can be fixed by using statistical data and local knowledge.

When categorizing a single satellite image, the specific spectral radiance is not important, and most image-processing studies are carried out using raw DN values. However, this method has limits since the spectral characteristics of a habitat cannot be accurately represented in digital values. These values are particular to each image because they depend on elements such as the position of the sun and the weather at the time of the satellite's observation, both of which affect the viewing geometry. Converting DN values into a spectral signature with measurable units is more useful due to its ability to facilitate picture comparison (Biedemariam et al., 2022).

Image calibration is necessary when comparing scenes captured over many years or when the research region exceeds the boundaries of a single scene. The positioning of the satellite images is suitable for variations in the phase angle, sun angle, earth-sun scale, atmospheric attenuation, and atmospheric path radiance. A linear transformation is carried out utilizing radiometric control sets that reflect characteristics that do not change over time in order to calculate gains and offsets. Various criteria may be used to define changes in land cover. There is no universal approach that is effective for all types of landscapes and land cover characteristics due to the unique benefits and limitations of each.

Two main methods exist for classifying remotely sensed pictures for various purposes. The algorithm is used for supervised classification to distinguish various land cover types based on the reflection of distinct pixels. The algorithm utilizes data gathered from fieldwork and environmental expertise to categorize pixels into comparable groups using predefined sample signatures (Hasan et al., 2020).

Changes on the Earth's Surface

The Earth's surface undergoes constant and diverse transformations. Firstly, improvements can occur over several time frames. This encompasses a variety of geological phenomena, such as continental drift, as well as catastrophic catastrophes like floods. These occurrences result in a combination of periodic and ongoing modifications. Furthermore, changes can occur at many geographical scales, ranging from regional activities such as road building to global phenomena such as ocean water temperature fluctuations. It is challenging to evaluate the complexity and magnitude of changes due to their vast spatiotemporal range because they are interdependent and related on several scales (spatial and temporal). Furthermore, recognizing shifts is difficult (Khan et al., 2014).

Context of the Change Detection Procedure

Change detection is the process of recognizing changes in the condition of an item or phenomenon by monitoring it continuously (Goswami et al., 2022). Change detection has its roots in the history of remote sensing, starting with Gaspard Felix Tournachon, also known as Nadar, who captured the first aerial image in 1859. Subsequently, the evolution of change detection technology, particularly during World Wars I and II, was closely linked to military advancements and the strategic advantages offered by the temporal data provided by remote sensing. As time progressed, change detection transitioned into civilian applications, with most events in the 20th century relying on traditional analog methods and human interpretation (Théau, 2011).

The digital change detection era began in July 1972 with the launch of Landsat-1, also known as the Earth Resources Engineering Satellite. Scientists have effectively detected variations over a wide area and acquired reliable data over time by consistently gathering digital information from the earth's surface in many spectral bands. The persistent work put into this project, together with the implementation of manyadditional strategies, led to advancements in change detection techniques, as stated by Coppin et al. (2004).

Swift and accurate identification of Earth's surface features is crucial for comprehending the relationships and interplay between human activities and natural phenomena. It enables better management and utilization of resources.
In order to precisely assess the temporal consequences of the phenomenon, the change detection process typically requires the utilization of information from many periods. Data collected from space, like Thematic Mapper (TM), radar, and Advanced Very High Resolution, is often used because it has benefits like being able to collect data repeatedly, giving a complete picture, and being in a digital format that computers can quickly process (Hussain et al., 2013).

Considerations Before Implementing Change Detection

To accurately monitor natural resources to identify changes, it is crucial to consider four key elements. These tasks involve determining the occurrence of a change, quantifying its magnitude, measuring its extent, and evaluating its spatial distribution. For a successful change detection study utilizing remotely sensed data, it is important to carefully assess the remote sensor device, the surrounding conditions, and image processing methods (Reba & Seto, 2020). The ability to identify changes in remote sensing largely depends on the collected data's temporal, geographical, spectral, and radiometric resolutions. Essential environmental elements encompass soil moisture levels, air temperatures, and phenological characteristics (Chen et al., 2014). The most critical preprocessing factors for identifying changes are multitemporal picture registration and radiometric and atmospheric adjustments. The significance of accurately registering the spatial information of multi-temporal imagery is evident since any inaccuracies in registration would predominantly result in erroneous identification consequences (Chen, 2005).

To do a multitemporal quantitative picture analysis, it is necessary to convert the digital values into surface radiance or reflectance. Various devices are available for atmospheric and radiometric normalization or correction, such as the second solar spectrum satellite signal (6S) simulation, dark object removal, and proportional calibration. Nevertheless, topographic adjustment may be necessary in a research region characterized by hills or harsh terrain (Droll et al., 2005). Successful change detection analysis requires meeting the following prerequisites: (1) Recording multiple images accurately at various time points; (2) Precisely capturing images at different intervals; (3) Maintaining consistent phenological conditions in images taken at different times; (4) Acquiring spatial and spectral images that are identical whenever feasible; and (5) Conducting radiometric and atmospheric calibration or normalization between images taken at different times (Lu et al., 2004).

Different remote sensing data formats are available for use in change detection applications. The commonly utilized data sources in the past encompassed radar, aerial photographs, TM, SPOT, AVHRR, and Landsat Multi-Spectral Scanners (MSS). Nevertheless, contemporary sensors are more important, especially when choosing distant sensing data for innovative detection applications. Two examples of these sensors are the Moderate Resolution Imaging Spectroradiometer (MODIS) and the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) (Panuju et al., 2020).

For consistency in data collection, it is advisable to employ identical sensors, radiometric parameters, and spatial resolution data for photos captured on or around the same day each year to reduce the impact of external factors like sun angle, seasonal changes, and phenological fluctuations. Before selecting the optimal change detection method, it is essential to determine the trajectory of the change. Post- classification comparison thoroughly assesses improvement directions, whereas image differentiation provides information on changes or lack thereof. To achieve a research objective, it is crucial to carefully evaluate the appropriate change detection approach for detecting remotely sensed data and study regions to produce a superior quality alteration identification product (Lu et al., 2004).

Change Detection Techniques

Typically, change is identified by comparing two maps or an outdated remote sensing image with an updated map. Studying remotely sensed data may be advantageous for mapping and analyzing change detection. Natural resource management and land cover maps need to be updated. Numerous techniques for change detection have been created and applied in various contexts. Some shift identification techniques and their uses are as follows (Mushore et al., 2017)

Image Differencing

Probably the most popular algorithm for change detection is image differencing. One picture date can be subtracted from a second date accurately recorded to the first. Giardino (2011) states that image differentiation typically outperforms other techniques for detecting transformation.

This simple method is commonly used to remove captured images taken at various times, band by band and pixel by pixel. Pixel values of 0 result from no changes over time; instead, changes should result in either positive or negative values. However, accurate radiometric corrections and precise image registration for multidate images are rare. Additionally, images reveal consistent brightness differences that are not the result of changes in land cover. Identifying changes in brightness values (BV) between two dates may be difficult even after radiometric normalization and correction due to

variables like sensor variances and meteorological conditions at different periods.
The subsequent task for this approach is determining the threshold values that distinguish between changes and no changes in the generated pictures.
The standard deviation is commonly employed as a criterion for selecting reference values for thresholds. To mitigate the impact of scene and size on the distinction of outcomes, several techniques, such as standardization, histogram matching, and normalizing, are employed on multidate photos. The picture differentiation approach may be utilized for structured data, such as vegetation with multidate indices or primary components, while its primary application is for single bands (Abd El-Ghany et al., 2020).

Image Rationing

This method's simplicity and challenges are comparable to those of the picture differencing method. But its use is less common. It is a ratio of images that were taken, band by band and pixel by pixel, at different points in time. Pixel values larger or less than one is used to indicate changes. A single name would be assigned to unaltered pixels. Choosing threshold values between change and no change is the task of this technique in practice, and it is motivated by the same factors as image differentiation. This approach is also prone to picture defects and jumbled pixels. Gad and Kusky (2006) introduced a methodology to address the effects of misregistration on change detection methods. The model was evaluated using multi-temporal Thematic Mapper (TM) pictures of rapidly urbanizing landscapes using the image differentiation approach.

According to Zareie et al. (2016), the misregistration compensation approach enhances land use, safeguards characteristics at or near a pixel scale, and reduces noise from mis- registered multi-temporal data. Because of the non-normal distribution of outcomes, this method is frequently criticized for limiting the validity of threshold selection by using the standard deviation of resulting pixels. Zareie et al. (2016) described how band rationing of MSS bands 5 and 7 detected ecological changes.

Image Regression

The pixel values in the same region at two distinct times are assumed to have a linear relationship by this method. It indicates that many pixels did not change over the two years. In each spectral band, a regression function that best captures the relationship between the pixel values at two dates is determined. The areas of transition are understood to be the regression residuals. This method has the advantage of lessening the impact of radiometric heterogeneity between multidate images (i.e., environment, sunlight angle, and sensor calibration). The challenging parts are selecting an appropriate regression function and establishing cutoff points between areas with and without changes (Yang et al., 2003).

Change Vector Analysis

The approach relies on a spatial depiction of the change in spectral space. A pixel's location in n-dimensional spectral space is anticipated to shift as it moves between two dates. A vector determined by the magnitude and direction of two variables is used to depict this change. This method is applied when comparing multidimensional images. For every related band, differential images are created using change vector analysis. After that, the difference's photos are squared and applied. The magnitude of the vector to be changed can be found by taking the square root of the squared number. The difference between the positions of dates 1 and 2 is the picture magnitude, measured in the same unit as the input units (Baisantry et al., 2012).

The extent of the change indicates its magnitude, while the direction reveals the essence of the transition. One benefit of the method is that it can process multiple spectral bands simultaneously. It includes details on how to modify it as well. The most complex parts are figuring out magnitude thresholds, telling the difference between a change and nothing at all, and interpreting vector trajectory in light of the type of change. This strategy is frequently applied to transformed data using Tasseled-Cap techniques (Nordberg and Evertson, 2005).

Post-Classification

This approach is usually known as "delta classification." It is easy to understand and widely used. Two photos shot at different times are first given separate categories before being compared. Ideally, every label ought to belong to a distinct theme class. A shift matrix representing the number of pixels in each class can be used to visualize the changes between the two dates. You can use this formula to determine the modifications made in a particular class. The primary benefit of this technique is that multidate photographs are relatively unaffected by geometric and radiometric variations. On the other hand, the overall accuracy of the final result is determined by combining the accuracies of the two distinct classifications. For example, if each independent classification has an accuracy of 80 percent, the final accuracy would be 64 percent (Serra et al., 2003).

Vegetation Index Differencing

Researchers that study plants use vegetation indices, which are based on the ratio of near-infrared to red reflectance, to make the difference between the strong reflectance of plants in the near-infrared range and the absorption band (red component) of chlorophyll in the spectrum stand out more. Three often-used vegetation indicators are the Transformed Vegetative Index, the Vegetation Index for Standardized Difference, and the Vegetation Ratio Index. The normalized difference vegetation index is calculated by using reflection data from the red and near-infrared spectral bands. It pertains to the proportion of artificially produced photographic radiation. The most significant factor influencing near-infrared reflectivity in Landsat TM channel 4 is the quantity of plant structures that are readily available and contain chlorophyll (Fan et al., 2015).

A significant correlation was discovered between crown closure, leaf area index, several plant characteristics, and the normalized difference in brightness values derived from the visible and near-infrared red bands.

The Normalized Difference Vegetation Index (NDVI) is found by comparing how much the visible (20%) and near-infrared (60%) parts of the electromagnetic spectrum are reflected. These parts can be seen in Landsat channels 2 and 4 (Jiang et al., 2006; Wu et al., 2017).

Linear Transformations

This approach combines several techniques that have the same theoretical basis. The most prevalent method is the tasseled-cap transformation combined with principal component analysis (PCA). By generating fewer new components, linear transformations are frequently used to decrease the dimensionality of spectral data. The majority of the variance in the results can be explained by the first components, which are uncorrelated. When assembling multidate images into a single dataset, linear transformations are employed for change detection (Shi & Xu, 2019).

PCA mapping involves mapping areas of transformation in the final components (i.e., information specific to each of the various dates) and regions of unchanged areas in the first component (i.e., details common to multidate images). A variance/covariance matrix is typically used to compute PCA. Nonetheless, a hierarchical matrix—a correlation matrix, to be exact—is also employed. Interpreting the results of the scene-specific PCA can be challenging. The challenging steps are determining changes from the essential components and choosing boundaries between changed and unchanged areas. It is imperative to possess a firm grasp of the analysis field (Masini & Lasaponara, 2006).

There is another linear transformation: The Tasseled Cap. Nevertheless, unlike PCA, it is not dependent on the scene. Predefined vegetation spectral properties are used to determine the new component directions. Four new components are being measured and designed to increase visibility, greenness, wetness, and greed. It is frequently challenging to interpret the results, and changing the labeling is challenging. Unlike PCA, shift detection in multidate imagery requires precise atmospheric calibration of the Tasseled-Cap transition (Lein, 2011).

Direct Multidate Classification

Another name for this technique is "composite analysis." Examples of combined analyses are "Classification of spectral-temporal changes" and "Spectral-temporal analysis." "The investigation of shifts in spectral patterns" or "Multidate clustering." Before classification, multidate images are merged into a single dataset. Compared to non-changeable areas, change areas are more likely to have distinct classes and separate statistics (Xu et al., 2018). The system has only one classification process, which can be used unattended or tracked. Conversely, this process typically yields many corresponding groups, spectral variations within each image, and transient variations across images. Substantial results information in the field of study is necessary for the often difficult-to-interpret findings. To reduce the complexity of the data or the coupling of spectral and temporal changes, one can employ combined techniques such as component analysis or Bayesian classifiers (Volpi et al., 2013).

Multitemporal Spectral Mixture Analysis

The idea behind spectral mixture analysis is that you can figure out a pixel's reflectance value by adding up the values of its parts (called endmembers) and giving each one a weight based on how much of it there is. In this instance, linear mixing of such elements is assumed. This technique can be used for change detection and extracting sub-pixel information by conducting independent analysis. One benefit of this approach is that it produces consistent and dependable outcomes. The challenge with this strategy is finding the right end members (Hemissi et al., 2013)

Combined Approaches

The most popular techniques for identifying transformation are those previously mentioned. Although they can be used independently, they are typically used in tandem with or in addition to other image-processing methods to achieve more consistent results. You have several different options. Examples include combining vegetation indices with image differentiation, post-classification, image enhancement, direct multi-date classification, primary component analysis, multi-temporal spectral analysis and image differentiation, shift vector analysis, and principal component analysis (Kesikoğlu et al., 2013).

Chapter Three

Methodology

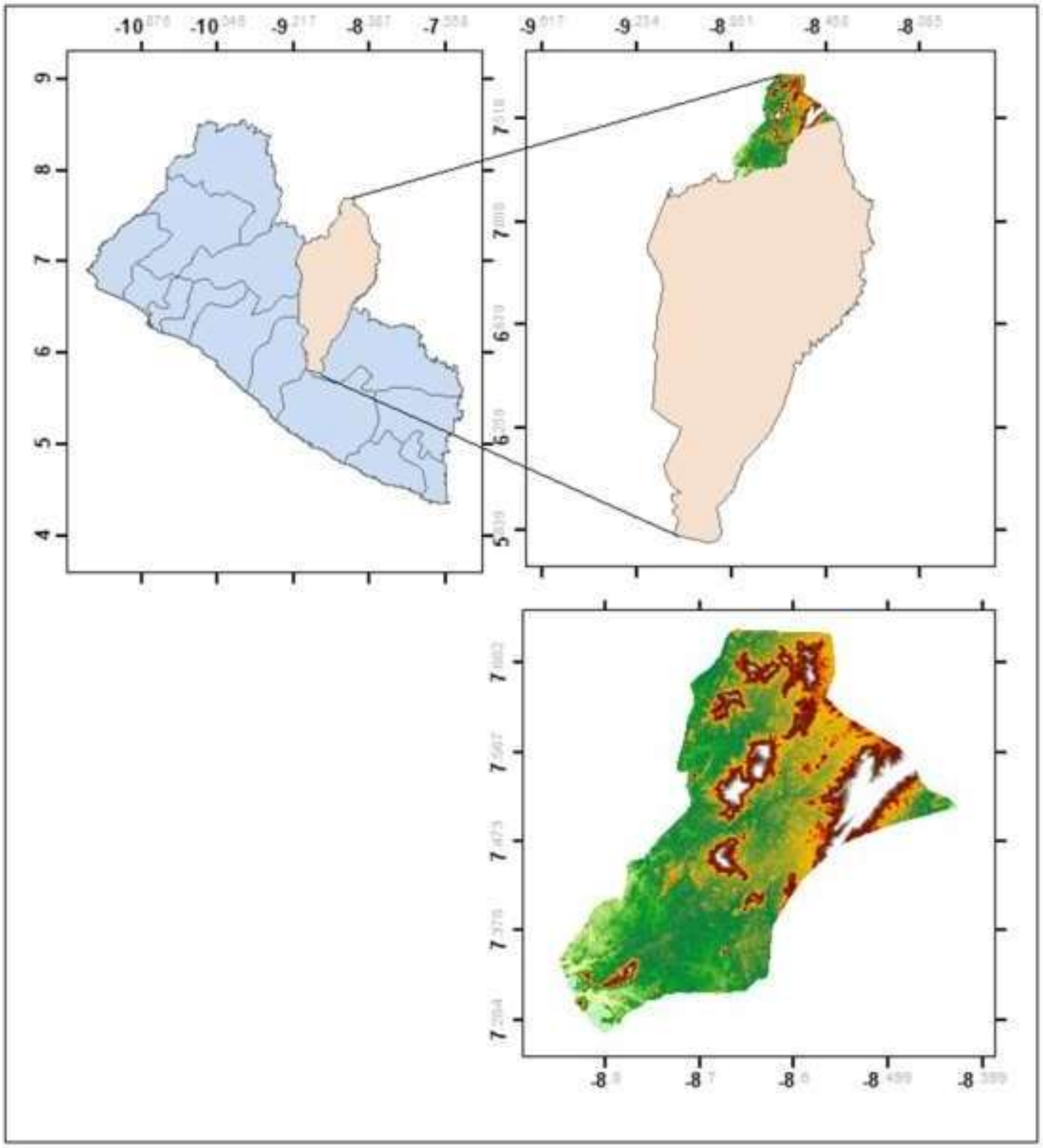
Description of the Study Area

The research was conducted in Sanniquelleh-Mehn District, Nimba County, in Northern Liberia, where the distraction of forests is high due to extensive mining and other human activities. The study area is selected owing to its fragility and susceptibility to forest fragmentation and biodiversity loss. It occupies an area of 946 km^2 and is divided into three major communities: Goah, Sehyi, and Yermein. It lies around 500 m above sea level altitude and is located at 7.44001º latitude and -8.6827º longitude. Sanniquelleh-Mehn has a tropical climate with an average annual temperature of 25 °C and an average yearly rainfall of 13 millimeters. The rainfall is spread out between May and October. The cold climate makes the area a desirable destination for some tourists in the country. Not only for its vast natural forest but also for its ragged topography and high mountains, it is considered the best tourist destination in the country.

Its natural forest is massive, and it is home to the most protected national forest in the country. In addition, it is home to 40% of the remaining upper Guinean rainforest. Tree logging is playing a major role in the country's economy. In addition to wood products, the forest provides food and other raw materials for domestic and industrial use. However, a large quantity of the original forest in the study area has been degraded due to the high involvement of iron ore mining, tree logging, and other uncontrollable human interferences. However, it is still home to some primary and secondary forests, mainly in its northern part. The soils of the district mainly include latosols, lithosols, and regosols. Most land use in Sanniquelleh-Mehn is linked to agriculture; cassava, rice, and maize are cultivated primarily in the area. Consequently, the land use in Sanniquelleh-Mehn has witnessed dramatic changes, with forests decreasing at a higher rate while construction land expands gradually. In summary, this study in Sanniquelleh-Mehn is significant for sustainable forest management practices.

Figure 1.

Map of Liberia, Nimba County, and the Study Area



Data Acquisition

The research used images from Landsat-5 Thematic Mapper, Landsat-7 Enhanced Thematic Mapper (ETM+), and Landsat-9 Operational Land Imager 2 (OLI-2). The USGS provided satellite pictures for the years 2002, 2012, and 2022. Satellite images for January were collected from the WRS2 with a path/row of 199/55, as this month is free from cloud and haze effects. The Landsat-5 TM and Landsat-7 ETM+

satellites are equipped with seven spectral bands, each with a spatial resolution of 30 meters. The Landsat-9 OLI-2 contains nine spectral bands and a spatial resolution of 30 meters. The scene measures about 170 km north-south and 183 km east-west.

Remotely Sensed Imagery and Pre-Processing

The Landsat-7 ETM+ and Landsat-9 OLI-2 images are geo-referenced (Universal Transverse Mercator-UTM, WGS84) by the General Directorate of Mapping using the nearest neighbor resemblance process. Radiometric corrections such as haze and noise reduction were executed for better outputs.

Land Use Classification Scheme

A categorization method was developed to define the land use groupings precisely and prepare the land use map using satellite images. Using ground control points and satellite imagery from 2002, 2012, and 2022, we identified the primary categories of land use: vegetation, built-up areas, degraded land (bare land), water bodies, and agriculture. A temporal analysis methodology was employed to comprehend better the alterations that transpired inside the designated time intervals. In addition, the changes in land use throughout the given years were determined by analyzing Landsat photos using a mix of remote sensing methodologies and GIS techniques.

Post Processing

Image Classification and Accuracy Assessment

After developing a classification system, the most often employed approach for picture classification, maximum likelihood classification, was utilized. An extensive evaluation utilizing observational satellite image analysis using Google Earth images was carried out before selecting training samples. For each class, a minimum of 30 training samples were collected. Supervised classification techniques classify each pixel into a cluster by comparing its spectral signature to computer-generated cluster signatures. The computer evaluates the natural variation and establishes cluster identification for Landsat-7 ETM+ picture categorization without needing a prior understanding of the elements in the scene.

Supervised classifications require a high level of knowledge about the scene region to enable the machine to identify specific content categories, commonly called training classes. Regions containing relevant content within a scene are visually marked and saved for utilization in the supervised classification procedure. The supervised classification approach groups two photographs of different dates individually. The ERDAS Imagine 2014 software was employed to construct a supervised classification system with a maximum likelihood algorithm. Ground control point (GCP) data from each land use was obtained for the accuracy assessment. The supervised classification method was used in this study.

Field Survey and Accuracy Assessment

A field survey was undertaken for authentication and precision ground verification. Accomplishing this task was made possible with the assistance of GPS, which covers all the central land uses available. The Kappa statistic was used to determine accuracy. The Kappa statistic is a tool for comparing observed accuracy to predicted accuracy (random chance). The accuracy was determined by analyzing the diagonal components of the error matrix and considering the change agreement, which considers the off-diagonal parts of the error matrices. This refers to the degree of agreement achieved by eliminating the agreement that would be anticipated to happen by random chance. The error matrices were utilized to compute the aggregate precision, consumer and producer accuracies, and the Kappa statistic.

Chapter Four

Findings and Discussion

Patterns of Land Use in the Study Area

Land use maps were created for 2002, 2012, and 2022 using data collected from Landsat 5 (TM), Landsat 7 (ETM+), and Landsat 9 (OLI2) satellites. The research region was analyzed using supervised classification, which found five distinct land use categories. The land use categories resulting from iron ore and other mining operations encompass built-up areas, barren land, vegetation, water bodies, and agricultural areas.

Accuracy Assessment

Tables 1–3 display the error matrix, together with the kappa coefficient, producer's accuracy, and user's accuracy. The number was calculated by dividing the accurately classified data from the error matrix by the overall accuracy. In 2002, the classification accuracy reached 91.79%, and the Kappa statistics obtained a value of 0.8940. The classification accuracy and Kappa numbers 2012 were 94.52% and 0.9302, respectively. In 2022, the total classification accuracy reached 95.42%, with Kappa statistics measuring 0.9416.

Figure 2.

Land Use Map of Sanniquelleh-Mehn District, 2002

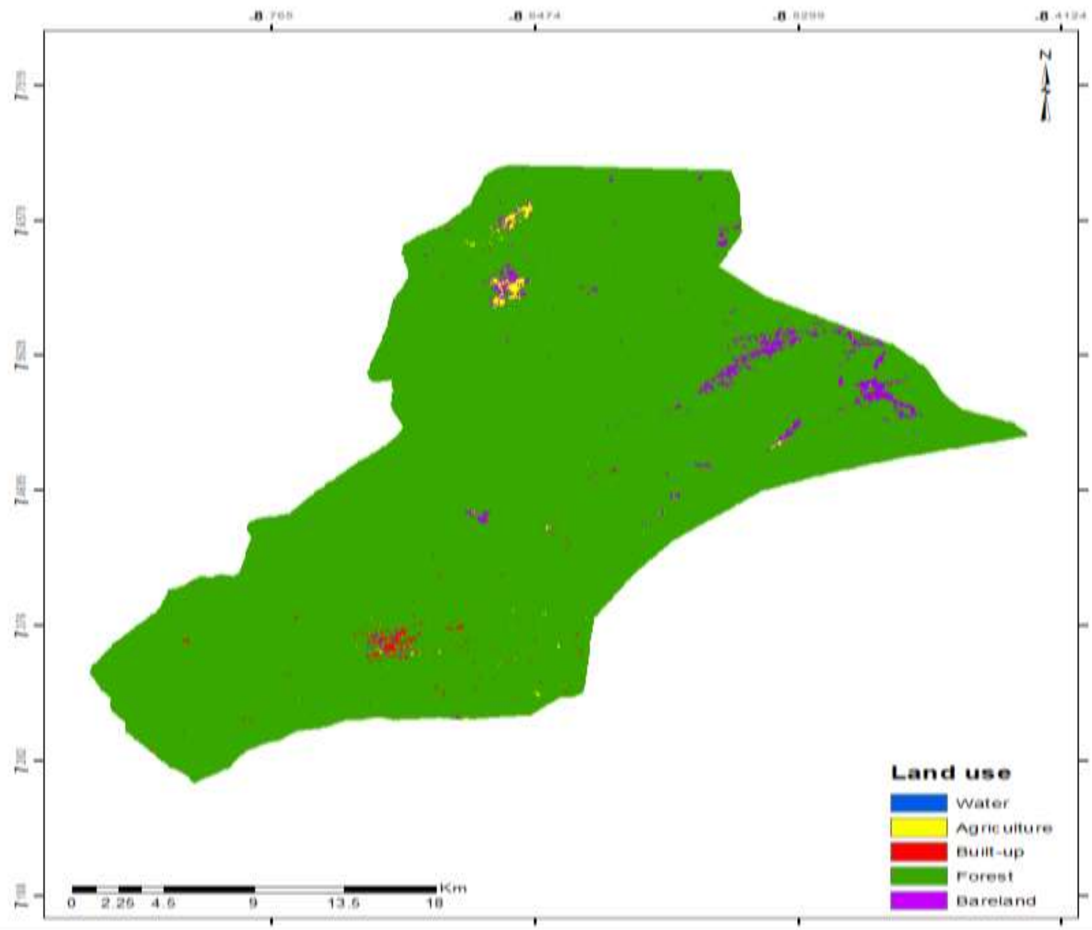


Table 1.

Accuracy Assessment Using Error Matrix and Kappa Statistics for the Year 2002

Class name	Reference totals	Classified totals	Number correct	Producers accuracy	Users' accuracy
Water	63	34	34	53.97	100
Agriculture	65	64	64	98.46	100
Built-up	62	62	61	98.39	98.39
Forest	134	133	133	99.25	100
Bare land	66	97	66	100	68.04
Total	390	390	358		

Table 1 (Continued).

Overall Classification Accuracy = 91.79%

Overall Kappa Statistics = 0.8940

Figure 3**.**

Land Use Map of Sanniquelleh-Mehn District, 2012

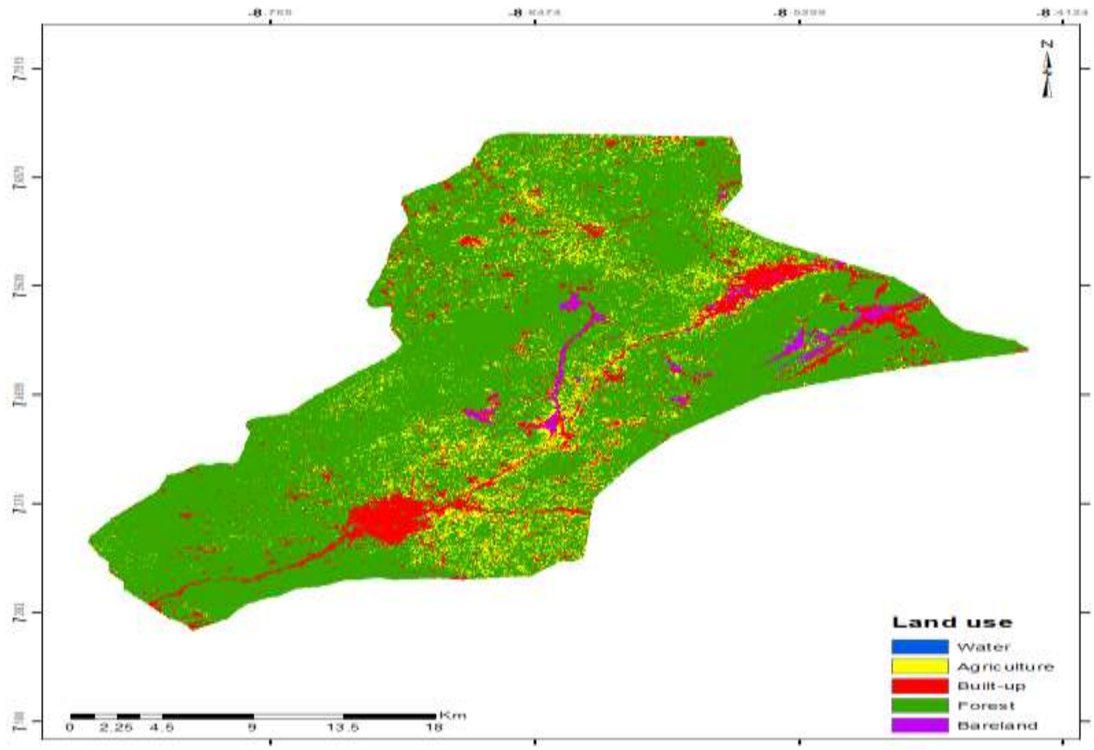


Table 2**.**

Accuracy Assessment Using Error Matrix and Kappa Statistics for the Year 2012

Class name	Reference totals	Classified totals	Number correct	Producers accuracy	Users' accuracy
Water	87	57	57	65.52	100
Agriculture	82	82	82	100	100
Built-up	105	105	105	100	100
Forest	127	156	127	100	81.41
Bare land	146	147	146	100	99.32

Table 2
(Continued).

Total	547	547	517

Overall Classification Accuracy = 94.52%

Overall Kappa Statistics = 0.9302

Figure 4.

Land Use Map of Sanniquelleh-Mehn District, 2022

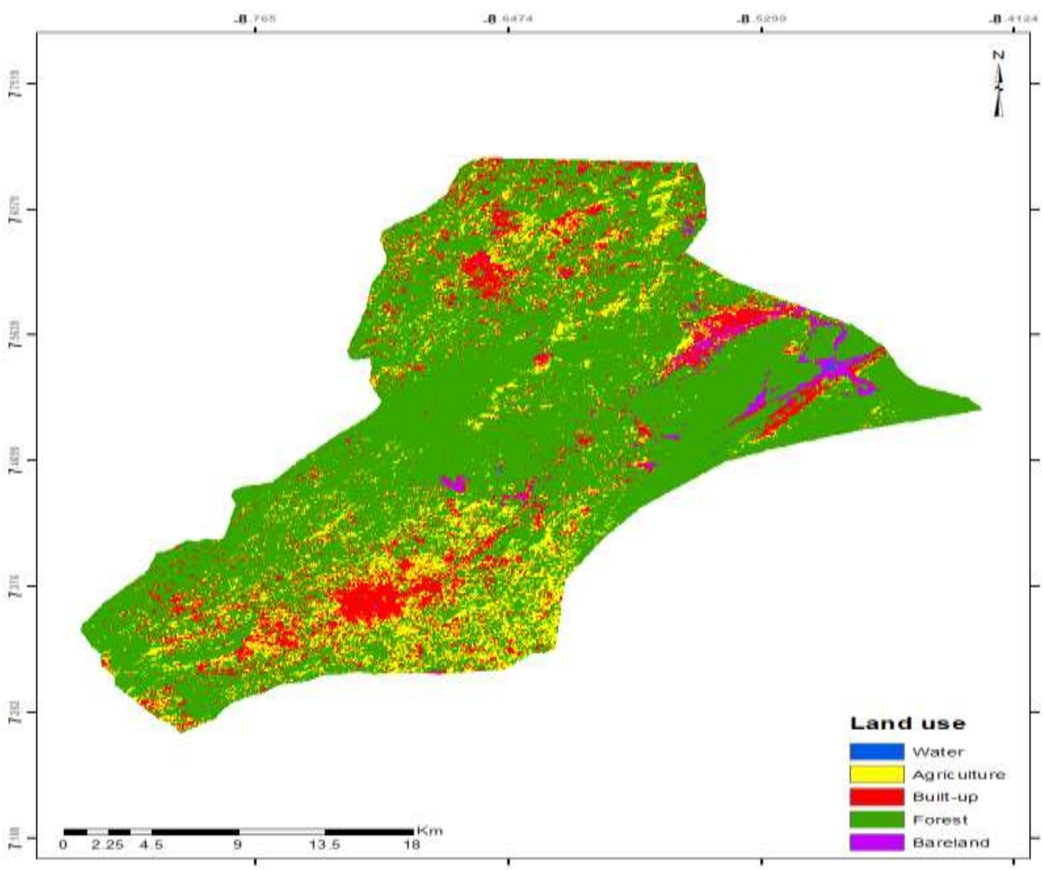


Table 3.

Accuracy Assessment Using Error Matrix and Kappa Statistics for the Year 2022

Class name	Reference totals	Classified totals	Number correct	Producers accuracy	Users' accuracy
Water	63	43	43	68	100
Agriculture	75	75	75	100	100
Built-up	123	123	123	100	100

Table 3
(Continued)

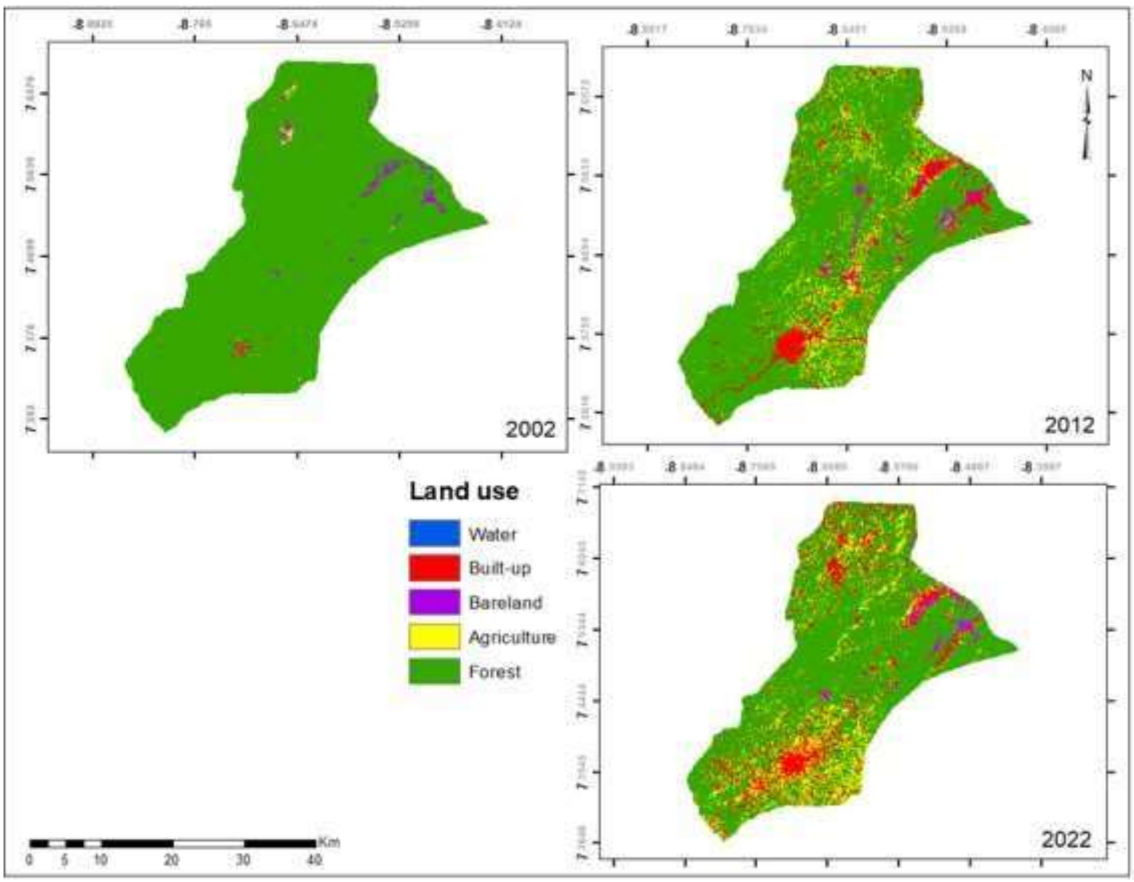
Forest	111	111	111	100	100
Bare land	65	85	65	100	76
Total	437	437	417		

Overall Classification Accuracy = 95.42%

Overall Kappa Statistics = 0.941

Figure 5**.**

A Summary Land Use Map of Sanniquelleh-Mehn District from 2002-2022



Land Use Change Analysis

The Sanniquelleh-Mehn district underwent analysis to determine the amount of land each land use class covers and the rate at which land use changes. The data in Table 4 shows that in 2002 forests were the most prevalent land use category, covering 97.85% of the district's total area (964 km2). Agriculture (0.3%), built-up areas (0.33%), and bare ground (1.5%) came after this. Forest coverage saw a decrease from 925.73 km2 (97.85%) in 2002 to 763.94 km2 (80.75%) in 2012 and further dropped to 681.97 km2 (72.09%) in 2022 (Table 4). In contrast, agricultural and built-up areas saw a significant increase, resulting in the depletion of forest resources. The area dedicated to agriculture expanded from 2.87 km2 (0.30%) in 2002 to 82.63 km2 (8.7%) in 2012 and further rose to 127.56 km2 (13.48%) in 2022 (Table 4).

In the same vein, the size of developed areas grew from 3.16 km2 (0.33%) in 2002 to 86.88 km2 (9.17%) and 119.75 km2 (12.66%) in 2012 and 2022, respectively (Table 4).

The comprehensive (20-year) change detection investigation results indicate that the waterbody had a 0.03% rise, whereas the built-up area saw a 12.32% growth. Similarly, the area of undeveloped land had a 0.23% rise, while agricultural land saw a significant increase of 13.18%. The expansion of these land uses came at the detriment of forest resources, which experienced a decrease of 25.77%. Table 4 includes a comprehensive review of the changes detected in each 10-year interval from 2002 to 2022.

Table 4.

The Extent of Land Use Change Extracted from Landsat Images 2002-2022

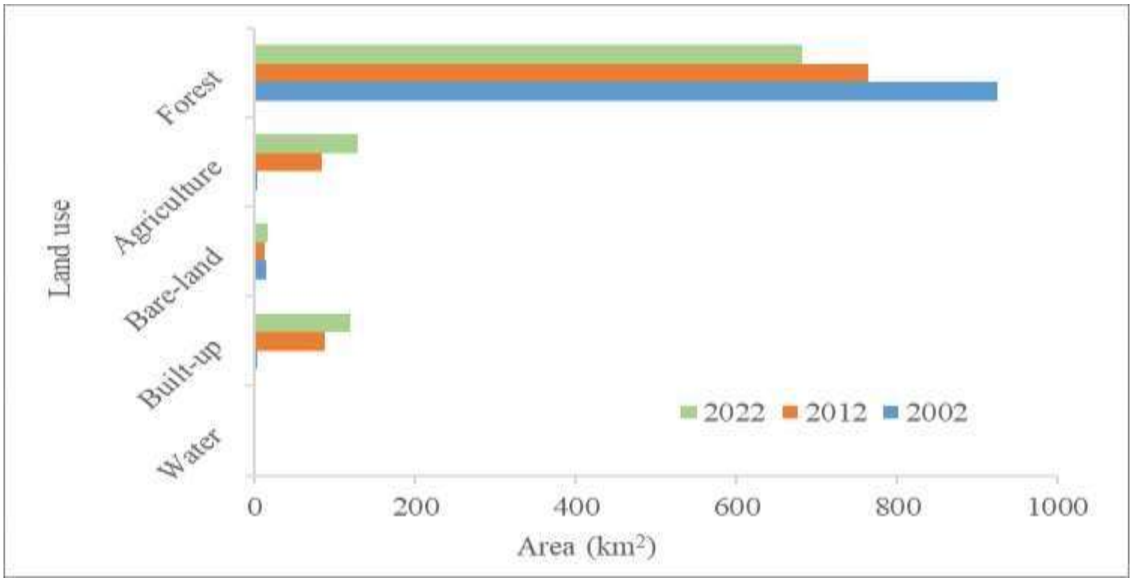
	Year						% change in land use		
	2002		2012		2022				
Land use	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%	2002-2012	2012-2022	2002-2022
Water	0.10	0.01	0.32	0.03	0.49	0.04	0.02	0.01	0.03
Built-up	3.16	0.33	86.88	9.17	119.75	12.66	8.84	3.49	12.32
Bare land	14.19	1.50	12.37	1.31	16.38	1.73	-0.19	0.42	0.23

Table 4 (Continued).

Agriculture	2.87	0.30	82.63	8.73	127.56	13.48	8.43	4.75	13.18
Forest	925.73	97.85	763.94	80.75	681.97	72.09	-17.10	-8.66	-25.77
Total	946								

Figure 6.

Land Use Change Comparisons from 2002 to 2022



Land Use Change Matrix

Tables 5 and 6 present the land use change matrix findings for the first period (2002– 2012) and the second (2012–2022). During the first phase (2002–2012), a substantial portion of forested land, measuring 75.30 km2, was transformed into agricultural land, built-up areas, and bare land, measuring 74.49 km2 and 9.12 km2, respectively.

Conversely, during the second phase (2012–2022), 32.87 km2 were transformed into built-up areas, 4 km2 became bare ground, and 44 km2 were changed from forest to agricultural land.

Table 5.

Land Use Change Matrix Between 2002 and 2012

Land use	Water	Built-up	Bare land	Agriculture	Forest	G. Total (2012)
Water	0.01	0.01	0.01	0.01	0.04	0.08
Built-up		2.30	0.02	0.10	0.44	2.86
Bare land		8.10	2.84	0.53	2.46	13.94
Agriculture		0.49	0.18	0.45	1.67	2.79
Forest	0.29	74.49	9.12	75.30	766.98	926.17
G.Total (2002)	0.30	85.39	12.19	76.38	771.59	945.85

Table 6.

Land Use Change Matrix Between 2012 and 2022

Land use	Water	Built-up	Bare land	Agriculture	Forest	G.Total (2022)
Water	0.04	0.01	0.19	0.01	0.17	0.42
Built-up	0.00	33.97	2.51	12.48	67.41	116.37
Forest	0.25	27.53	4.61	50.65	604.74	687.78
Agriculture		14.49	0.32	12.74	97.75	125.30
Bare land	0.00	9.40	4.55	0.51	1.50	15.96
G.Total (2012)	0.30	85.40	12.19	76.39	771.56	945.83

Chapter Five

Discussion

Pattern of Land Use in the Study Area

Intricate interactions between people and their natural surroundings influence land-use change patterns. Landsat 5 (TM), Landsat 7 (ETM+), and Landsat 9 (OLI-2) satellite data were used to analyze land use patterns in the specified area from 2002 to 2022. The images underwent pre-processing to provide high-quality outcomes. The next step was to carry out a supervised classification and, after that, assess its accuracy. In 2002, the overall classification accuracy was 91.79%, with Kappa statistics of 0.8940. An accuracy rate of 94.52% and a Kappa value of 0.9302 were achieved in 2012. The overall classification accuracy for 2022 was 95.42%, with a Kappa score of 0.9416.

The findings indicate that the research region may be classified into five main land use categories: agricultural, forest/vegetation, built-up areas, bare ground, and water bodies (Figures 2-4). Ismail & Jusoff (2008) categorized the kappa statistic's classification result as terrible, exemplary, or outstanding based on its value.

Specifically, a value less than 0.4 was considered wrong, between 0.4 and 0.7 was considered good, and greater than 0.75 was considered excellent. It indicates that the supplied values were precise, and the categorization fell within a satisfactory range. The kappa coefficients for each land use category consistently fell within the good range after the assessment, indicating a high degree of agreement between the ground reference data and the classification map. The main land uses in the study area are listed below.

Forest/Vegetation

In 2002, the study area was predominantly covered by vegetation, constituting approximately 925.73 km² (97.85%) of the total area (Table 4). Vegetation, the area's most extensive land use type, experienced a significant reduction in the following years, with a decrease of 17.10% in the first period and 8.66% in the second. The data shows a shift from forest to many different land uses, including agricultural, urban, and barren terrain. The adjustments are shown in the conversion matrix found in Tables 5 and 6.

There has been a significant decline, especially from 2002 to 2012, with a fall rate of 17.10% in quantity. The increase in population and extension of built-up areas in Sanniquelleh-Mehn may be related to the phenomenon of agricultural expansion, which is caused by a significant migration of people from other regions of the nation. The reduction in forest cover in the area may be mainly ascribed to the establishment of ArcelorMittal, the largest and most historic iron ore mining firm in the territory, which was introduced in 2005. Over the past 18 years, this enterprise has engaged in iron ore mining activities inside the study region, destroying several hectares of forest land and causing significant habitat degradation. However, the historical connection between forest resources and economic growth is undeniable and uncontrollable in the study area due to its strategic location. It is located at the main intersection of Liberia and the Republic of Guinea, making the area a hotspot for forest destruction due to the expansion of agriculture and urbanization.

Agriculture

Nimba County, where the study area is situated, has historically been an agricultural surplus county. Although it may not be as vibrant today as it once was due to urbanization, the economic crisis, and climatic barriers, agriculture remains an integral part of Sanniquelleh-Mehn. This category of land includes mainly farmlands. The classified map confirmed a significant expansion of agricultural land from forest land. Agriculture, as predicted, covered a large portion of the land in Sanniquelleh- Mehn's in 2022, accounting for 127.56 km2 (13.48%). This continuously increased from 2.87 km2 in 2002 to 82.63 km2 in 2012 and 127.56 km2 in 2022. Throughout the study period, a 13.18% increase was observed (from 2002–2022).

Built-Up Area

Although the bulk of the transition occurred between 2002 and 2012, the proportion of built-up area rose more than quadrupled as much (from 3.16% to 12.66%) between 2002 and 2022 (Table 4). The rapid increase in demand for plots of land for settlements, which was directly related to the town's continuous growth in population due to the influx of people, maybe the reason for the constant shift of forest land into the built-up territory. Consequently, this study's built-up area or settlement had a net positive increment.

The results of this research align with those from earlier studies conducted in Liberia, such as those by Osuman (2019) and Olatunji & Charles (2020). Research was conducted to evaluate the effects of changes in land use on plant resources in the peri- urban region of Monrovia and adjacent areas of Liberia. Over a 34-year period (1986– 2020), the total vegetation loss was 32.88%, with an annual rate of 0.96%. Many of these studies found that settlement areas had expanded during their research. As a result, population growth may be the reason for extending settlement areas to other territories.

Bare Land

At a mine site, the areas designated for waste rock disposal and open pits are the ones that cause the most physical disturbances. Mining buildings that take up a tiny amount of the area disturbed after the mine closes, like shops, offices, and mills, are typically salvaged or demolished. Waste rock disposal areas and open pits are the primary visual and aesthetic effects of mining in the study area. The areas designated for disposing of waste rock produced by underground mining are usually relatively small, ranging from a few to tens of acres. Usually, these areas are found close to the openings in the underground workings. Open pit mining has more severe visual and physical effects than underground mining because it disturbs larger areas. As seen in Figure 7, the iron ore mining activities are jeopardizing the future of the forest resources in the area. The images below are very few and show how mining affects the forest.


Google Earth

Figure7.

Evidence from Google Earth Images (A and B) Showing Bare Land Due to Iron Ore Mining in Sanniquelleh-Mehn District, Location: (Lat: 7.452978°, Long: -8.672270°) and (Lat: 7.537445°, Long: -8.494817°) for Images A and B, respectively.

Waterbody

The waterbodies received the least investigation, representing a smaller proportion in the study region. The proportion of land area occupied by water has increased from 0.01% in 2002 to 0.04% in 2022 (Table 4), mainly due to mining operations that generate extensive and exposed excavations, subsequently transforming into bodies of water. The development of tiny hydroelectric dams was also attributed to another factor. Contrary to urban or farming regions, the expansion of the waterbody was negligible.

Land Use Change Matrix

It is essential to determine the kind and number of changes and the particular type of land use impacted for change detection (Agidew & Singh, 2017). According to Wondie et al. (2011), overlay analysis compares images from the study years' pixel-by-pixel. The segment (land use change matrix) illustrates both the change in direction and the consistent land use form. Urbanization is an inevitable process necessary for the progress and development of civilization. Over the years, Yekepa, a town in the Sanniquelleh-Mehn district, has experienced a significant increase in the number of residents from both Liberia and Guinea. The rise in population and the corresponding need for food production mainly account for this. Consequently, the expansion of agricultural areas and urbanization have had a significant and lasting effect on forest resources. In addition to these critical changes, it emphasizes the advantages of adopting land-use strategic planning.

The results revealed a diverse range of alterations in land utilization throughout the past two decades (2002– 2022). The data indicates a growing inclination towards converting land plots for residential and farming use. In contrast, a considerable portion of forest land remains undeveloped, mostly due to iron ore mining operations. Furthermore, the importance of the waterbody increases due to its potential for hydropower generation or irrigation. In contrast, a substantial portion of forested areas have been depleted, resulting in fragmentation. Hence, the consequences of such a transformation might exemplify the need for land-use planning in dynamic contexts such as this, where rural agricultural land is gradually integrated into urban areas. The findings align with other studies, indicating that urban areas had the highest annual growth rate of 6.43%, while water bodies demonstrated the lowest yearly growth rate of 0.54% (Getu and Bhat, 2021). In research carried out in Harbin, Heilongjiang province, China, Wang et al. (2022) found that the overall changes in forest land were negative (indicating loss) between 1990 and 2015. However, built-up areas and agricultural lands saw positive net changes over the same period.

Chapter Six

Conclusion and Recommendation

Conclusion

The utilization of remote sensing and GIS techniques to measure the effects of land-use alterations on the fragmentation of forests over time has proven to be highly useful in the current study. Over the past two decades, there has been an increase in all land uses except for forest cover. The categories encompass agricultural areas, built-up areas, bare ground, and water bodies. The studied region exhibits a persistent upward trajectory of urban sprawl, leading to the continuous development of built-up areas, the conversion of agricultural land to accommodate the rising population, and the presence of bare ground resulting from extensive mining operations. The forest resources have significantly declined over the past two decades (2002–2022), primarily due to agricultural activities, urban development, and bare land. This decline is evident in a loss of 25.77%, with forest coverage decreasing from 97.85% in 2002 to 72.09% in 2022.

These three prominent lands use predominantly drove this transformation or conversion.

Recommendation

Based on the overall analysis of the study, it is expected that future land use changes in the study area will continue at a concerning pace. Hence, further research is required to grasp the forest dynamics of the region comprehensively. Although image preprocessing was employed in this investigation, the quality of satellite pictures in relation to cloud impacts remains unknown, potentially compromising the precision of the findings. Furthermore, forthcoming investigations should primarily concentrate on identifying the factors contributing to land use changes in the study region. Conducting socio-ecological surveys and utilizing different remote sensing (RS) images from various years can help achieve this. Additionally, it is recommended that the precision of RS image categorization algorithms be enhanced.

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Appendices

Appendix A

Classification Accuracy Assessment Report

Classification Accuracy Assessment Report For 2002

			Reference Data

Water	Built-up	Bareland	Agricultur
34	0	0	0
0	64	0	0
0	0	61	1
0	0	0	133
0	0	0	0
0	0	0	0
0	0	0	0
29	1	1	0
63	65	62	134
			Reference Data

			Vegetation
0	0	0	0.00%
0	0	0	0.00%
0	0	0	0
0	0	0	0
0	0	0	66
0	0	0	66

----- End of Error Matrix -----

Reference Totals	Classified Totals	Number Correct	Producers Accuracy
63	34	34	53.97%
65	64	64	98.46%
62	62	61	98.39%
134	133	133	99.25%
66	97	66	100.00%
390	390	358	

Overall Classification Accuracy = 91.79%

----- End of Accuracy Totals -----

KAPPA (K^) STATISTICS

Overall Kappa Statistics = 0.8940

Conditional Kappa for each Category.

Kappa
1
1
0.9808
1
0.6153

----- End of Kappa Statistics -----

Classification Accuracy Assessment Report For 2012

Classified Data	Unclassifi			Reference Data -------------- Water
---------------	----------	----------	----------	----------
Water	0	0	0	57
Agriculture	0	0	0	0
Built-up	0	0	0	0
Forest	0	0	0	29
	0	0	0	0
Bareland	0	0	0	1
Column Total	0	0	0	87

Classified Data	Agricultur	Built-up	Forest	Reference Data --------------
---------------	----------	----------	----------	----------
Water	0	0	0	0
Agriculture	82	0	0	0
Built-up	0	105	0	0
Forest	0	0	127	0
	0	0	0	0
Bareland	0	0	0	0
Column Total	82	105	127	0

Reference Data

Classified Data	Bareland	Row Total
Water	0	57
Agriculture	0	82
Built-up	0	105
Forest	0	156
	0	0
Bareland	146	147
Column Total	146	547

----- End of Error Matrix -----

ACCURACY
TOTALS

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
----------	----------	----------	-------	---------	-----
Water	87	57	57	65.52	100.00%
Agriculture	82	82	82	100.00%	100.00%
Built-up	105	105	105	100.00%	100.00%
Forest	127	156	127	100.00%	81.41%
Bareland	146	147	146	100.00%	99.32%
Totals	547	547	517		

Overall Classification Accuracy = 94.52%

----- End of Accuracy Totals -----

KAPPA (K^) STATISTICS

Overall Kappa Statistics = 0.9302

Conditional Kappa for each Category.

Class Name	Kappa
Water	1
Agriculture	1
Built-up	1
Forest	0.7579
	0
Bareland	0.9907

----- End of Kappa Statistics -----

Classification Accuracy Assessment Report For 2022

ERROR MATRIX

Reference Data

Classified Data	Unclassifi			
Water	0	0	0	0
Agriculture	0	0	0	0
Built-up	0	0	0	0
Bareland	0	0	0	0
Vegetation	0	0	0	0
Column Total	0	0	0	0

Reference Data

Classified Data	Water	Agricultur		
Water	43	0	0	0
Agriculture	0	75	0	0
Built-up	0	0	0	0
Bareland	0	0	0	0
Vegetation	20	0	0	0
Column Total	63	75	0	0

Reference Data

Classified Data	Built-up		Bareland	Vegetation
Water	0	0	0	0
Agriculture	0	0	0	0
Built-up	123	0	0	0
	0	0	0	0
Bareland	0	0	111	0
Vegetation	0	0	0	65
Column Total	123	0	111	65

----- End of Error Matrix -----

ACCURACY
TOTALS

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Water	63	43	43	68.25%	100.00%
Agriculture	75	75	75	100.00%	100.00%
Built-up	123	123	123	100.00%	100.00%
Bareland	111	111	111	100.00%	100.00%
Vegetation	65	85	65	100.00%	76.47%
Totals	437	437	417		

Overall Classification Accuracy = 95.42%

----- End of Accuracy Totals -----

KAPPA (K^) STATISTICS

-

Overall Kappa Statistics = 0.9416

Conditional Kappa for each Category.

Class Name	Kappa
Water	1
Agriculture	1
Built-up	1
Bareland	1
Vegetation	0.7236

----- End of Kappa Statistics -----

Appendix C

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