DEDAN KIMATHI UNIVERSITY OF TECHNOLOGY

INSTITUTE OF GEOMATICS, GIS & REMOTE SENSING (IGGReS)

SPATIAL-TEMPORAL ASSESSMENT OF EFFECTS OF BIOMASS ON CARBON SEQUESTRATION USING MACHINE LEARNING.

A CASE STUDY OF KEDOWA LONDIANI FOREST

BY

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DECLARATION

I, Ezra Cheruiyot, declare that this project is my original work. To the best of my knowledge, the work presented here has a degree in any other Institution of Higher Learning.

Ezra Cheruiyot 15/04/2024

Sign Date

This project has been submitted for examination with our university supervisor(s) approval.

Dr. Kuria Thiongo

04.06.2024

Sign Date

DEDICATION

First, I dedicate to the Almighty God for His love, grace, and favour for guiding me through the difficulties in this life. I also dedicate this project to my loving parents Mr. and Mrs. Chesor, and my entire family for their support in all spheres and their coaching regarding achieving my goals, without forgetting my friends who came through with all sorts of advice.

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Table of Contents

LIST OF TABLES

LIST OF FIGURES

ABBREVIATIONS AND ACRONYMS

AGB- Above-ground biomass

AVI – Advanced Vegetation Index

ANN- Artificial Neural Network

BSI – Bare Soil Index

GEE- Google Earth Engine

GFW- Global Forest Watch

GV- Green Vegetation

Mg/Ha-Milligrams per hectare

NIR – Near Infrared

NDFI- Normalized Difference Fraction Index

NPV- Non-Photosynthetic Vegetation

PCA –Principal Component Analysis

PCA –Principal Component Analysis

RF- Random Forest

SI – Shadow Index

SOC-Soil Organic Carbon

SVM- Support Vector Machine

SWIR- Short Wave Infrared

UNFCC- United Nations framework convention Centre

ABSTRACT

Globally, it has statistically been evidenced that there is forest loss, especially in third-world countries, unlike developed countries. Worldwide, empirical data consistently reveals forest depletion, particularly in developing nations, divergent from trends observed in more economically advanced countries. Deforestation emerges as a prominent factor influencing the reduction of forest cover. Within this context, the Kenyan government has taken a proactive stance, spearheading initiatives aimed at attaining a 10% forest cover nationwide, Kenya positions itself as a critical player in the global effort to combat deforestation and promote environmental sustainability. A case Study of Londiani Kedowa Forest aims to evaluate the effects of biomass on carbon sequestration within the specified ecological setting. The overall objective is to conduct a comprehensive spatial temporal assessment of the influence of biomass on carbon sequestration within the specified ecological setting the specific objectives to be addressed under this study are the following; identifying factors influencing biomass variation, evaluating the spatial distribution of biomass across ecosystems and assessing the effects of biomass on carbon sequestration. Google Earth Engine (GEE) stands as a cornerstone in the methodology of this study, facilitating an intricate analysis of biomass and carbon dynamics within Londiani Kedowa Forest. Leveraging GEE's support for machine learning algorithms, particularly the Random Forest classifier, the study employs historical data to establish relationships between remotely sensed features and ground-based measurements of biomass and carbon. This integration enables accurate predictions and classifications across the entire study area. GEE provides tools for calculating spectral indices, such as NDVI and EVI, offering insights into vegetation health and density key indicators of biomass, also climatic factors were accessed which proved to have a direct impact on biomass. The results indicated a fluctuation in biomass levels, with a notable increase in 2021 followed by relatively stable or slightly decreasing values in subsequent years. This was mainly due to the land use changes for example deforestation and natural disturbances such as wildfire with an average of 152Mg/ha of biomass which consequently had a direct impact on carbon sequestration in terms of carbon content there was a strong correlation between biomass and carbon content and that it means that the high values of biomass mean a significant higher carbon content in the study area. By conducting vegetation analysis through GEE, the study quantifies the impact of biomass on carbon sequestration. The spatial mapping and visualization capabilities of GEE are harnessed to create comprehensive maps, aiding in the identification of biomass hotspots and areas with high carbon sequestration potential across Londiani Kedowa Forest

CHAPTER 1: INTRODUCTION

1.1 Background

Forests play a key role in the environment and human well-being, providing ecosystem services such as carbon sequestration, biodiversity conservation, and climate regulation (IPCC, 2019). Human activities such as deforestation, degradation, fragmentation, and non-sustainable forest management threaten these ecosystems. To preserve these important resources, accurate and up-to-date information on forest structure, such as height, volume, and biomass, is essential for effective forest management policies. Forests are an indispensable component of the Earth's ecosystems (DA Perry, R Oren, SC Hart – 2008), contributing to climate regulation, biodiversity preservation, and the well-being of human societies (von Gadow, K. (2008). They are critical for carbon sequestration, oxygen production, and providing habitat for countless plant and animal species. However, forests worldwide are under constant threat due to a range of human activities, including deforestation (Allen, J. C., & Barnes, D. F. (1985), illegal logging, infrastructural development, and agricultural expansion. These activities result in forest degradation, leading to a loss of biodiversity (Barnosky et al., 2011, Turvey, 2009), altered climate patterns, and reduced ecosystem services. Londiani Forest was gazetted as a forest reserve in 1932 via gazette legal notice No. 44 of 1932 by the then-British colonial government. The forest station was under colonial foresters and the local community had to follow orders that were given by the foresters regarding management of the station. The colonial foresters maintained a command-and-control approach and controlled access and utilization of the forest resources. It was during this period that indigenous trees were replaced with exotic plantations through what came to be termed as compensatory forest practices (According to Londiani Forest Participatory Planning Act 2018-2022). While above-ground biomass includes both live and dead plant material, most of the recent research effort on biomass estimation has focussed on the ‘live’ component (live trees) due to the prominence of this component. Accurate estimates of biomass are a prerequisite for a better understanding of the impacts of deforestation and environmental degradation on climate change. Hence, mapping aboveground biomass (AGB) is an essential task for monitoring carbon stocks and dynamics across tropical African landscapes (Pan et al., 2011). Measuring AGB is also required for implementing payments for ecosystem services schemes and the United Nations Reducing Emissions from Deforestation and Forest Degradation (REDD+) mechanism (Remote

Sensing of Environment vol. 178(2016) pp: 158-171). The Kedowa Londiani Forest is a significant ecological region, is no exception to these challenges. According to Kenya Forest Service has embraced the Participatory Forest Management 2018-2022 (PFM) approach in managing its forest resources countrywide. This forest has faced increasing pressures from land-use changes, illegal logging, and deforestation. These activities threaten its integrity and the services it provides to local communities, including water regulation, agricultural support, and cultural heritage. Forest degradation causes include forest fires, climate change, pests and diseases, air pollution, forest fragmentation, soil erosion, and sedimentation. It is mainly brought as a result of anthropogenic and environmental changes which can eliminate vegetation cover, including forest cover. Assessing the state of the Kedowa Londiani Forest, specifically in terms of biomass and carbon stocks, is vital for effective conservation and sustainable management (Peres, C. A. (2011). Traditional methods of forest assessment are time-consuming, costly, and often lack the temporal and spatial resolution required to monitor changes accurately. To address these limitations, this project employs machine learning techniques and remote sensing technology to conduct a comprehensive analysis of the biomass and carbon sequestration trends during the period from 2019 to 2022 (Samadder, S. R. (2022). By applying machine learning models to this wealth of data, the project can offer precise and up-to-date insights into the forest's condition, identify areas of concern, and support the development of conservation and restoration strategies and bridge the gap between technological advancements and forest conservation (De Britez, R. M. (2006), it strives to provide actionable data for policymakers, conservationists, and local communities to work together to protect this vital ecosystem and ensure its continued contributions to the planet's well-being.

1.2 Problem statement.

The Kedowa Londiani forest in Kenya is a critical ecosystem with far-reaching ecological, social, and economic significance, faces multiple challenges associated with various forms of disturbances and forest degradation (Gerding, V. (2018). These disturbances include excessive extraction of indigenous tree species such as podo, olive, cedar, etc. (Oriaso, S. O. (2018), road construction within and near the forest, quarrying activities, and human encroachment in neighboring areas. It is essential to emphasize that not all disturbances result in forest degradation; therefore, a comprehensive approach is needed to classify these disturbances based on their impact on the forest ecosystem (Brewer, J. S. (2017). Many studies on the forest, especially the forest cover, have been done using LIDAR data obtained (Mambimba, A. N.

(2022), from an airplane in a particular study area. This method is a time-consuming and expensive method to discover and monitor the forest density or crown. The GEDI data was launched in late 2018 (J.R. Kellner. 2022) and started collecting data in April 2019 this has helped by providing comprehensive information on vertical forest structures, including canopy height, canopy cover, leaf area index, and topography. This dataset offers an unprecedented opportunity to comprehensively assess and quantify disturbances and forest degradation in the Kedowa Londiani Southern Mau Forest, allowing for a more precise understanding of its health and vitality. Faced with these problems, the country has been committed since 2011 to the International Mechanism for Reducing Emissions from Deforestation and Forest Degradation (REDD+) implemented in the United Nations Framework Convention on Climate Change (UNFCCC). This mechanism should enable developing countries to benefit from financial compensation for their efforts of reducing deforestation, and forest degradation and increase forest carbon stocks and forest conservation (UNFCCC, 2009). Assessments of forest carbon stocks are therefore critical for countries planning to contribute to climate change mitigation impacts through their forest activities (Picard et al., 2012). One of the strategic options is to increase carbon stocks and also to meet the high demand for fuel for domestic energy.

1.3 General objective

To conduct a comprehensive spatial-temporal assessment of biomass effects on carbon sequestration using machine learning techniques.

1.4 Specific Objective

1. To identify factors affecting biomass variation

2. To estimate biomass distribution in the study area

3. To assess the effects of biomass on carbon sequestration

1.5 Research questions

1. What factors contribute to variations in biomass within the study area?
2. How biomass is spatially distributed across different ecosystems within the study region?
3. What is the total carbon stock in the entire study area and how do they correlate with biomass estimate?

1.6 Justification for the Study.

It is of great benefit in tracking and the management of forest cover to combat climate change. However, some of the driving approaches to assessing the forest canopy have been examined in the research. The study results will provide forest management and enacting policies necessary for the preservation and conservation of forests. It contributes to biodiversity preservation, ensuring the survival of unique species, and sustains ecosystem services critical for local communities. Additionally, it aids in mitigating climate change and guides informed decision-making for balanced land use. Through local engagement and technological innovation, the project empowers communities and inspires advancements in environmental science. Its impact extends globally by aligning with international conservation efforts, and it ensures a sustainable future for generations to come.

1.7 Scope of work.

The study focused on the Londiani Kedowa forest. It aimed to assess the effects of biomass trends and carbon stocks using machine learning techniques change for 20192023. The scope encompasses data acquisition, pre-processing, feature extraction, classification, and accuracy assessment. The findings of this research are expected to provide valuable insights for land management, environmental planning, and policy formulation in Kedowa Londiani Forest and contribute to the advancement of remote sensing applications in biomass and carbon monitoring.

CHAPTER 2: LITERATURE REVIEW.

2.1 Overview

This chapter gives an insight into how the other studies have been regarding the effects of biomass on carbon sequestration. In this literature review, most of the previous research was carried out mainly to investigate change detection and classification changes over time with the utilization of Sentinel data.

2.2 Theoretical review.

It is a section showing a comprehensive analysis of existing theories and conceptual Frameworks on forest studies (Plakhotnik, M. S. (2009).

2.2.1 Factors Affecting Biomass Variation

Forests are dynamic ecosystems influenced by a myriad of factors that contribute to variations in biomass (Jiang, M. (2015). Understanding these factors is essential for the success of initiatives aimed at sustainable forest management and effective carbon sequestration (Allen, R. B. (2012). The literature presents a comprehensive exploration of the diverse elements shaping biomass dynamics within forested environments.

2.2.1.1 Climate Factors

(a) Rainfall

It is a critical determinant of vegetation growth and biomass accumulation. Adequate rainfall provides the necessary moisture for photosynthesis, promoting plant growth and contributing to increased biomass (Jiang, L. (2013). Conversely, prolonged periods of drought can lead to water stress, negatively impacting biomass production. The use of Climate Hazards Group Infrared Precipitation with Station data (CHIRPS, 2015) in assessing rainfall patterns is a significant advancement. CHIRPS provides high-resolution precipitation data derived from satellite observations, offering detailed insights into spatial and temporal variations. This technology enables a more accurate understanding of how rainfall, as a climate factor, influences biomass dynamics (Hyvönen, R. (2011).

(b) Temperature

Temperature plays a crucial role in influencing the rate of physiological processes in plants. Optimal temperatures support photosynthesis and metabolic activities, contributing to biomass accumulation. Extreme temperatures, whether too high or too low, can constrain plant growth and impact overall biomass production. Remote sensing technologies, including satellite-based sensors, capture temperature data across landscapes. These data, combined with machine learning models, allow for the assessment of temperature variations and their influence on biomass (Leuzinger, S. (2017). Understanding temperature fluctuations is integral to predicting potential shifts in biomass patterns.

(c) Humidity

Humidity levels influence plant water relations, affecting transpiration rates and water availability for vegetation (Hoeber et al., 2014). Optimal humidity conditions support efficient photosynthesis and plant growth, contributing to biomass accumulation. Low humidity, especially in arid regions, can lead to water stress and reduced biomass productivity. Humidity data, when integrated into biomass assessments, provides insights into the moisture conditions experienced by vegetation (Hyvönen, R. (2011). This information is particularly valuable in regions where water availability strongly influences biomass dynamics. Incorporating humidity data derived from various sources, including ground-based sensors and satellite observations, enhances the precision of climate-related factors in biomass modeling.

2.2.1.2 Human factors affecting biomass distribution

(a) Deforestation

Deforestation, marked by the direct removal of trees, not only results in an immediate loss of biomass but also disrupts the delicate balance of carbon sequestration within ecosystems. Extensive deforestation, as evidenced by studies such as (Hansen et al. 2013), is closely linked to a significant reduction in biomass, emphasizing the direct correlation between human induced land-use changes and biomass loss. The alteration of landscape connectivity due to deforestation-induced fragmentation, as highlighted by (Turner (1996), further influences the distribution and arrangement of biomass, with isolated forest patches exhibiting distinct patterns. Beyond biomass, deforestation contributes to biodiversity loss, impacting the structure and composition of ecosystems, as noted in studies by (Laurance et al. (2011). Remote sensing technologies, coupled with machine learning models, play a crucial role in identifying deforestation hotspots, providing valuable insights into patterns that necessitate targeted conservation efforts, as acknowledged by Achard et al. (2002).To address the challenges posed by deforestation, the literature, exemplified by (Chazdon et al. (2009), emphasizes the importance of implementing sustainable practices, such as reforestation and responsible logging, to restore biomass levels. Integrating these insights into the spatial-temporal assessment of biomass using machine learning is imperative for a comprehensive understanding of the intricate dynamics between human activities, deforestation, and biomass variations.

(b) Agricultural practices

The region predominantly engages in agricultural activities, notably maize farming, mixed farming through the shamba system, and subsistence farming, particularly near the forest. The cultivation of maize, a staple crop, contributes to the alteration of land use patterns, impacting the overall structure and composition of the forested areas this is according to the report by (Forest Management Agreement (FMA) produced by Londiani Forest Management Act of 2018 – 2022). The expansion of agricultural areas, driven by the cultivation of maize and the shamba system, involves clearing land for farming purposes. This land-use change can lead to localized deforestation and modifications in biomass distribution, as observed in various studies related to land-use changes and their effects on ecosystems. Mixed farming practices, characterized by a combination of crop cultivation and livestock rearing within the shamba system (Gitonga, J. M. (2005), introduce additional dynamics to biomass variations. The interaction between agricultural activities and the forest environment may lead to localized changes in biomass density, influenced by factors such as nutrient cycling, soil structure, and land cover alterations. Subsistence farming practices, often practiced near the forest, contribute to the intricate interplay between human activities and biomass dynamics (Aboud, A. A. (2015)). The proximity of subsistence farms to the forest boundary may result in edge effects, where the influence of agriculture extends into the forested area, affecting vegetation composition and potentially leading to changes in biomass distribution. Studies such as those by Foley et al. (2005) emphasize the global impact of agricultural expansion on land cover changes and carbon dynamics. Understanding the complex relationships between agriculture and biomass dynamics in this specific context is essential for informing conservation efforts and achieving a harmonious balance between human activities and environmental sustainability in the study area.

(c) Fuelwood harvesting

Local populations near protected tropical forests rely on them as their primary energy source. For wood fuel. Although the effects of fuelwood extraction in humid forests are seldom researched, they can alter the forest's formation, functioning, and biodiversity. About 1.1 and

2.0 m3 of fuelwood were gathered annually per person on average. Other operations exploiting wood fuel from the forest included charcoal production and unlawful Commercial fuelwood collection. Firewood collection had an impact on the amount of dead Wood up to at least 1000 m inside the park's boundaries (Hirschmugl et al., 2017). The park's dead timber was more quickly consumed in areas with higher human densities. However, those who planted more trees on their property regarded old-growth forests less as a source of wood and charcoal and thought that land from Outside Park was significant. According to the findings, this might further deteriorate the forest, which would be bad for conservation efforts as well as for those who rely on it. The development of more sustainable management strategies, including alternative fuel sources, can be aided by research into the local area's natural and cultural settings and perspectives on costs and advantages (Chen et al., 2021).

(d) Timber logging

According to estimates, an estimated 380,000 hectares of forest are cleared each year to meet the need for wood. Building homes and other constructions is only one of the many applications for this wood. Additionally, logging is responsible for 60% of the destruction of forests (M. Condé et al., 2019). Timber logging can lead to changes in the spatial arrangement of biomass, affecting both the quantity and quality of vegetation. The extraction of large, mature trees, which often store substantial amounts of carbon, directly influences the carbon sequestration capacity of the forest. This impact is particularly relevant in the context of the carbon sequestration-focused project, where the goal is to assess how biomass variations affect carbon sequestration.

2.2.1.3 Natural factors

(a) Forest fires

Globally, a million hectares of forest are destroyed by fire each year (M. Condé et al., 2019). Although fires occur, damaged forests are more susceptible than healthy forests. It included highly logged rainforests, forests on peat soils, or areas where long-term Suppression of forest fires has allowed an abnormal build-up of vegetation, increasing the fire's intensity. Its industry, weather, and ecosystem all suffer from the loss. Typically, forest burning is an everyday activity, particularly in Central and South America, to convert vast tracts of moist tropical forest to rangeland and farmland, as well as for hunting purposes and negligent combustion.2020 Additionally, they can influence sustainable human livelihoods, wildlife, health, biomass production, and outputs. A fire in an established forest may burn the rainforest, killing young trees and ground flora but sparing the older trees due to their thick bark's protective layer (M. Condé et al., 2019). The surviving forest can then regrow fast in such situations. However, under arid circumstances, where there is a lot of plant waste as fuel on the ground, the flames can quickly spread over a vast region because they are hot enough to reach the tree canopy the net effect of this is the decrease in forest cover and also biomass and carbon content.

(b) Climate change

Climate change could alter the intensity and frequency of forest disruptions such as insect outbreaks, invading species, wildfires, and storms. These disturbances can affect tree species' distribution, reduce the productivity of forests, and cause stable species to abandon their ecosystem or expand their distribution (2011). Within those situations, the new plant species that settle the region give rise to a new kind of forest. Temperatures, rainfall, and atmospheric carbon (IV) oxide level variations might impact the growth and spread of forests.

(c) Pest and diseases

The ecosystem of a forest includes natural pests and illnesses. Although natural pests and diseases often have modest population or infection levels, they may spread rapidly. By dying trees and other plants and increasing their susceptibility to ignition and severe wildfire, forest pests and diseases impact forest fuels and wildfire. Following California's multi-year drought in 2010, tree mortality caused by bark beetles has risen (van Lierop et al., 2015). This trend is particularly noticeable in the Southern Sierra Nevada, where the federal government manages and controls most of the afflicted forests.

(d) Soils

The availability of nutrients, a critical determinant of vegetation health, plays a significant role in shaping biomass patterns. Vitousek et al. (2010) emphasize the crucial link between soil nutrient content—particularly nitrogen, phosphorus, and potassium—and the density of biomass. Soils rich in these nutrients foster robust plant growth, contributing to higher biomass density. Additionally, soil texture, a key factor discussed by Lal (2015), contributes to biomass distribution by influencing water retention and drainage. Well-structured soils with balanced textures create favorable conditions for root development, supporting healthier vegetation and, consequently, higher biomass. Soil moisture, as highlighted by Sanaullah et al. (2012), emerges as another crucial factor, impacting plant water uptake and influencing the spatial variability of vegetation across landscapes. Furthermore, soil pH, as investigated by Jobbágy and Jackson (2001), introduces yet another layer to the soil-biomass relationship. Deviations from optimal pH levels can influence plant health, thereby altering the distribution patterns of biomass.

(e) Topography

Elevation emerges as a pivotal factor influencing the spatial distribution of biomass within Londiani Kedowa Forest, a region situated at an altitude of 2356 meters above sea level (asl). The variation in elevation across landscapes introduces distinct environmental conditions that significantly impact vegetation growth and, consequently, biomass density. Studies conducted by Körner (2007), highlight the relationship between elevation and ecological characteristics, including biomass distribution. As elevation increases, temperature and atmospheric pressure often decrease, leading to changes in vegetation composition and structure. In higher elevations, factors like decreased oxygen availability and lower temperatures can influence the types of plant species that thrive, ultimately shaping the overall biomass distribution. Elevation-driven changes in microclimates also contribute to variations in moisture levels and nutrient availability, influencing the spatial arrangement of biomass.

2.2.1.4 Factors affecting carbon sequestration

Environmental factors

Warmer temperatures can enhance plant growth and photosynthesis rates, but extreme temperatures can stress plants. Optimal temperatures promote higher photosynthetic efficiency, while extreme heat can lead to increased respiration and reduced carbon storage (Waring & Running, 2007). Increased precipitation can enhance plant growth and carbon uptake, while droughts can reduce productivity and lead to tree mortality, reducing carbon sequestration. Consistent moisture availability supports higher rates of photosynthesis and biomass accumulation (Piao et al., 2009). Sunlight is essential for photosynthesis. Areas with higher light availability generally support more biomass. Light influences the photosynthetic capacity of plants, impacting their growth rates and carbon storage potential (Gower, 2003).Different soils have varying capacities to store organic carbon. Clay soils tend to hold more organic carbon compared to sandy soils due to their higher cation exchange capacity and surface area (Six et al., 2002). Nutrient-rich soils support higher plant productivity, leading to greater carbon sequestration. Essential nutrients like nitrogen and phosphorus are critical for plant growth and biomass accumulation (Jobbágy & Jackson, 2000). Steeper slopes may experience more erosion, reducing soil carbon storage. Elevation can also influence temperature and precipitation patterns, affecting vegetation growth. Topographical variations can create microclimates that influence vegetation types and carbon dynamics (Baldocchi et al., 2000)

Anthropogenic factors

Clearing forests for agriculture or urban development reduces carbon storage, while planting trees increases it. Deforestation leads to immediate carbon emissions, whereas afforestation and reforestation can enhance long-term carbon sequestration (Canadell & Raupach, 2008). Sustainable farming practices, such as agroforestry and no-till farming, can enhance soil carbon storage. Practices that minimize soil disturbance and integrate trees into agricultural systems improve carbon sequestration (Lal, 2004). Replacing natural landscapes with urban infrastructure reduces the area available for carbon sequestration. Urban development often leads to habitat loss and decreased carbon storage capacity (Seto et al., 2012).Moreover events like wildfires, storms, and pest outbreaks can release stored carbon and affect ecosystem productivity. Disturbances can create heterogeneity in carbon storage across landscapes (Turner, 2010).Additionally protected areas and reforestation projects help maintain and increase carbon stocks. Conservation strategies that prevent land conversion and promote natural regeneration enhance carbon sequestration (Chazdon, 2008).

Biological factors

Denser vegetation cover generally correlates with higher carbon sequestration. Dense forests with multiple canopy layers can store large amounts of carbon both above and below ground (Brown, 2002).In terms of species diversity the ecosystems with higher biodiversity tend to be more resilient and productive, enhancing carbon sequestration. Diverse plant communities can utilize resources more efficiently and provide greater carbon storage (Tilman et al., 2001).Mature forests have accumulated more biomass over time, but young, rapidly growing forests can sequester carbon more quickly. Young forests exhibit high growth rates and carbon uptake during their early successional stages (Luyssaert et al., 2008).In terms of tree species different tree species have varying capacities for carbon storage. Some species grow faster and sequester more carbon than others. For example, fast-growing species like Eucalyptus can sequester significant amounts of carbon quickly (Kirschbaum, 1999).

2.3 BIOMASS

Refers to the total mass of living or once-living organisms in a given area or ecosystem. It encompasses a diverse range of organic materials derived from plants, animals, and microorganisms. Biomass is a renewable and sustainable energy resource, as it is composed of biological matter that can be utilized for various purposes, including energy production (Himmel, M. E. (2012). Globally, almost 50% of the wood harvested from forests is used to generate energy, especially for cooking and heating services. Of the total wood fuel used for cooking, 17% is converted to charcoal with the production of charcoal expected to rise (van Dam, 2017). Worth noting is that the informal charcoal sector predominantly creates income opportunities for over 40 million people. Biomass energy provides 68% of Kenya's national energy requirements and it is expected to remain the main source of energy for the foreseeable future. In 2000, Kenya was reported to use 34.3 million tons of biomass for fuel of which 15.1 million tons was in the form of fuelwood while 16.5 million tons was wood for charcoal processed in kilns with only 10% efficiency. Up to 43% of the national consumption was from sustainable supplies while 57% was from unsustainable supplies. Of Kenya's total land area of 57.6 million hectares, only 6% (3,456,000) is forest cover and is estimated to be decreasing at the rate of 52,000 hectares (0.09%) per year. In 1980, 94% of all the wood harvested in the country was used for wood fuel, 4% for poles, and 2% for timber. By 1997, the proportions were estimated to be 90% wood fuel, 5% for industrial feedstock, and another 5% for poles and posts. These proportions were projected to remain the same in the year 2000 (Mugo, F., & Gathui, T. (2010). Although biomass is a renewable resource, the high rate of its extraction and inefficient utilization renders it non-renewable, a trend that needs to be reversed. However, recently, the demand for solid biomass has grown such that it cannot be met by what is being supplied. It is currently estimated that Kenya has a wood fuel demand of 41.7 million m^3 vis-a-vis a potential supply of 31.4 million m^3.

2.3.1 Methods of Estimating Biomass

Above-ground biomass can be measured or estimated both destructively and non-destructively. In the destructive method ((Fayolle et al., 2013; Gibbs et al., 2007; Goodman et al., 2014), sometimes also known as the harvest method, the trees are actually cut down and weighed. Sometimes a selected sample of trees are harvested and estimations for the whole population are based on these, especially where there is uniformity in tree size, for example a pine plantation (Ecol. Manag. 2009). The destructive method of biomass estimation is limited to a small area due to the destructive nature, time, expense and labour involved. It is also not suitable where there may be threatened flora and fauna. The non-destructive methods include the estimation based on allometric equations or through remote imagery. Allometric equations have been developed through the use of tree dimensions such as diameter at breast height (dbh) and tree height, however these are not very useful in heterogenous forests. Allometric equations are most useful in uniform forests or plantations with similar aged stands (Xiao, C. W., & Ceulemans, R. (2004).

2.3.2 The scale of current biomass uses in different forms

(a) Firewood and charcoal

Firewood remains a primary and widespread form of biomass use globally, particularly in developing regions (Ma, H. O. (2018). The scale of firewood use is significant, driven by its accessibility and affordability for households with limited access to alternative energy sources. Charcoal is a more concentrated and energy-dense form of biomass compared to raw firewood. Its popularity is notable in both urban and rural settings, where it is often used for cooking and heating purposes. It is currently estimated that Kenya has a wood fuel demand of 41.7 million m^3 vis-a-vis a potential supply of 31.4 million m^3 ((Ma, H. O. (2018). Globally, almost 50% of the wood harvested from forests is used to generate energy, especially for cooking and heating services. Of the total wood fuel used for cooking, 17% is converted to charcoal with the production of charcoal expected to rise (van Dam, 2017). Worth noting is that the informal charcoal sector predominantly creates income opportunities for over 40 million people, with A bigger proportion of the charcoal consumed in Kenya being produced in arid and semi-arid lands (ASALs), which covers more than 70% of the land mass in the country with the Mau ecosystem, Ukambani region, and the coastal region being the major charcoal production zones. In the year 2000, fuelwood supplied 89% of rural energy with a per capita annual consumption of 741 kg and 7% of urban household energy with a per capita annual consumption of 691 kg. Charcoal on the other hand was reported to supply 82% of urban household energy with a per capita annual consumption of 152 kg, while for rural households, it contributed 34% with a per capita consumption of 156 kg. As for the case of fuelwood, restaurants and kiosks consumed the highest estimated at 0.43 million tonnes per year. This reflects the importance of fuelwood and charcoal in supplying energy and creating employment. There is a huge demand for wood fuel in the county (Kericho). This is mainly for KTDA /Private and multinational tea factories and households. There is a good opportunity for the farmers to market their tree products and improve their livelihood. However, the factories have also accelerated the rate of deforestation because they also buy wood from fruit trees and indigenous trees for wood fuel. Farmers are also practicing agroforestry targeting this readily available market. Moreover, the rate of urbanization and economic growth in SSA has resulted in a marked shift in the consumption of charcoal and firewood. The increasing demand for charcoal is directly attributed to population growth in several cities. It is projected that the demand for biomass energy will rise by 40% by 2040 in SSA (Smith et al 2019). 75% of growth in urban areas within SSA is expected to take place in cities that have a population of fewer than 1 million people with the transformation of big villages into secondary urban centres.

(b) Wood waste and Agricultural products

Wood biomass is a cornerstone of bioenergy, with applications ranging from traditional uses, such as cooking and heating, to modern biofuel production. This energy source includes timber off-cuts and wood rejects, wood shavings, and sawdust from wood used in construction and other industrial purposes. The wood by-product is often used at the factory for steam generation and where it is not used on site, households may collect it free or purchase it at a small fee The total demand for biomass fuel is 34.3 million tons with the demand for charcoal accounting for 16.5million tons and 15.1 million tons for firewood (Ndegwa et al 2020). However, recently, the demand for solid biomass has grown such that it cannot be met by what is being supplied. It is currently estimated that Kenya has a wood fuel demand of 41.7 million m^3 visa-vis a potential supply of 31.4 million m^3. The national percentage of households using wood waste is low at 2.5% with higher use being in urban areas at 3.7% as compared to rural areas at 2.1%. This indicates a drop in the use of wood wastes from 5.1% in 1980. This is because wood waste has become scarcer and considerably more expensive for most people. Major uses for wood waste are cooking (96%), water heating (60%), lighting (8%), home business (6%), and other industrial purposes with the most common type of wood waste being off-cuts (64%) and sawdust/shavings (34%). Across agro ecological zones, consumption is highest in the medium zone (3%) followed by the high zone (2.7%) while the low agro ecological potential zone has the least (0.2%). This is possibly a reflection of availability i.e. more tree plantations and sawmills occur in the environments with higher production potential. Field and Campbell (2011) highlight the significance of utilizing agricultural residues for bioenergy, reducing reliance on fossil fuels. Most biomass used today is home-grown energy. Wood logs, chips, bark, and sawdust account for about 44 percent of biomass energy. But any organic matter can produce biomass energy. Other biomass sources can include agricultural waste products like fruit pits and corncobs. Wood and wood waste are used to generate electricity. Much of the electricity is used by the industries making the waste; it is not distributed by utilities, it is a process called cogeneration. Paper mills and saw mills use much of their waste products to generate steam and electricity for their use. However, since they use so much energy, they need to buy additional electricity from utilities.

(c) Solid waste

Burning trash turns waste into a usable form of energy. One ton (2,000 pounds) of garbage contains about as much heat energy as 500 pounds of coal. Garbage is not all biomass; perhaps half of its energy content comes from plastics, which are made from petroleum and natural gas. Power plants that burn garbage for energy are called waste-to-energy plants. These plants generate electricity much as coal-red plants do, except that combustible garbage—not coal—is the fuel used for their boilers. Allesina et al. (2010) explore the potential of solid waste biomass in generating renewable energy, mitigating the environmental impact of landfill disposal. Innovative technologies, such as anaerobic digestion and incineration, contribute to harnessing energy from solid waste while minimizing its environmental footprint.

2.3.3 Existing models for assessing Biomass

Random Forest (RF) (Guo, W. (2016), a popular ensemble learning algorithm, proves advantageous in handling the complexity of relationships within the data. Its application often involves integrating remote sensing data, such as LiDAR and satellite imagery, to estimate biomass variations across ecosystems. Support Vector Machines (SVM) offer an alternative approach, excelling in capturing non-linear relationships. Utilizing features like vegetation indices and climate data, SVM can provide accurate biomass estimates (Schaepman, M. E. (2007). Artificial Neural Networks (ANN) stand out for their ability to learn intricate patterns, making them suitable for modeling biomass using diverse datasets, including vegetation indices and topographic information (Yang, Y. (2017). Gradient Boosting Machines (GBM) contribute to biomass estimation by sequentially building multiple learners, enhancing predictive accuracy, and robustness. Hybrid models (Wang, K. (2016), combining the strengths of Random Forest and Support Vector Machines, offer a comprehensive solution, leveraging the robustness of RF and the non-linear capturing capabilities of SVM. These hybrid models are adept at integrating LiDAR, spectral indices, and climate variables for more accurate biomass predictions. With the advancement of AI methods, machine learning offers a fresh approach to modeling forest growth, with the benefits of no distribution restrictions, deep information extraction from the data, and high accuracy. Solutions in forest growth and yield remain pale compared to those in other fields (Uzhinskiy, 2022).

(a) Allometric models and Equation

Allometric equations are relations that link biomass with one or two independent variables such as diameter and height (Lotfi, 2008), depicting the empirical relationships between tree attributes like diameter at breast height (DBH) or height and biomass or carbon content. These equations, developed from field data through regression analyses, come in single-variable or multi-variable forms and may be region-specific or tailored to tree species (Fayad, I. (2023). They play pivotal roles in forest inventory, carbon accounting, and climate change mitigation efforts by providing non-destructive ways to estimate biomass and carbon stocks, although they require accurate field data and may not capture fine-scale variations in biomass distribution or short-term changes (Calders et al., 2022; Demol et al., 2022; Disney et al., 2019; Liang et al., 2016).

2.3.4 Existing machine learning algorithms models for biomass estimation

(a) Random forest algorithm

A random forest is a machine-learning technique for solving classification and regression problems. It uses ensemble learning to integrate several classifiers to solve complex problems. The (random forest) algorithm chooses the outcome based on the predictions made by the decision trees. It provides predictions by averaging or averaging out the outcomes from various trends. As there are many trees, the accuracy of the outcome improves. With a random forest, its decision tree algorithm's drawbacks are removed. Accuracy is increased, and the dataset fitting problem is decreased. Without many package settings, it generates projections. There are numerous possible decision trees in a random forest algorithm (Ramdani & Furqon, 2022). A "forest" is created by the random forest algorithm and trained using bagging or bootstrap aggregation. Bagging, an ensembles meta-algorithm, improves the accuracy of machine learning methods. Decision trees are the fundamental building blocks of a random forest algorithm. A decision tree is a decision support technique with a structure like a tree. Decision trees and the operation of random forest techniques will be covered. (Uzhinskiy, 2022). A decision tree's three components are decision nodes, leaf nodes, and the root node. A decision tree method divides a training dataset into branches and then further divides those branches. This procedure continues until it reaches a branch node. Additional separating the tree structure is not achievable. Information theory can shed additional light on how decision trees work. Entropy and information acquisition constitute the basis of a decision tree. Reviewing these fundamental concepts will make it easier for us to understand how decision trees are built. Entropy can be used to quantify uncertainty. Knowledge gain assesses how much uncertainty in the target variable is minimized given a set of independent variables. The decision tree algorithm's periodic selection of the root nodes and grouping of the nodes sets it apart from the random forest technique. The random forest uses the bagging procedure to provide the required forecast. Using multiple data samples (training data) instead of a single sample is what bagging entails (Calders et al., 2022; Demol et al., 2022; Disney et al., 2019; Liang et al., 2016). A training dataset's traits and occurrences are used to make predictions. The outputs from the decision trees vary depending on the training data the random forest algorithm receives. The outcome with the top position will be used to create the final product. Random forest classification produces the desired outcome. The training data is used to train various decision trees. When the nodes are split, observations and traits from this dataset will be randomly selected. In a rainforest system, various decision trees are employed. In this case, the outcome that most decision trees have chosen is the output of the rainforest system. The rainforest algorithm is a flexible machine-learning system that is user-friendly. By employing ensemble learning, organizations can get around categorization and regression problems. Developers should use this strategy because it overcomes the problem of dataset overfitting. Developing the precise projections necessary for an organization's strategy judgment is an essential tool.

(b) Support vector model

Support Vector Machine, sometimes known as SVM, is one of the most used supervised learning techniques for regression and categorization problems (Ramdani & Furqon, 2022). However, it is used to solve Classification problems in machine learning. In order to quickly categorize new data points in the future, the SVM algorithm aims to identify the best line or target variable that can divide n-dimensional spaces into categories. The name of this best decision limit is a hyperplane. Support vectors are the data points or vectors that are physically closest to the feature space and have the most impact on the position of the hyperplane. Because they preserve the hyper-plane, these vectors are known as support vectors. Consequently, the SVM method assists in locating the optimal boundary or region, frequently referred to as a hyperplane (Ramdani & Furqon, 2022). The hyper-plane with the most significant margin is the optimum one.

(c) Neural networks

Machine learning includes neural networks, often known as artificial neural networks. Neural networks, which mimic the composition and function of the human brain, are built using artificial neurons (Ramdani & Furqon, 2022). Each artificial neuron in a neural network connects with a vast number of other neurons, and because there are many neurons connected, a sophisticated conceptual framework is created (Uzhinskiy, 2022). An inputs layer, two or many hiding layers, and one output layer make up a neuronal network's multi-layered structure. Information is transferred from one layer to the other neuron in the following layers because each neuron is linked to another neuron. The information eventually reaches the neural network's last layer, the input layer, where it produces output.

(d) Logistics regression algorithms

Within Supervised learning, the linear model is one of the Machine Learning methods most frequently utilized. It forecasts the categorical dependent variable using a specified set of individual factors. Logistic regression is used to predict the result for a categorical dependent variable (Ramdani & Furqon, 2022). The outcome must therefore be a discrete or categorical value. It offers the probabilistic values between 0 and 1 rather than the exact values between 0 and 1. It can be either True or False, 0 or 1, or Yes or No. Logistic regression and linear regression are similar, save for the application. Linear regression solves nonlinear equations and logistic regression addresses classification issues. Logistic regression can rapidly pinpoint the variables that will effectively classify observations using various data sources.

(a) Hybrid models

It involves combining the strengths of different algorithms to enhance predictive accuracy Therefore, hybrid models seek to use proper physiological understanding while simultaneously adding inputs and outputs helpful in managing forests (Kuusk et al., 2014). The likelihood of environmental change has highlighted the value of the hybrid strategy even more.

2.3.5 Unsupervised Machine Learning

Unsupervised Machine learning models utilize unsupervised learning instead of supervised learning, allowing the model to gain knowledge from the unlabeled training data. Based on the unlabeled dataset, the system predicts the outcomes. Unsupervised learning enables the model to find hidden correlations in the data without external assistance.

(a) **Clustering**

An unsupervised learning approach called clustering includes grouping or "groping" the data points into several clusters according to their similarities and differences. The items with the most commonalities stay in the same group and have little to no overlap with those from other groups (2022). Clustering techniques are extensively applicable to a variety of activities, including the Segmentation of images.

(b) **Dimensionality Reduction**

The dimensionality of a dataset refers to how many features or variables are present, while the dimensionality-reducing methodology refers to the method used to decrease the dimensionality (Sule, 2020). Though additional data yields are accurate findings, it can negatively affect the model's or algorithm's efficiency due to overfitting problems. Methods for dimensional reducing are applied in these situations. The procedure ensures that the information provided by the lower-dimensional dataset is similar to that of the higher-dimensional dataset. An excellent example of such is Principal Component analysis.

2.4 Effects of biomass on carbon sequestration.

Carbon sequestration- This is the process of capturing, securing, and storing carbon dioxide from the atmosphere (Lal, R. (2008). The idea is to stabilize carbon in solid and dissolved forms so that it doesn't cause the atmosphere to warm. Carbon- A chemical element, like hydrogen or nitrogen, carbon is a basic building block of biomolecules. It exists on Earth in solid, dissolved, and gaseous forms. For example, carbon is in graphite and diamond, but can also combine with oxygen molecules to form gaseous carbon dioxide ($CO2$). Carbon dioxide- is a heat-trapping gas produced both in nature and by human activities. Manmade sources of carbon dioxide come from the burning of fossil fuels such as coal, natural gas, and oil for uses in power generation and transportation. Carbon dioxide is also released through land use changes, biologically through oceans, the decomposition of organic matter, and forest fires. The build-up of carbon dioxide and other greenhouse gases in the atmosphere can trap heat and contribute to climate change.

2.4.1 Types of carbon sequestration

(a) Biological

Biological carbon sequestration is the storage of carbon dioxide in vegetation such as grasslands or forests, as well as in soils and oceans Prakash, P. (2014). They include;

(i) Forest

About 25 percent of global carbon emissions are captured by plant-rich landscapes such as forests, grasslands and rangelands. When leaves and branches fall off plants or when plants die, the carbon stored either releases into the atmosphere or is transferred into the soil. Wildfires and human activities like deforestation can contribute to the diminishment of forests as a carbon sink.

(ii) Oceans

Oceans absorb roughly 25 percent of carbon dioxide emitted from human activities annually. Carbon goes in both directions in the ocean. When carbon dioxide releases into the atmosphere from the ocean, it creates what is called a positive atmospheric flux. A negative flux refers to the ocean absorbing carbon dioxide. Think of these fluxes as an inhale and an exhale, where the net effect of these opposing directions determines the overall effect. Colder and nutrientrich parts of the ocean can absorb more carbon dioxide than warmer parts. Therefore, the Polar Regions typically serve as carbon sinks. By 2100, much of the global ocean is expected to be a large sink of carbon dioxide, potentially altering the ocean chemistry and lowering the pH of the water, making it more acidic. Many practices can increase the amount of carbon stored in soils, although the amount and duration of the carbon sequestered depend on regional climate and soil type, among other factors. Planting cover crops when fields are otherwise bare can extend photosynthesis throughout the year; using compost can improve yields while storing the compost's carbon content in the soil; and scientists are developing crops with deeper roots, making them more resistant to drought while depositing additional carbon into the soil. Many of the practices that increase soil carbon also improve soil health and can make agricultural systems more resilient to climate change.

(iii) Soils and Farms

Carbon is sequestered in soil by plants through photosynthesis and can be stored as soil organic carbon (SOC) Baldock, J. (2009). Agroecosystems can degrade and deplete the SOC levels but this carbon deficit opens up the opportunity to store carbon through new land management practices. Soil can also store carbon as carbonates. Such carbonates are created over thousands of years when carbon dioxide dissolves in water and percolates the soil, combining with calcium and magnesium minerals, forming "caliche" in desert and arid soil. Carbonates are inorganic and can store carbon for more than 70,000 years, while soil organic matter typically stores carbon for several decades. Scientists are working on ways to accelerate the carbonate forming process by adding finely crushed silicates to the soil to store carbon for longer periods.

(b) Geological carbon sequestration

Geological carbon sequestration is the process of storing carbon dioxide in underground geologic formations, or rocks (Cole, D. R. (2013). Typically, carbon dioxide is captured from an industrial source, such as steel or cement production, or an energy-related source, such as a power plant or natural gas processing facility, and injected into porous rocks for long-term storage. The permanence of geologic sequestration depends on the effectiveness of several CO2 trapping mechanisms. After CO2 is injected underground, it will rise buoyantly until it is trapped beneath an impermeable barrier or seal. In principle, this physical trapping mechanism, which is identical to the natural geologic trapping of oil and gas, can retain CO2 for thousands to millions of years. Some of the injected CO2 will eventually dissolve in groundwater, and some may be trapped in the form of carbonate minerals formed by chemical reactions with the surrounding rock. All of these processes are susceptible to change over time following CO2 injection. Scientists are studying the permanence of these trapping mechanisms and developing methods to determine the potential for geologically sequestered CO2 to leak back to the atmosphere. The capacity for geologic carbon sequestration is constrained by the volume and distribution of potential storage sites. According to the U.S. Department of Energy, the total storage capacity of physical traps associated with depleted oil and gas reservoirs in the United States is limited to about 38 gigatons of carbon, and is geographically distributed in locations that are distant from most U.S. fossil-fuel power plants. The potential U.S. storage capacity of deep porous rock formations that contain saline ground water is much larger (estimated by the U.S. Department of Energy to be about 900 to 3,400 gigatons of carbon) and more widely distributed, but less is known about the effectiveness of trapping mechanisms at these sites. Unmendable coal beds have also been proposed for potential CO2 storage, but more information is needed about the storage characteristics and impacts of CO2 injection in these formations. Scientists are developing methods to refine estimates of the national capacity for geologic carbon sequestration. To fully assess the potential for geologic carbon sequestration, economic costs and environmental risks must be taken into account. Infrastructure costs will depend on the locations of suitable storage sites. Environmental risks may include seismic disturbances, deformation of the land surface, contamination of potable water supplies, and adverse effects on ecosystems and human health. Scientists are pioneering the use of new geophysical and geochemical methods that can be used to anticipate the potential costs and environmental effects of geologic carbon sequestration.

(c) Technological carbon sequestration

Scientists are exploring new ways to remove and store carbon from the atmosphere using innovative technologies (Srivastava, R. D. (2008). Researchers are also starting to look beyond the removal of carbon dioxide and are now looking at more ways it can be used as a resource.

(d) Biomass density

High biomass density indicates substantial plant growth and productivity, contributing to increased carbon storage. Studies by Pan et al. (2011) emphasize the positive correlation between biomass density and carbon sequestration. In forests with dense vegetation, a larger amount of carbon is assimilated through photosynthesis, stored in plant tissues, and subsequently contributes to long-term carbon sequestration. Understanding the dynamics of biomass density provides valuable insights into the carbon sequestration potential of forming a foundational element in the assessment of biomass effects on carbon storage. Biomass density is positively correlated with carbon storage capacity. As the density of living plant material increases, the amount of carbon sequestered through photosynthesis and stored within the biomass also rises. This relationship is well-established in ecological literature, as highlighted by studies such as Pan et al. (2011). Forests with high biomass density generally exhibit elevated levels of carbon sequestration. Different plant species contribute to biomass density in distinct ways. Some species may have higher wood density, while others contribute more to the herbaceous layer. Studies like Chave et al. (2006) emphasize the importance of considering species-specific biomass characteristics when assessing overall biomass density and its subsequent influence on carbon sequestration.

(e) Biodiversity and Carbon storage

Biodiversity within a forest ecosystem plays a pivotal role in shaping carbon storage patterns. Higher biodiversity is often associated with increased carbon storage due to the diverse functional traits of different plant species. Hooper et al. (2005) suggest that ecosystems with a greater variety of plant species exhibit enhanced carbon storage potential (Kapos, V. (2020). Diverse plant communities contribute to a wider range of organic matter inputs, root structures, and litter fall compositions, fostering varied pathways for carbon sequestration.

(f) Carbon sequestration

The carbon trading initiative in Kenya is at an early stage with many who are involved trying to understand the details and opportunity (Lal, R. (2008). Those pioneering the initiative include a. The Greenbelt movement which is currently coordinating a carbon-financed community-based reforestation program of 1,800 ha in Mt Kenya/Aberdare's (Hunt, K. P. (2014). The International Small Group Tree Planting Programme (TIST) Escarpment Environment Conservation Network is currently involved in the afforestation and reforestation of the Kikuyu Escarpment, Kenya Forest Service and Partners supporting a 500-ha community afforestation program in Kakamega Forest. The (Clinton Climate Initiative) Rehabilitation of EnoosupukiaForest Trust Land and adjoining areas in Narok. This last project is expected to act as a demonstration site for the National Carbon Accounting System (NCAS). To participate in the carbon trade through REDD, developing countries need to have the capacity to implement and monitor a reduction in the rate of national deforestation and woodland degradation (Sapkota, C. (2012). Kenya entered this process in 2009 by submitting it's REDD readiness proposal to the World Bank. Kenya is estimated to be emitting 14.4 million tonnes of carbon dioxide per year through deforestation (Raihan, A. (2023). This is equivalent to 52,000 ha per year. At a minimal imaginary price of US$ 5 per tonne, this is equivalent to US$ 72 million or Ksh5.7 billion annually. KFS is the National REDD Focal Point and is spearheading a multi-stakeholder effort to develop a strategy for the implementation of REDD activities in the country (Kirchoff, I. S. (2020). REDD readiness proposal identified the following as the key drivers of deforestation: a. Pressure for expansion of agricultural land, settlement and development, unsustainable utilization of forest resources, high dependency on wood energy for cooking especially charcoal, overgrazing and forest fires, and institutional failures arising from weak governance structures, inadequate capacity, to enforce the law and lack of real stakeholder participation in forest management. Interventions have been proposed to address each of the identified factors.

(g) Decomposition and carbon release

Decomposition, a vital ecological process within forest ecosystems, significantly influences carbon sequestration dynamics (Oetting, J. N. (2023). As organic matter, including biomass, undergoes microbial and enzymatic breakdown, carbon is released back into the atmosphere and soil. The primary form of carbon release during decomposition is carbon dioxide (CO_2), generated through the microbial conversion of complex organic compounds. Bradford et al.

(2016) emphasize the role of environmental factors in this process, highlighting how temperature, humidity, and nutrient availability regulate decomposition rates. The diverse nature of biomass introduces differential decomposition rates, with leaves decomposing more rapidly than woody material, as discussed by Cornwell et al. (2008). Disturbances, both natural and human-induced, can disrupt biomass structure and influence decomposition dynamics, leading to immediate carbon emissions, according to the findings of Harmon et al. (1986). Furthermore, decomposition contributes to the formation of soil organic carbon, as highlighted by Conant et al. (2017).

(e) Photosynthesis

One of the fundamental mechanisms by which biomass influences carbon sequestration is through photosynthesis (Abdelly, C. (2008). Plants and trees absorb CO2 from the atmosphere during photosynthesis, converting it into organic matter (biomass) using sunlight energy. This conversion process not only produces oxygen but also removes CO2 from the air, making it a key driver of carbon sequestration in terrestrial ecosystems. The carbon stored in biomass through photosynthesis represents a vital component of the Earth's carbon balance and contributes to offsetting anthropogenic CO2 emissions (Maroa, S. (2019).

(F) Soil carbon

In addition to storing carbon in aboveground biomass, ecosystems also sequester carbon in soils through various processes (Lal, R. (2004). Dead plant material, such as leaves, branches, and roots, decomposes over time, adding organic carbon to the soil. This input of carbon-rich organic matter enhances soil fertility, structure, and moisture retention while sequestering carbon for extended periods (Freeman II, O. W. (2019)). Soil organic carbon plays a crucial role in ecosystem health, nutrient cycling, and climate resilience, making it a significant aspect of carbon sequestration in natural environments.

2.4.2 Role of remote sensing in Mapping Above ground biomass

While biomass derived from field data measurements is the most accurate, it is not a practical approach for broad-scale assessments. It can provide data over large areas at a fraction of the cost associated with extensive sampling and enables access to inaccessible places. Data from Remote Sensing satellites are available at various scales, from local to global, and from several different platforms. There are also different types of data, such as optical, radar and LiDAR, with each one having certain advantages over the others (Steininger, M. K. (2000). Optical

Remote Sensing probably provides the best alternative to biomass estimation through field sampling due to its global coverage, repetitiveness, and cost-effectiveness. Optical Remote Sensing data is available from several platforms, such as IKONOS, Quickbird, Worldview, SPOT, Sentinel, Landsat, and MODIS. The spatial resolutions vary from less than one meter to hundreds of meters. Optical Remote Sensing data has been used by numerous researchers for biomass estimation (Enclona, E. (2004). Radar Remote Sensing has gained prominence for above-ground biomass estimation in recent years due to its cloud penetration ability as well as detailed vegetation structural information. While airborne Synthetic Aperture Radar (SAR) systems have been operating for many years, space-borne systems such as Terra-SAR, ALOS, and PALSAR have become available since 2000. This has enabled repetitiveness and cost-effectiveness. A large number of recent studies have explored the use of radar data for aboveground biomass estimation (Harcombe, P. (2000). LiDAR is a relatively new technology that has found favor in biomass estimation. It can sample the vertical distribution of canopy and ground surfaces, providing detailed structural information about vegetation. This leads to more accurate estimations of basal area, crown size, tree height, and stem volume. Several studies have established strong correlations between LiDAR parameters and above-ground biomass (Popescu, S. C. (2007).

2.5 Empirical Reviews

This part mainly tackles various researchers that have done some relevant research about GIS and Remote Sensing.

2.5.1 Impacts of Forest Biomass and Carbon Sequestration

(a)Climate change variability

Forested areas are particularly sensitive to climate variability and change, impacting biomass distribution and carbon sequestration. Studies indicate that increased inter- and intra-annual precipitation variability, driven by climate change, significantly affects vegetation growth, as observed through proxies like the Normalized Difference Vegetation Index (NDVI) (Sloat et al., 2018) ,the study mainly utilized the Normalized Difference Vegetation Index (NDVI) as a proxy to measure vegetation health and growth. Changes in NDVI values were used to infer variations in biomass and the effects of precipitation variability however this could be limited in trying to get the right precision of the results hence the need to overlook other vegetation indices such as EVI, NDFI, BSI and also the rainfall received in an area as the factors that really affect the vegetation stress and consequently the biomass distribution in the area. Over the past century, forests have experienced heightened precipitation variability, leading to fluctuations in biomass and reduced carbon sequestration capacity (Sloat et al., 2018) the findings alone from this study about precipitation alone and how it particularly affects forest biomass is not sufficient and thus the need to overlook at the land use land cover changes over the past years to understand more insights about how vegetation stressed are being affected. These climatic changes pose significant threats to forest ecosystems, necessitating accurate biomass estimation and carbon stock quantification to inform mitigation strategies and enhance forest resilience in the face of climate change.

(b) Land cover mapping

High-resolution satellite imagery, such as that from Landsat and MODIS, has been instrumental in producing accurate land cover maps that highlight changes in forest cover over time (Hansen et al., 2013; Friedl et al., 2010). These maps enable the detection of deforestation, afforestation, and other land use changes that significantly impact biomass distribution and carbon stocks. Advances in remote sensing and machine learning techniques have improved the precision of land cover classification, allowing for more detailed and reliable assessments of forest structure and composition (Giri et al., 2013; Xie et al., 2008). Through integrating various data sources and leveraging robust algorithms, land cover mapping provides essential insights into the spatial-temporal dynamics of forests, supporting better environmental management and conservation efforts and also conducting a comprehensive multi-temporal analysis of how various climate variables (temperature, precipitation, extreme weather events) affect biomass distribution and carbon sequestration over time.

(c) Forest disturbance mapping

Changes in forest cover over time can be monitored using remote sensing imagery, which can be compared to previous images to detect areas of deforestation or degradation. Forest disturbance refers to changes in forest structure and composition due to natural events (e.g., hurricanes, fires, droughts) or human activities (e.g., logging, agriculture, and urbanization). These disturbances can significantly impact the ecosystem services provided by forests, including carbon sequestration, habitat for wildlife, and recreation opportunities (Souza Jr., 2016). Remote sensing provides high-resolution images of large areas of land, which can be used to detect changes in forest cover and structure. For example, satellite imagery can detect areas of deforestation (Kennedy et al., 2010), forest degradation, and changes in the size and shape of individual trees. GIS can then be used to analyze the spatial distribution of forest disturbances and to assess the impact of different disturbances on the ecosystem services provided by forests. For example, GIS can be used to map the extent of deforestation, quantify the number of carbon emissions resulting from forest disturbance, and evaluate the impact of disturbances on wildlife habitat. A new shift will be through the use of advanced algorithms and machine learning techniques which will enable the analysis of temporal changes in forest cover, allowing for the identification of disturbance events and their severity over time by analyzing the biomass trends and its effects on carbon sequestration. These methods provide detailed insights into the spatial patterns of forest disturbances and their effects on biomass and carbon stocks by quantifying both biomass and understanding the relationship between the two in terms of correlation analysis.

2.5.2 The use of machine learning biomass in estimation

The use of machine learning in assessing biomass involves employing algorithms and models to analyze and interpret vast amounts of remote sensing data, such as LiDAR, satellite imagery, and GIS data, to estimate biomass more accurately and efficiently. Techniques like Random Forest Regression, Support Vector Machines, and Neural Networks have been particularly effective in this domain (Belgiu & Drăguţ, 2016; Fang et al., 2019). These models can handle complex, nonlinear relationships between various input features (such as canopy height, NDVI, and climatic data) and biomass, enabling more precise predictions (Mutanga & Skidmore, 2004; Rodríguez-Galiano et al., 2015). Machine learning approaches also allow for the integration of multi-source data, improving the robustness of biomass estimates. This integration enhances our understanding of spatial-temporal biomass distribution and its impacts on carbon sequestration, which is crucial for climate change mitigation efforts (Lary et al., 2016; Zhang et al., 2020). One of the significant advantages of using machine learning for biomass estimation is the ability to process and analyze large datasets efficiently. Traditional methods often require extensive fieldwork and manual data collection, which can be time-consuming and labor-intensive. In contrast, machine learning models can quickly process remote sensing data to provide near-real-time biomass estimates. For instance, Convolutional Neural Networks (CNNs) have been used to extract features from high-resolution satellite images, improving the accuracy of biomass estimation in heterogeneous landscapes (Liu et al., 2018). Similarly, the integration of LiDAR data with optical imagery using machine learning techniques has shown promising results in estimating forest biomass and structure (Dandois & Ellis, 2010) though its cost makes the use of free remote sensing satellite data such as ESA global land cover, Sentinel 1 and 2 more convenient to use in studying biomass and carbon sequestration. The flexibility and adaptability of machine learning models make them particularly suitable for biomass estimation in diverse ecosystems. Different types of ecosystems, such as forests, grasslands, and wetlands, exhibit unique structural and spectral characteristics that can be effectively captured by machine learning algorithms. For example, Support Vector Machines (SVM) have been successfully applied to classify vegetation types and estimate biomass in tropical forests, where the dense canopy and complex vegetation structure pose challenges for traditional remote sensing techniques (Foody & Mathur, 2004).However, the use of ensemble learning methods, such as Random Forests, will be more effective in improving the accuracy and reliability of biomass estimates by combining the predictions of multiple models. In addition to improving the accuracy of biomass estimation, machine learning approaches also provide valuable insights into the factors influencing biomass distribution. By analyzing the relationships between various environmental variables and biomass, machine learning models can help identify key drivers of biomass variability, such as soil moisture, temperature, and land use changes. This information is critical for developing effective conservation and management strategies aimed at enhancing carbon sequestration and mitigating climate change impacts (Harris et al., 2012). For instance, research has shown that integrating climate data with remote sensing observations using machine learning can improve our understanding of how climatic factors influence biomass dynamics over time (Peters et al., 2013). The ability to handle multi-temporal data is another significant advantage of using machine learning for biomass assessment. Remote sensing platforms, such as Landsat and Sentinel, provide continuous, long-term observations of the Earth's surface, allowing researchers to monitor changes in biomass over time. Machine learning models can leverage these multi-temporal datasets to detect trends and patterns in biomass dynamics, providing valuable insights into the impacts of natural disturbances, such as wildfires and hurricanes, as well as human activities, such as deforestation and urbanization (Kennedy et al., 2010). For example, time-series analysis using machine learning has been used to assess the recovery of forest biomass following disturbance events, providing critical information for forest management and restoration efforts (Cohen et al., 2018).

2.5.3 The use of machine learning in carbon sequestration

One of the significant advantages of using machine learning for carbon sequestration estimation is the ability to process and analyze large datasets efficiently. Traditional methods often rely on extensive field measurements and manual data collection, which can be time-consuming and labor-intensive. In contrast, machine learning models can quickly process remote sensing data to provide near-real-time estimates of carbon sequestration. For instance, Convolutional Neural Networks (CNNs) have been used to extract features from high-resolution satellite images, improving the accuracy of carbon sequestration estimates in diverse landscapes (Chen et al., 2020) demonstrated the effectiveness of machine learning, particularly the XGBoost model, for estimating aboveground biomass (AGB). Their study found that XGBoost, a scalable tree-structured model, significantly improved the accuracy of biomass estimation by handling complex, nonlinear relationships between variables however to improve on the accuracy it would be more convenient to use other models such as random forest, getting the forest biomass trends over time and understanding the factors that will likely influence such variation. Similarly, the integration of LiDAR data with optical imagery using machine learning techniques has shown promising results in estimating carbon storage in forest ecosystems (Qi et al., 2019). The flexibility and adaptability of machine learning models make them particularly suitable for carbon sequestration estimation in various ecosystems. Different types of ecosystems, such as forests, grasslands, and wetlands, exhibit unique structural and spectral characteristics that can be effectively captured by machine learning algorithms. For example, Support Vector Machines (SVM) have been successfully applied to estimate carbon sequestration in mangrove forests, where the dense canopy and complex vegetation structure pose challenges for traditional remote sensing techniques (Drake et al., 2019) his study however analyzed the performance of various machine learning which tend to be time consuming and also use of the allometric equation to estimate biomass would require appropriate and approved equation for a particular site of study and since my area of study being a closed frosted stand it was more convenient to use the global land cover classes in the estimation of forest biomass which is not time consuming and cost effective. Moreover, the use of ensemble learning methods, such as Random Forests, has proven effective in improving the accuracy and reliability of carbon sequestration estimates by combining the predictions of multiple models (Breiman, 2001) however understanding the most important predictor variables would be more relevant in order to get detailed insights on the factors that really affect biomass variation and its effect on carbon sequestration in the ecosystem.

2.5.4 Review of related studies.

(Olokeogun, 2022) evaluated that forest degradation impacts carbon stock, biodiversity, and the capacity of the forest to produce valuable products such as medicine, wood, timber, or habitat for wildlife. Some of the anthropogenic drivers mentioned included; forest fires, storms, and agricultural activities. He further argued that to quantify forest degradation, it is necessary to understand forest structure. However what could be done differently to supplement and improve the same is to identify and quantify the aboveground biomass as an indicator of forest degradation. Additionally I will conduct a time-series analysis of biomass and carbon stock changes over multiple years to identify trends and seasonal variations. This can help in understanding the long-term impacts of different environmental factor.

From (Schwartz, M., Ciais, P., De Truchis, A., Chave, J., Ottlé, C., Vega, & Fayad, I. (2023)) the study emphasizes the importance of accurate forest mapping for carbon storage and biodiversity conservation. It involves creating canopy height maps at 10m resolution and above-ground biomass density maps at 30m resolution for French forests in 2020 the research combines remote sensing data with Allometric equations to produce detailed maps that outperform existing models, aiding in climate-efficient forest management policies and providing valuable insights for monitoring forest resources and carbon levels. The study's results are validated against various datasets, showcasing the effectiveness of the approach in enhancing forest monitoring and management practices. Since it can be time consuming to undertake the field data collection and also due to its expensive part I would undertake the same project by using remote sensing data and without going for the use of global allometric equations I would use the various feature classes of the global land cover to quantify biomass and consequently look at the effects of biomass on carbon sequestration and since am only dealing with a close forest stand I would extract the forest mask The research above also tend to use the Lidar data that is so expensive to acquire with global allometric equation which may not be practical to the Kenyan case and also with the forest structure present in Londiani Kedowa forest.

The arguments from (Zhao, F., Guo, Q., & Kelly, M. (2012) researchers compared biomass estimates using different Allometric equations and found that the choice of the equation had a substantial impact on the final biomass estimates. They concluded that it is crucial to carefully select appropriate allometric equations when using LIDAR data to estimate forest biomass, as the choice can lead to very different results. This study highlights the importance of considering the limitations and assumptions of allometric equations when using remote sensing data like lidar for forest biomass estimation. The findings emphasize the need for further research to develop more robust and widely applicable allometric models to improve the accuracy of Lidar based biomass mapping. This can be done by using machine learning specifically the random forest algorithm to estimate biomass by using the GEDI data to do the training and testing this would not require the use of global allometric equation and would hence mean the project is less vulnerable to criticism since the any allometric equation employed would need reassessment and field calibration.

2.6 Critical analysis and research gaps

The research above emphasizes the necessity of using improved allometric models in conjunction with field data and remote sensing techniques for large-scale forest biomass and carbon stock estimation. This highlights a gap in the development and application of precise and widely applicable allometric equations for more accurate estimations. Significant variations in aboveground biomass (AGB) estimation in tropical forests are observed, attributed to the lack of accurate local/regional allometric models and methodologies. This variability underscores the importance of developing standardized and reliable methods for estimating carbon stocks to ensure consistency in national and global carbon storage. The complexity and uncertainty involved in biomass estimation methods, including the selection of trees for destructive sampling, fitting regression models, and assessing the effect of subsampling design and sample size, present challenges in accurately quantifying carbon stocks. Kenya, for example, is well-known, where it is difficult to collect up-to-date information on forest loss and degradation. The forest managers use only traditional and unreliable ways.

CHAPTER 3: METHODOLOGY

3.1 Overview

This chapter introduces the study area's geographic location and other variables such as Topography, climate, soils, and geology.

3.2 Study Area

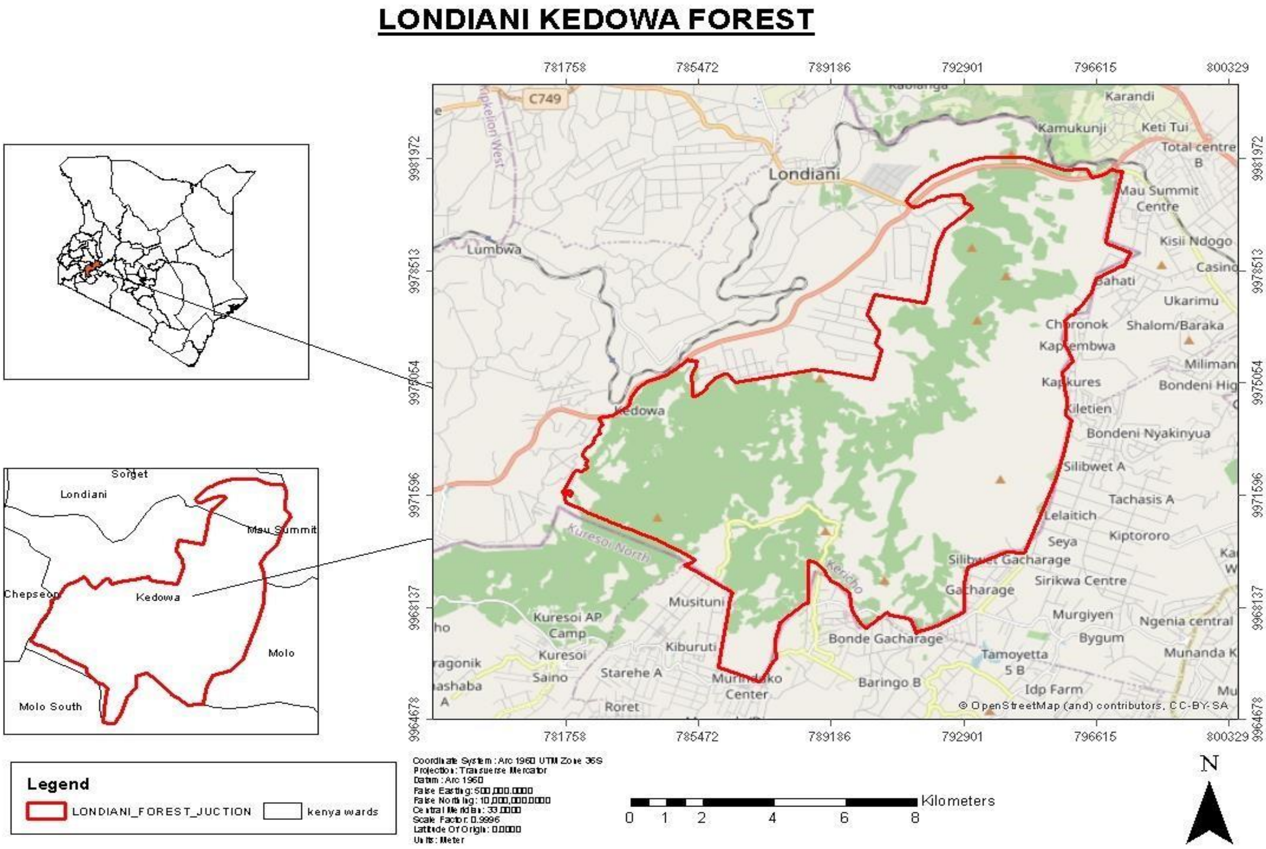

Figure 3.1 Study area map of Londiani Kedowa Forest, Kericho County

Figure 3.1: shows the study area map of Londiani Kedowa forest, the uniqueness of the study area is that there has been human encroachment, Roads, Settlements at the forest margin, and querying activities around the area that lead to changes in forest biomass and consequently carbon trends changes (Tanui, Nikko. "State launches Sh75m forest initiative". The Standard. Retrieved 27 March 2024).

3.2.1 Geographical Location

It is along Nakuru–Kericho Highway. They are composed of different trees species. The study area is within the Rift Valley region of Kericho County, a few kilometers from Londiani town, with an estimated coverage of about 20 square kilometers. It lies between 0.40° N longitude: 35.7525 latitude: -0.1269444 (Londiani forest participatory planning).

3.2.2 Topography

The area has an approximate elevation of about 2576 meters above sea level, and generally, the soils are well-drained red soil with well-developed crumbs and can support agricultural activities, located in a mountainous region, is characterized by its rugged terrain, lush vegetation, and diverse ecosystems (Ronoh, J. K. (2017). The area is known for its rich biodiversity, including dense forests, meandering rivers, and diverse wildlife. The steep slopes and varied elevations contribute to microclimatic conditions and habitat diversity, influencing the distribution of vegetation and carbon sequestration potential.

3.2.3 Climate

The agricultural sector is the main activity from growing large-scale plantations of coffee and tea to small-scale farming such as maize growing, banana, beans, potatoes, vegetables. The area experiences vast climatic conditions of cool, short, dry, and partly cloudy throughout the year, with an average temperature range between 10°C to 27°C and annual precipitation of about 1589 mm per year. It is structured with a more significant portion of the area covered by agricultural land, forest, open or transition, and urban areas, respectively, but over the years, the land under cultivation has reduced due to an increase in demand for land use for residential purposes. (Opanga, V. A. L. E. N. T. I. N. E. (2018).

3.2.4 Soils and Geology

It is made up of well-drained soils.

3.3 Materials and Methods

Materials

source	**data**	**relevance**
KENSOTER	soil	Soil type Soil characteristic
CHIRPS	rainfall	Mean annual rainfall
CORPENICUS ACCESS HUB	Sentinel 1 &2	Vegetation indices Predictor variables LULC

USGS	SRTM	Dem slope
GEDI data	Google earth engine	Training, testing and validation
Forest mask	ESA land cover	Feature classes

Table 3.1: Summary of all the datasets which were used in the study area

3.3.1 Data Requirements

Most of the data used in the Project was obtained from the Google Earth Engine Data Catalog Sentinel 1 & Sentinel 2 (Lang et al., 2023; Morin et al., 2022; Potapov et al., 2021; Schwartz et al., 2022). The data for 2000-2020 was obtained by clipping on the Google Earth Engine by study area. All the pre-processing was also done to get the required output of the results. The spatial resolution of 10m.

Digital Elevation Model (DEM) and Slope

The DEM made up of 30m Resolution was obtained from the SRTM available on the Google earth engine Data catalog. Afterward, the slope was extracted for use in the process.

GEDI Data

It was obtained from the google earth engine that is made up of the training data for the tree heights. It was explicitly used for estimating Biomass at Londiani Kedowa forest (Dubayah et al., 2022; Duncanson et al., 2022).

ESA World Cover

The forest mask used in the model was obtained from the ESA World Cover (ESA World Cover 10 m 2020 v100). It excluded other land cover classes such as the grasslands, agriculture, water, bare land, and other classes (Gong, P. (2018)).

Platform and Software

All the process was executed using Google Earth Engine, a cloud computing platform. The Scripts are then written for each process, and the outputs are executed afterward. ArcMap was used in generating the final maps from the exported outputs. GEDI L4B product is used to estimate mean aboveground biomass density (AGBD) at a 1 km x 1 km resolution (Dubayah et al., 2022; Duncanson et al., 2022).

3.3.2 Methodological flowchart

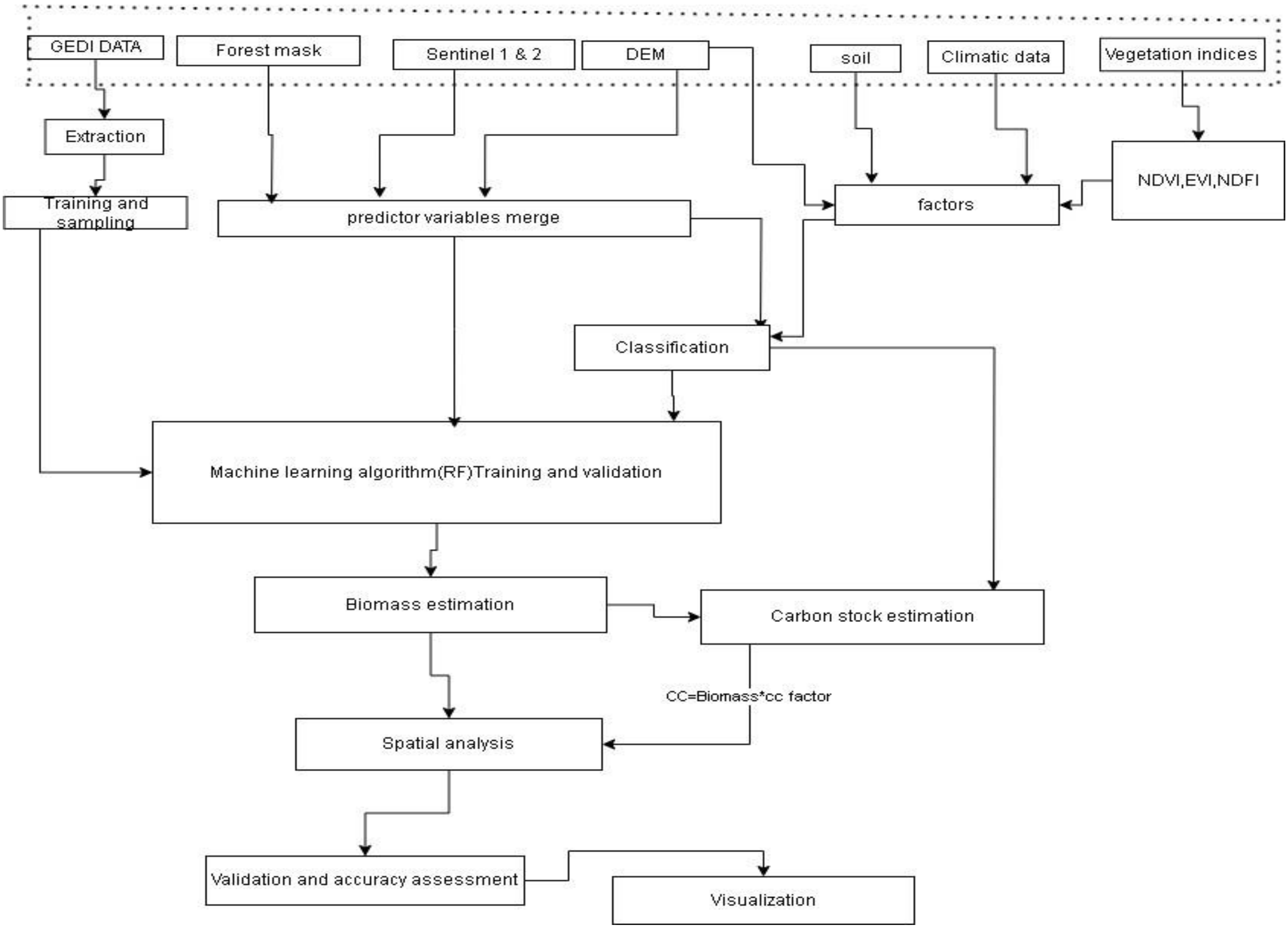

Figure 3. 2 Methodological flowchart showing how to achieve the effects of biomass on carbon sequestration

The Figure 3.2 begins with the collection and preparation of diverse data sources including Sentinel-1 (Filipponi, F. (2019, June)) and Sentinel-2 imagery (Lang et al., 2023; Morin et al., 2022; Potapov et al., 2021; Schwartz et al., 2022), SRTM elevation data, and climatic information such as rainfall and temperature, after data collection pre-processing is done which involves feature extraction such as deriving the inter-quartile range (IQR) from radar data and creating a forest mask from ESA global land cover (Arsanjani, J. J. (2019) data. To achieve the first objective on factors affecting biomass distribution in the study area vegetation health (Ullo, S. L. (2016)) was determined using various vegetation indices such as NDVI, EVI, NDFI (Herold, M. (2016), climatic data (Gao, J. (2023))such as rainfall distribution and temperature experienced in the area across the study period that is 2019-2023. Through analyzing temporal trends on factors this will give more insights to vegetation health which will eventually aid in assessing the changes in biomass over time, highlighting areas of consistent growth or decline with darker shades indicating higher biomass and lighter shades suggesting lower levels in the case of temperature, NDVI, EVI and NDFI while a notable higher rainfall in an area will signify health growth in plants and hence the high biomass. In order to now quantify above ground biomass (Zhang, et al. (2021)) in an area data is loaded in the google earth engine that is sentinel 1 deriving measures of backscatter variability, backscatter power has been used as a basis for forest height estimation and improving estimates incorporating optical data. The SMA obtains layers containing the pixel wise fraction for each specified end member. As a result, the unmixing of the pixels that results brings out details in the subpixels and may therefore produce better results than traditional classification techniques and sentinel 2 spectral reflectance data is then processed to create a cloud-masked composite image. Furthermore, SRTM elevation data is utilized along with forest area extraction from the ESA Global Land Cover dataset (N.E., Ramoino, F., Arino, O., 2021).Merging the predictor variables (S2 composite, Sentinel-1 IQR, elevation, slope, and forest mask) into a single collection then sampling the GEDI L4B ((Dubayah et al., 2022; Duncanson et al., 2022).)dataset for training points within the study area and then Split the sampled points into training (70%) and validation (30%) datasets Predictor variables are prepared, training data is sampled from the GEDI L4B dataset (J.B. Blair, and S.B. Luthcke. 2022), and random forest regression is performed. The resulting biomass map is visualized and assessed for model performance using charts and statistics before being exported for further analysis. The biomass is expressed in Mg/Ha for the entire study area. To now overlook on effects of biomass on carbon sequestration we have to estimate carbon content, where a conversion factor is typically applied, which converts biomass density to carbon content. This conversion factor depends on the type of vegetation and its carbon storage characteristics (Boutton, T. W. (2005)) and since the area being studied was a forested ecosystem the conversion factor applicable then become 0.5 of the biomass obtained (Tapias, Á. D. J. L. (2010). The same results is then visualized and a correlation analysis done between biomass and carbon content before the maps are generated. The method is transparent and reproducible. It can assist in increasing the authenticity of tracking, trying to report, and verification (MRV), which is necessary for minimizing emissions caused by forest degradation (REDD+) (Atmadja, S., & Verchot, L. (2012).). It can identify sub-pixel disruption occurrences as tiny as 0.005 ha. Lastly the model's performance is evaluated using Root Mean Squared Error (RMSE) and scatter plots to compare predicted AGB with observed values, ensuring the accuracy of AGB predictions. All the outputs are then exported to ArcMap software for map making and further visualization the statistics are then also exported to excel for further analysis and visualization.

3.3.3Biomass

As seen in Figure 3.2 data was prepared and used within Google Earth Engine Environment. First, Sentinel 1 & 2 was merged by their specific bands, as shown on Figure3.2 above. The elevation and the extracted slope are added, which act as the predictor variables. The ESA Global Land Cover dataset was used to create a forest mask by retaining only the pixels classified as forest and this is because the area of study was closed forest stand ecosystem. The model is prepared using a regression model by random forest classifier. GEDI data ((Dubayah et al., 2022; Duncanson et al., 2022).) is used to train the model by separating it into train and test, where 70% was used for training, then 30% was used for validation. The model's accuracy is performed using Root Mean Square Error (RMSE) and R Squared(R^2).The outputs of the same are then exported to google drive thereafter downloaded and open via ArcMap software for map making and visualization the zonal statistics of the same are open via excel and further analysis done additionally the graphs are exported by downloading directly from google earth engine platform.

3.3.4 Carbon Sequestration

Figure 3.2 begins with Loading Sentinel-1, Sentinel-2, SRTM elevation, and slope data as predictor variables. Derive the forest mask from the ESA Global Land Cover dataset (for a respective year), followed by preparation of data through loading of Sentinel-1 data for the post-rainy season and prepare inter-quartile range (IQR), masking clouds from Sentinel-2 spectral reflectance data and create a composite image. Clip elevation and derive slope from the SRTM data. Extract forest areas from the land cover dataset to create the forest mask. Merging the predictor variables (S2 composite, Sentinel-1 IQR, elevation, slope, and forest mask) into a single collection then sampling the GEDI L4B ((Dubayah et al., 2022; Duncanson et al., 2022).Dataset for training points within the study area and then Split the sampled points into training (70%) and validation (30%) datasets. Training a random forest regression model using the training dataset and predict AGB values for the study area. Evaluate model performance using training and validation RMSE and correlation analysis between biomass and carbon content. Setting the biomass-to-carbon conversion factor (0.47) and calculate carbon content by multiplying AGB predictions with the conversion factor lastly a correlation analysis is done between biomass and carbon content to evaluate the relationship between the two variables. The outputs of the same are then exported to google drive thereafter downloaded and open via ArcMap software for map making and visualization the zonal statistics of the same are open via excel and further analysis done additionally the graphs are exported by downloading directly from google earth engine platform.

3.4 Factors influencing biomass distribution

Advanced Vegetation Index

The advanced vegetation Index was computed using Near Infrared and Red Bands (NIR & Red (Huete, A. (1995). The Table 3.2 shows values ranging from -1 to 1. Zeros indicated no vegetation, while the values were close to one-showed places with a high density of leaves.

Formula:

$$('NIR * ((1 - RED) * (NIR - RED)) *(1/3)$$

Equation 3.1

The bands were obtained from sentinel two imagery.

Table 3.2: The classes and assigned weights of enhanced vegetation index

class	description	weight
1	low	EVI < 0.3
2	moderate	0.3 ≤ EVI < 0.6
3	Relatively higher	0.6 ≤ EVI < 0.8
4	denser	EVI ≥ 0.8

Bare Soil Index

The Bare Soil Index was computed using four bands. It includes; Red, Near Infrared, Blue, and Short-Wave Infrared.

Formula:

BSI = ((SWIR1 + Red) - (NIR + SWIR2)) / ((SWIR1 + Red) + (NIR + SWIR2)) ..Equation 3.2

Where SWIR1 is the Short-Wave Infrared band 1 reflectance, SWIR2 is the Short-Wave Infrared band 2 reflectance, NIR is the Near-Infrared band reflectance, and Red is the red band reflectance.

Normalized Difference Vegetation Index

The Normalized Difference Vegetation Index (NDVI) is a widely used vegetation index that quantifies the amount of live green vegetation in an area. It is calculated using the following formula:

NDVI= (NIR+Red)/ (NIR−Red)

Equation 3.4

Where:

NIR (Near-Infrared) is the reflectance in the near-infrared spectrum (typically satellite band 5 or 8). Red is the reflectance in the red spectrum (typically satellite band 4).Table 3.3 shows the NDVI values ranging from -1 to 1, where higher values indicate healthier and more abundant vegetation.

Table 3.3: The NDVI range, its description, and assigned weights.

class	Description	NDVI	Weight
1	good	NDVI>0.1	1
2	moderate	0.01<NDVI≤0.1	0.2
3	poor	0<NDVI≤0.01	0

4	No vegetative	NDVI≤0	-1

CHAPTER 4: RESULTS AND DISCUSSIONS

4.1 Overview

The chapter contained a quick results explanation of the corresponding objectives of the Project according to the methodology. Contained the maps and graphs

4.2 Factors Affecting Biomass Distribution

4.2.1 Digital Elevation Model

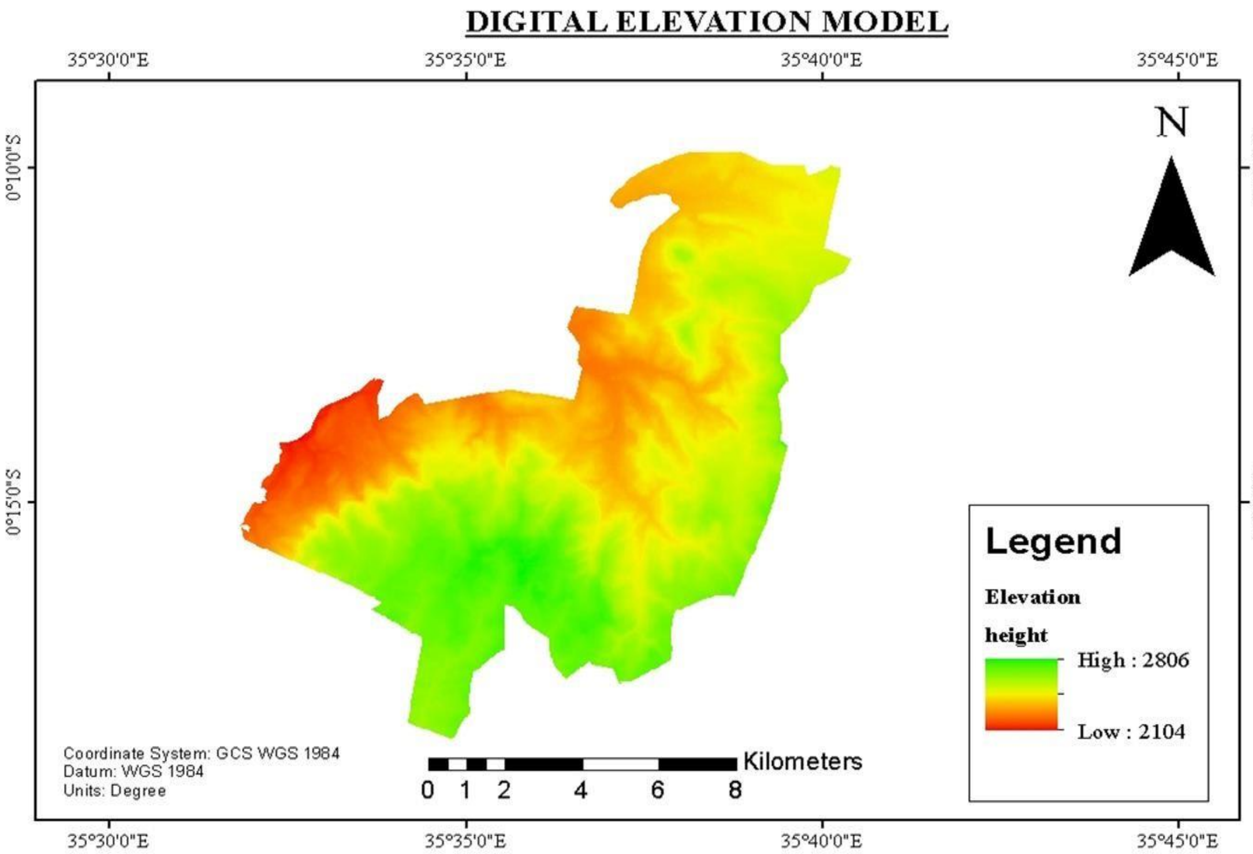

Figure4. 1 The digital elevation model displaying both high and low areas in meters

Figure 4.1 shows a higher elevation at the southern and western parts of the map compared to low areas sloping towards the northwestern part of the map. Considering the general outlook of the study area higher areas are the mountainous part of the site which slopes towards the North Western areas. This high area is normally composed of thick forest vegetation that has remained undisturbed for a longer due to its tough terrain this has consequently showed a higher biomass (Luoto, M. (2017) in such altitude compared to low altitude areas is which can be accessed much easier for forest exploitation. Altitude affects various environmental factors like temperature, precipitation, and soil characteristics, which in turn impact vegetation growth and biomass accumulation. Higher altitudes generally experience lower temperatures and different precipitation patterns, leading to changes in vegetation types and densities. Altitude exerts significant influence on several environmental factors, including temperature, precipitation patterns, and soil characteristics (Pan et al., 2011). These factors collectively impact vegetation growth and the subsequent accumulation of biomass. Higher altitudes typically experience lower temperatures, altering microclimates and affecting the types and densities of vegetation present. Precipitation variations associated with altitude contribute to nuanced ecological niches, further influencing biomass distribution across the landscape as compared with results obtained by (Wang, Y., Zhang, X., & Guo, Z. (2021).

4.2.2 Normalized difference vegetation index (NDVI)

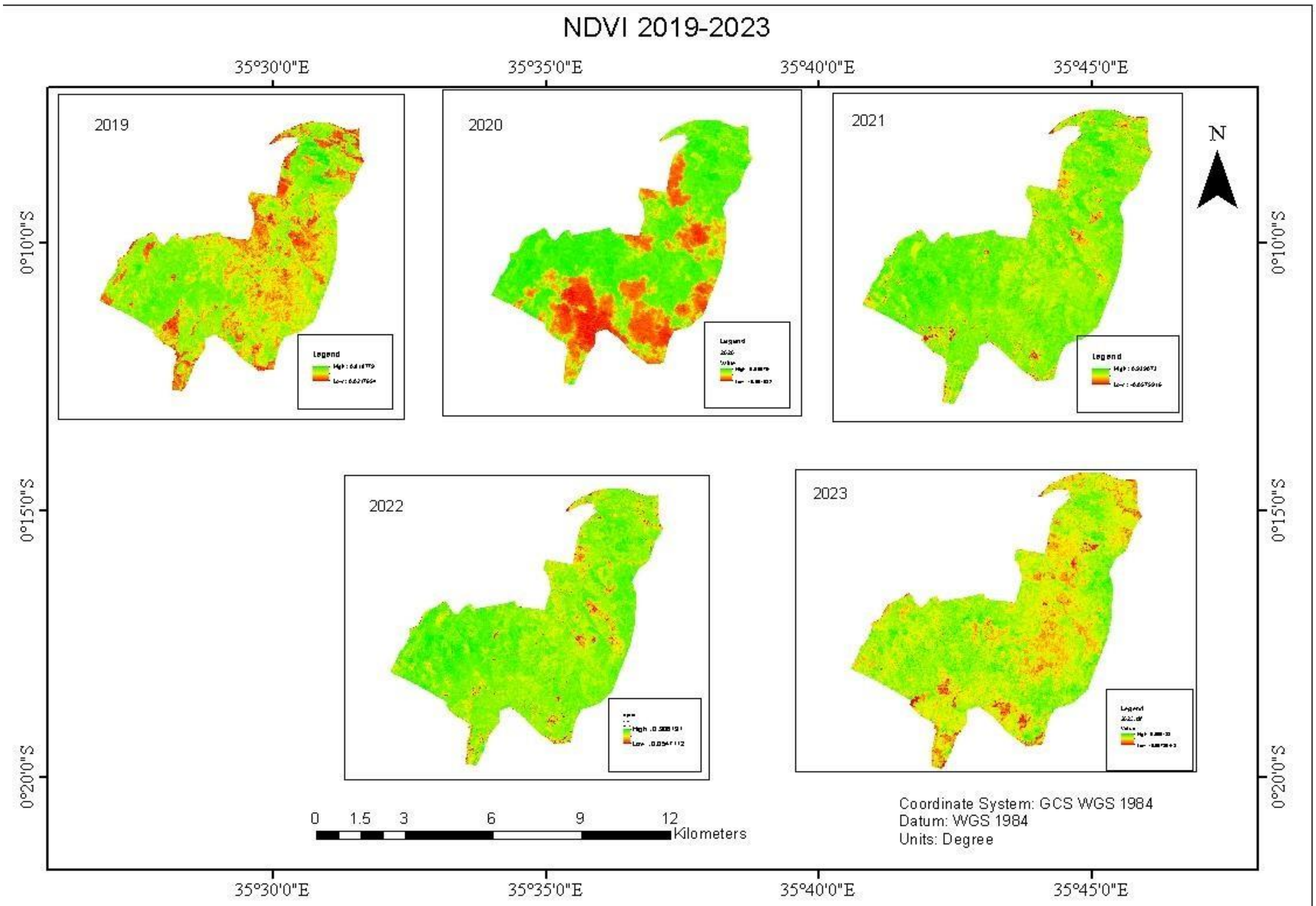

Figure4. 2 The normalized difference vegetation index maps for the year 2019 to 2023

4.2.3 NDVI time series chart

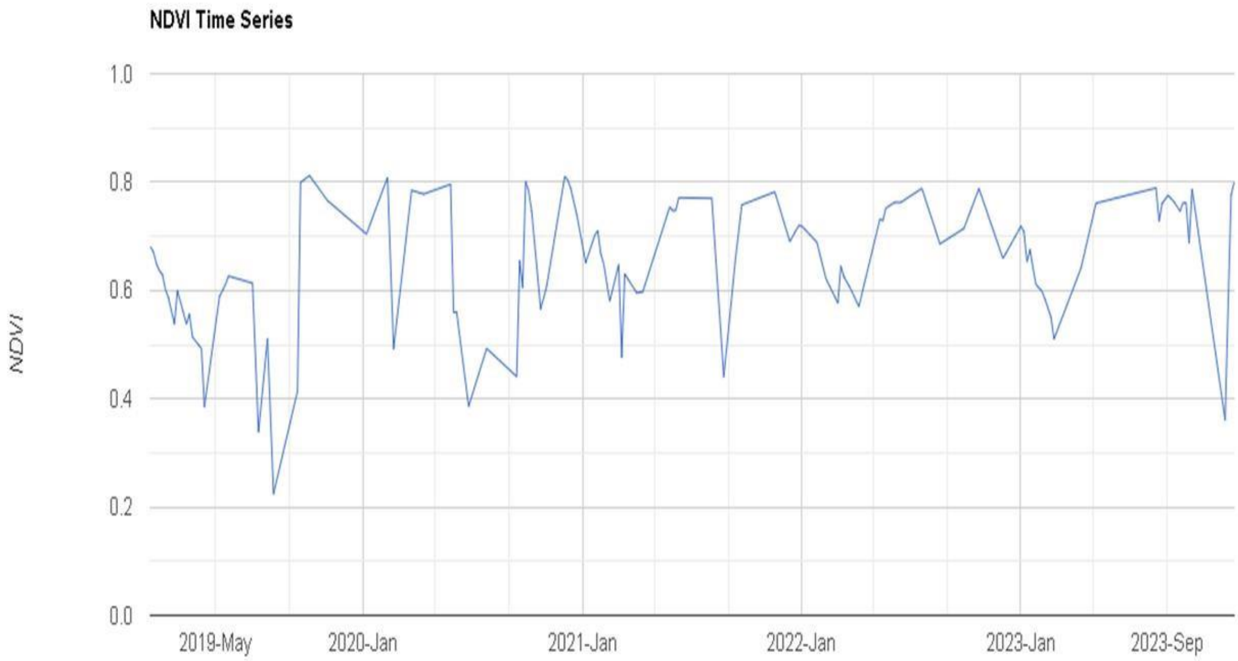

Figure4. 3 A map of a trend series chart for the NDVI values for the year 2019 to 2023

Figures 4.3 and 4.2 highlight the sensitivity of the Normalized Difference Vegetation Index (NDVI) to vegetation stress. The observed decline in NDVI values over time indicates unhealthy vegetation, with lower values suggesting stress conditions that negatively impact biomass accumulation. These changes can be attributed to environmental stressors such as climate change, land use changes, or disturbances that affect the ecosystem's ability to maintain or increase biomass levels. Notably, higher NDVI values were recorded from April to July, extending towards the end of August, correlating with periods of higher rainfall. From a carbon sequestration perspective, decreasing NDVI values and associated biomass suggest a reduced carbon storage capacity in the ecosystem as seen compared to results by (Damdin, B., & Natsagdorj, E. (2022)). This decline in biomass and carbon sequestration capacity emphasizes the need to address environmental stressors to sustain and enhance the ecosystem's role in mitigating climate change through effective carbon storage.

4.2.4 Enhanced vegetation index (EVI)

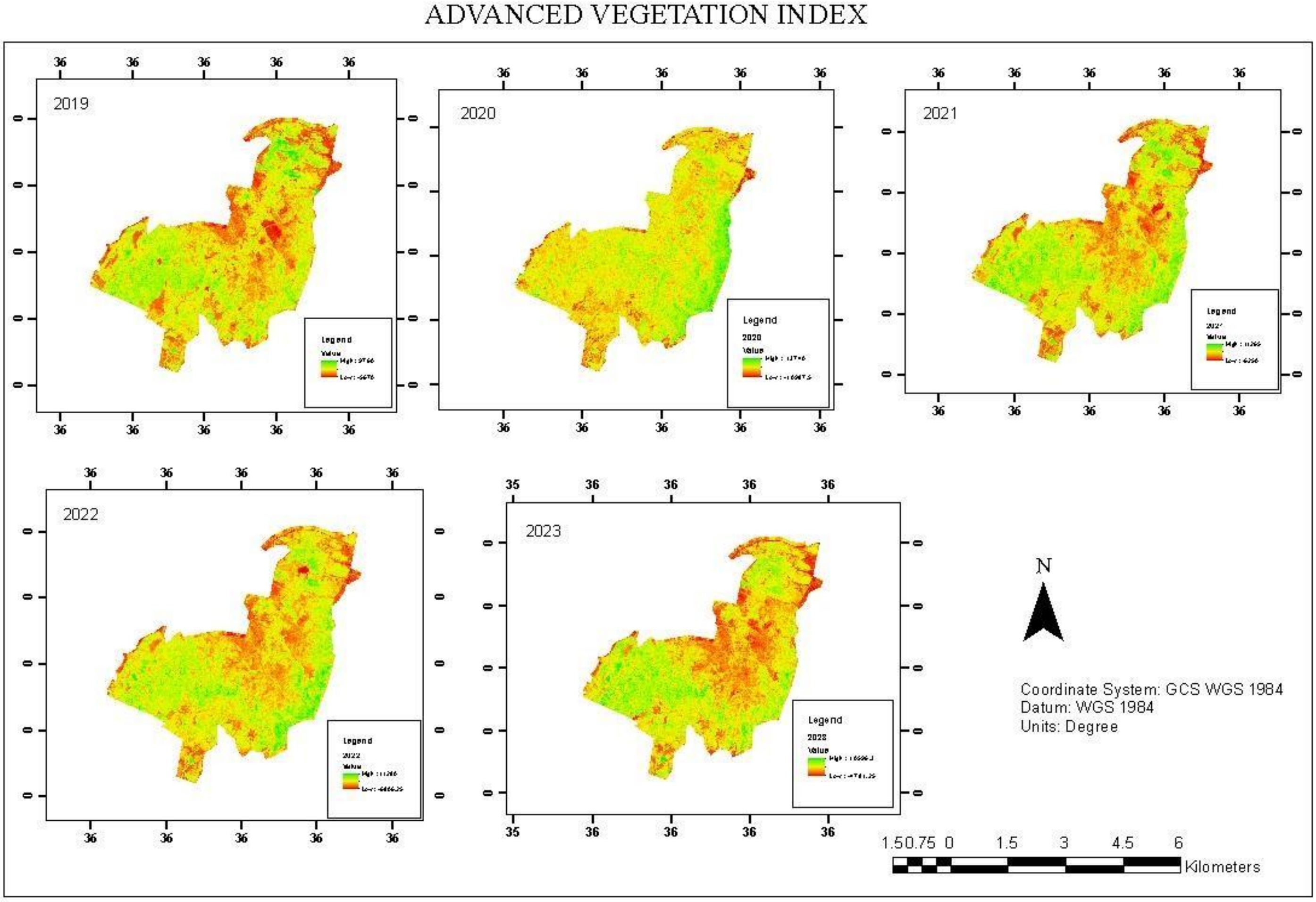

Figure4. 4 A map depicting vegetation stressed of Enhanced vegetation index for the year 2019 to 2023

4.2.5 Time series chart EVI

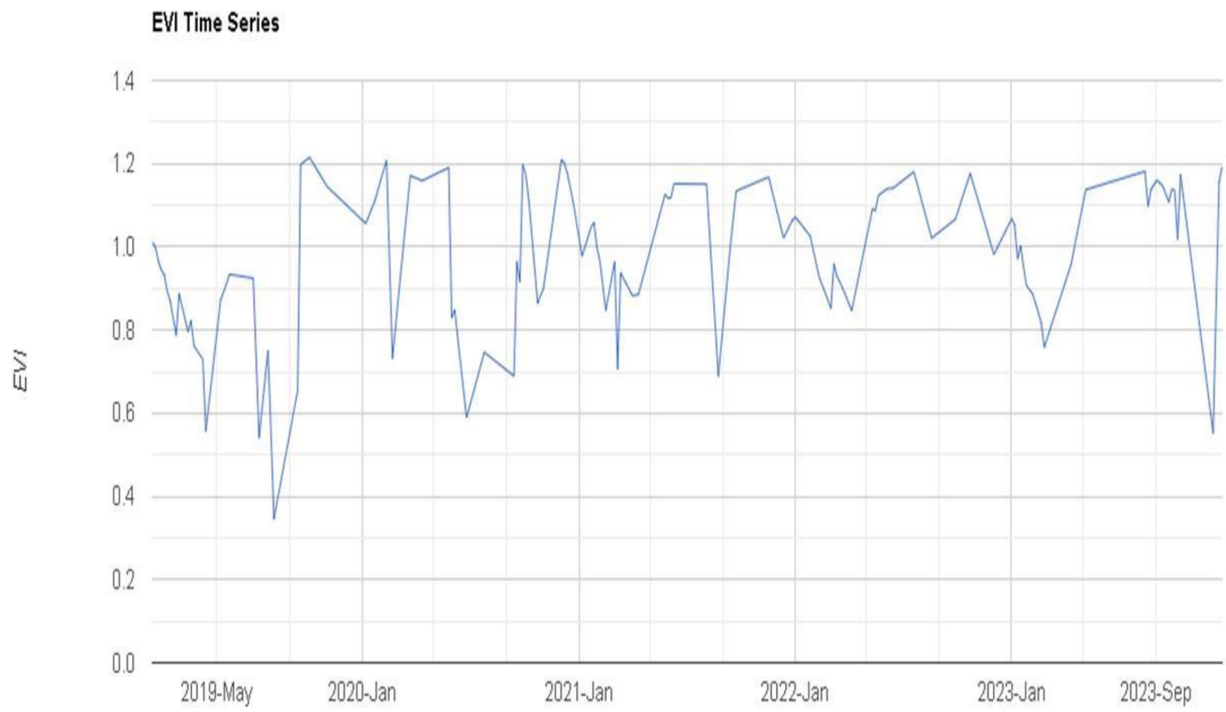

Figure4. 5 A time series trend for the Enhance vegetation index for the year 2019 to 2023

The results from Figures 4.4 and 4.5 highlight the significant impact of vegetation health on biomass and its distribution within the study area. The Enhanced Vegetation Index (EVI) values, which offer improved sensitivity to vegetation changes over the Normalized Difference Vegetation Index (NDVI), indicate that higher vegetation health correlates with increased biomass(Zhu, X., & Liu, D. (2015). These values were highest between May and August each year, reflecting peak growing conditions, but showed a declining trend from 2019 to 2023, suggesting a reduction in vegetation productivity and, consequently, biomass accumulation over time. Spatially, consistently high EVI values in the mountainous areas suggest these regions maintain robust, undisturbed vegetation that contributes significantly to carbon sequestration by storing higher biomass. In contrast, areas with declining EVI values indicate stressed vegetation, leading to reduced biomass and carbon storage capacity. This pattern underscores the importance of preserving healthy vegetation and managing stress factors to maintain biomass and enhance carbon sequestration across the study area.

4.2.6 Time series rainfall distribution

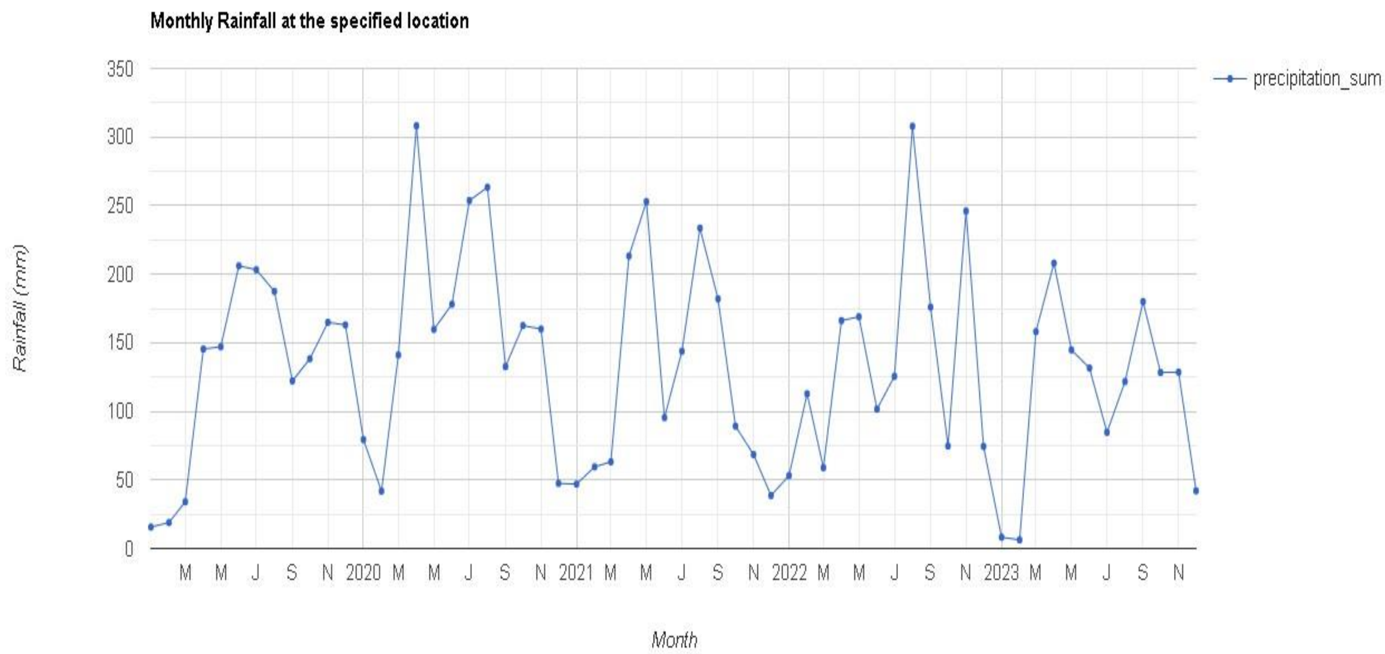

Figure 4. 6 Time series rainfall distribution expressed in millimeters (mm) for year 2019 to 2023

Figure 4.6 demonstrates that the study area experiences high rainfall primarily between April, May, and August, while receiving lower rainfall from December to February. The mean annual rainfall is 1589mm, which is crucial for supporting vegetation growth. Adequate rainfall during these months provides the necessary moisture for plant growth, resulting in higher biomass production and healthier vegetation cover. This positive correlation between rainfall and vegetation health directly affects the aboveground biomass (AGB) estimates (M., Noguchi, K., & Hirano, Y. (2011)). Conversely, periods of lower rainfall or drought conditions can stress vegetation, leading to reduced biomass and compromised ecosystem health. Therefore, consistent and sufficient rainfall is essential for maintaining robust biomass and effective carbon sequestration in the study area (Newton, P. C., & Wills, K. E. (2014)).

4.2.7 Land use land cover change

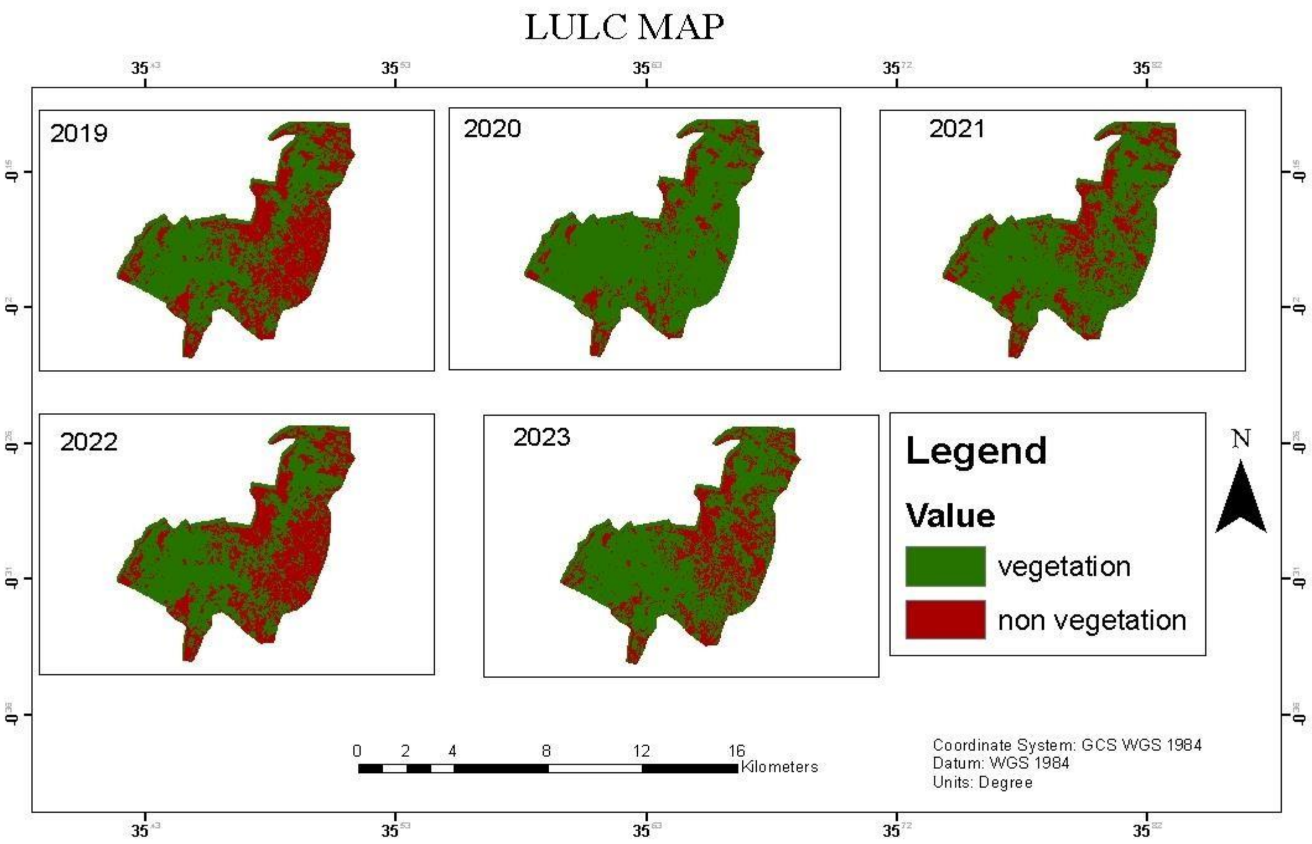

Figure 4. 7 A Map of land use land cover classified into two classes for the year 2019 to 2023

Figure 4.7 illustrates the characterization of land use and land cover into vegetation and non-vegetation categories, highlighting the dynamic nature of ecosystem responses to environmental factors over time. In 2019 and 2022, the number of vegetation features was lower compared to 2020. This reduction in vegetation cover during 2019 and 2022 may be attributed to extreme weather events, land disturbances, or other ecological changes that negatively impacted vegetation growth. Conversely, the higher number of vegetation features observed in 2020 suggests that conditions were favorable for vegetation growth and health during that year. These favorable conditions could include optimal rainfall patterns, suitable temperatures, or reduced anthropogenic pressures, all of which support increased biomass and healthier vegetation cover. Such variations underscore the importance of understanding and mitigating environmental stressors to maintain and enhance biomass and carbon sequestration in the study area which concur with the results by (Thompson, J. R., Foster, D. R., Scheller, R., & Kittredge, D. (2011).

4.3 Biomass estimation

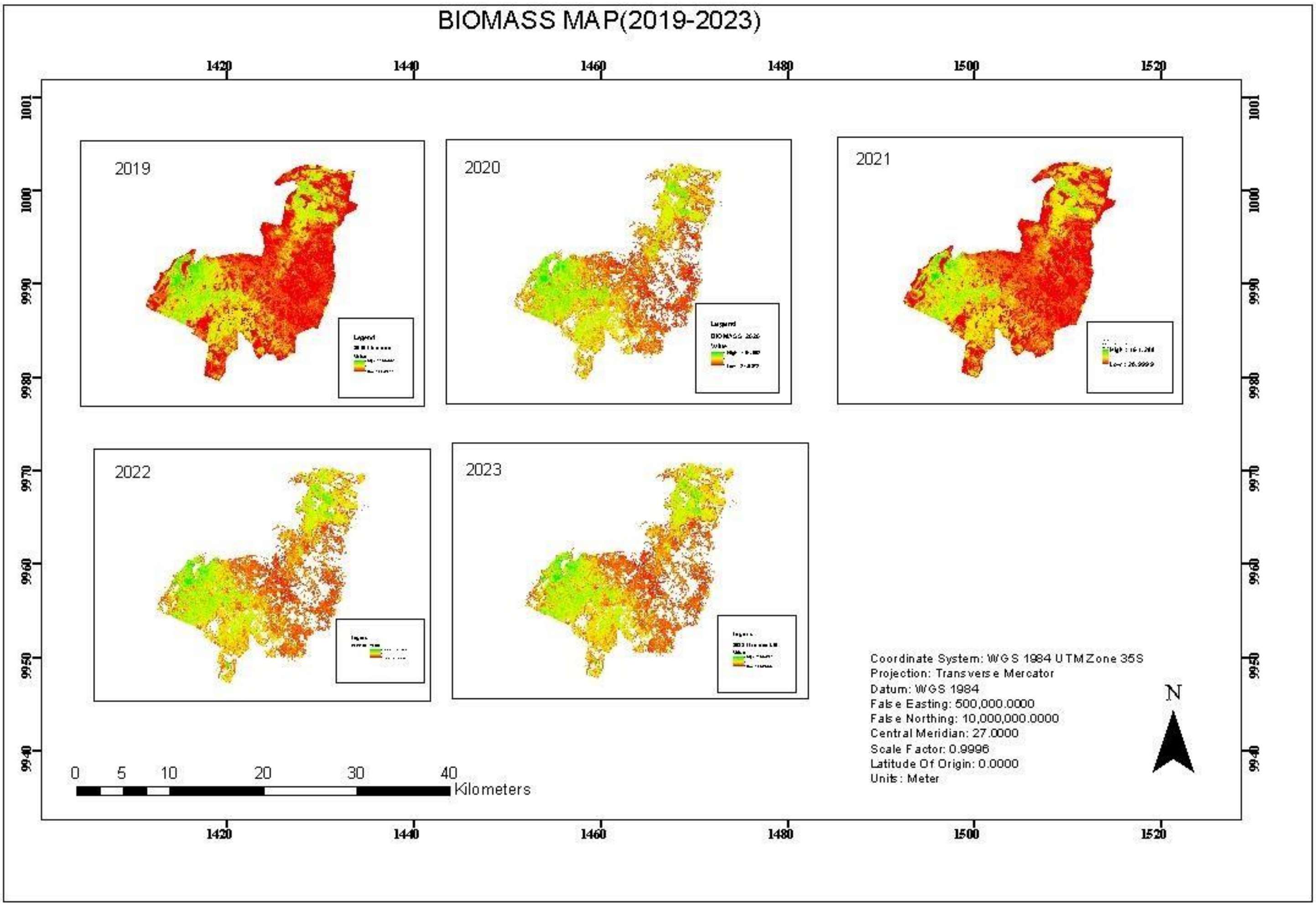

Figure 4. 8 A map showing the biomass distribution and its changes for the year 2019 to 2023

4.3.1 Zonal statistics of biomass

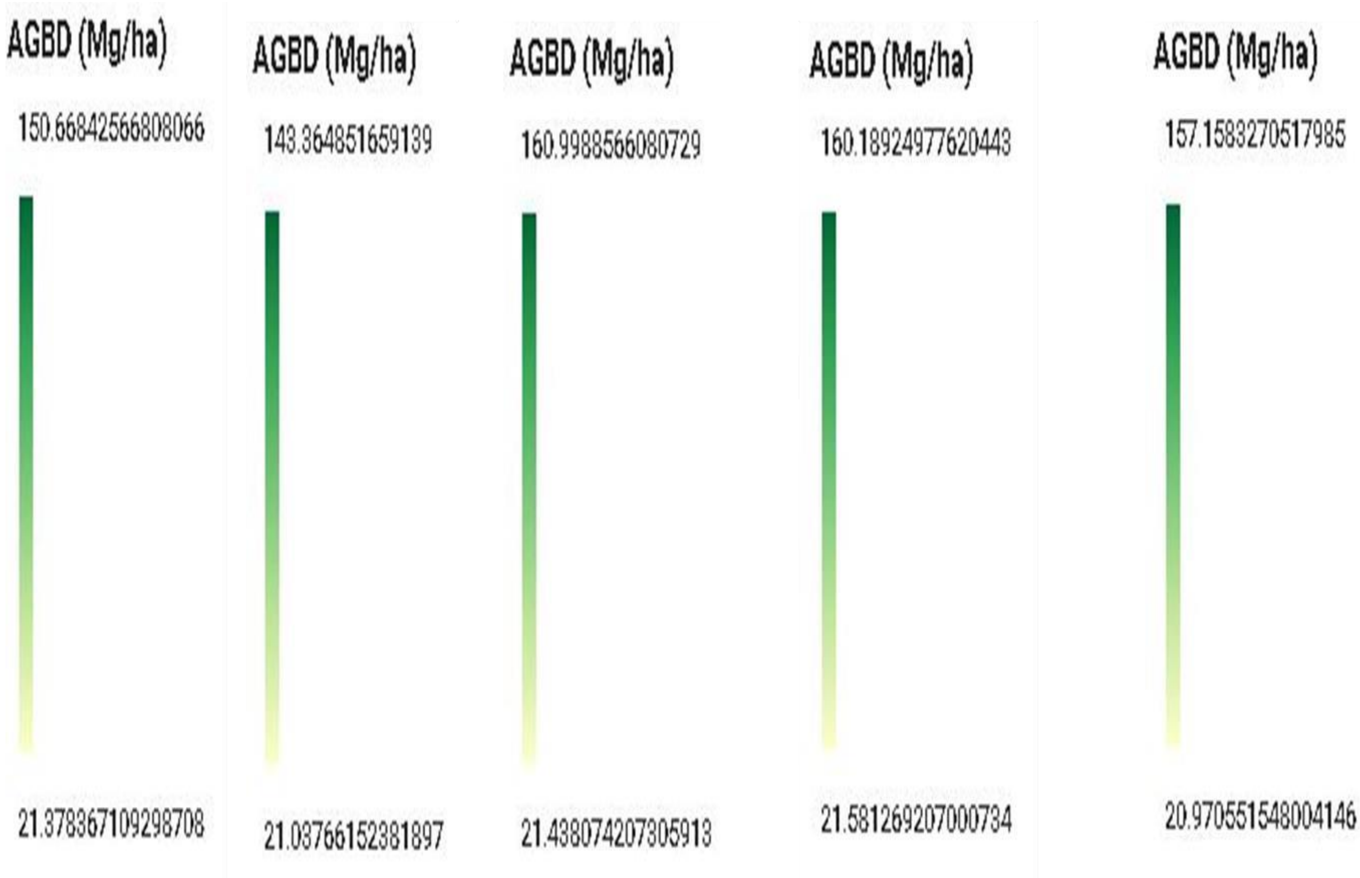

Figure4. 9 The zonal statistics of biomass distribution in values across the study area for the period between 2019 to 2023 expressed in Mg/ha

From figure 4.9: and Figure 4.8 show the trend shows a fluctuation in biomass levels, with a notable increase in 2021 followed by relatively stable or slightly decreasing values in subsequent years. This was mainly attributed to land use changes for example deforestation and natural disturbances such as wildfire. The low vegetation features observed in 2019 and 2023, corresponding to lower biomass levels, may indicate periods of environmental stress or disturbances impacting vegetation growth. The high number of vegetation features and biomass recorded in 2020 suggests a period of favorable conditions for vegetation growth and recovery (Johnson et al. (2021). This could be attributed to factors such as improved rainfall patterns, land management practices, or natural regeneration processes, contributing to increased biomass levels and healthier vegetation cover. The high number of vegetation features and biomass recorded in 2021 and 2022 suggests a period of favorable conditions for vegetation growth and recovery. This could have been attributed to factors such as improved rainfall patterns, land management practices, or natural regeneration processes, contributing to increased biomass levels and healthier vegetation cover. Brown et al. (2020) reported that improved rainfall patterns and effective land management practices contribute to increased biomass levels and healthier vegetation cover during recovery periods.

A graph showing predicted, observed and validation of training samples over the years between 2019-2023

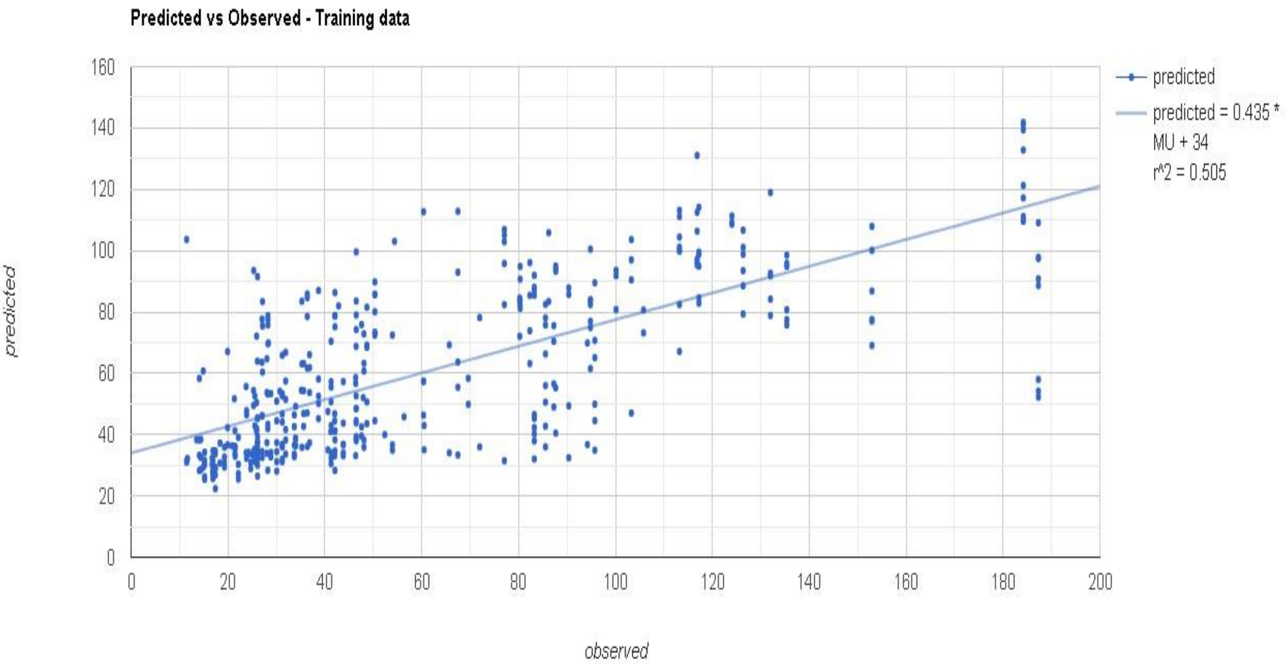

Figure4. 10 A graph of predicted versus the observed training data used in Biomass estimation

From Figure 4.10: there was a strong positive correlation between the predicted, observed and validation of the above training samples from 2019-2023.This proofed the efficiency of the model trained as noted by (Zhang et al. (2020)) though his study focused on few environmental variables this study will looked at the samples trained using GEDI data. A line of best fit is drawn where the trained sample points should lie close to the line of best fit.

4.3.2 Variable importance

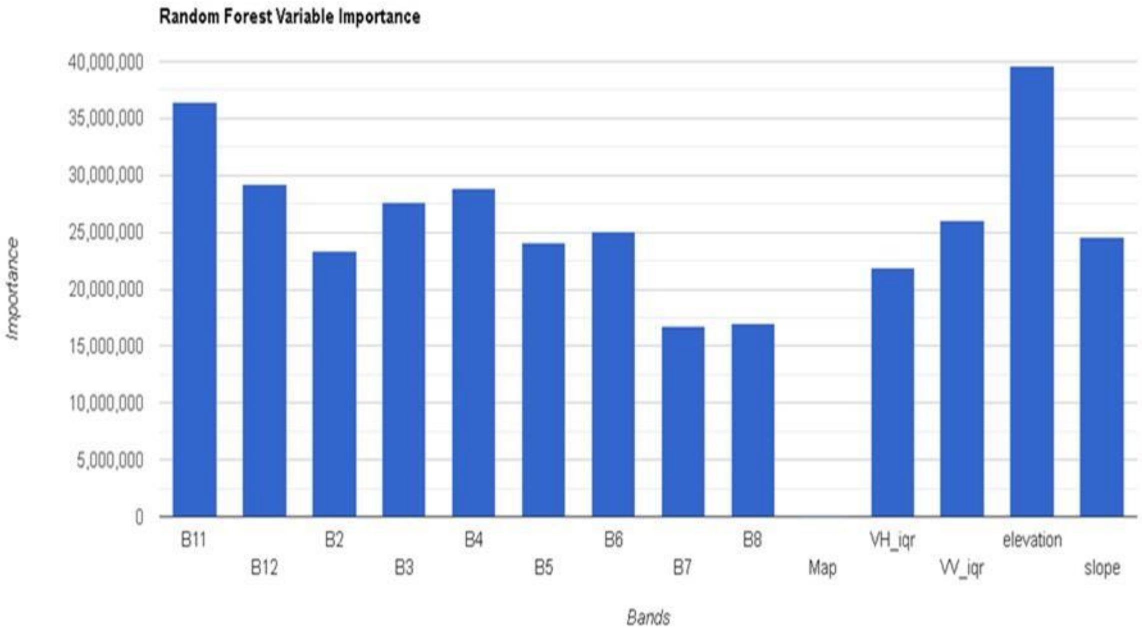

Figure4. 11 A graph of variable importance used in biomass estimation highlighting the significance of each variable used

From the fig 4.11: elevation and band 11 proved to be the most valuable variables in estimating biomass. The main reason behind the elevation significance is the mountainous region that has remain undisturbed (Mount Londiani). The fact that elevation is crucial due to the undisturbed nature of the mountainous region underscores the importance of considering local environmental characteristics in biomass estimation. Band 11 is sensitive to vegetation stress and was relevant in biomass estimation. Its ability to detect stress conditions in vegetation helps in accurately assessing the health and productivity of plant cover, thereby improving biomass estimation models. The inclusion of Band 11 in biomass estimation reflects the importance of monitoring vegetation stress and health to understand variations in biomass distribution and carbon sequestration effectively. Similar results was justified by (Luoto et al. (2017) who emphasized the significance of elevation in biomass estimation in mountainous regions.

4.4 Carbon Estimation

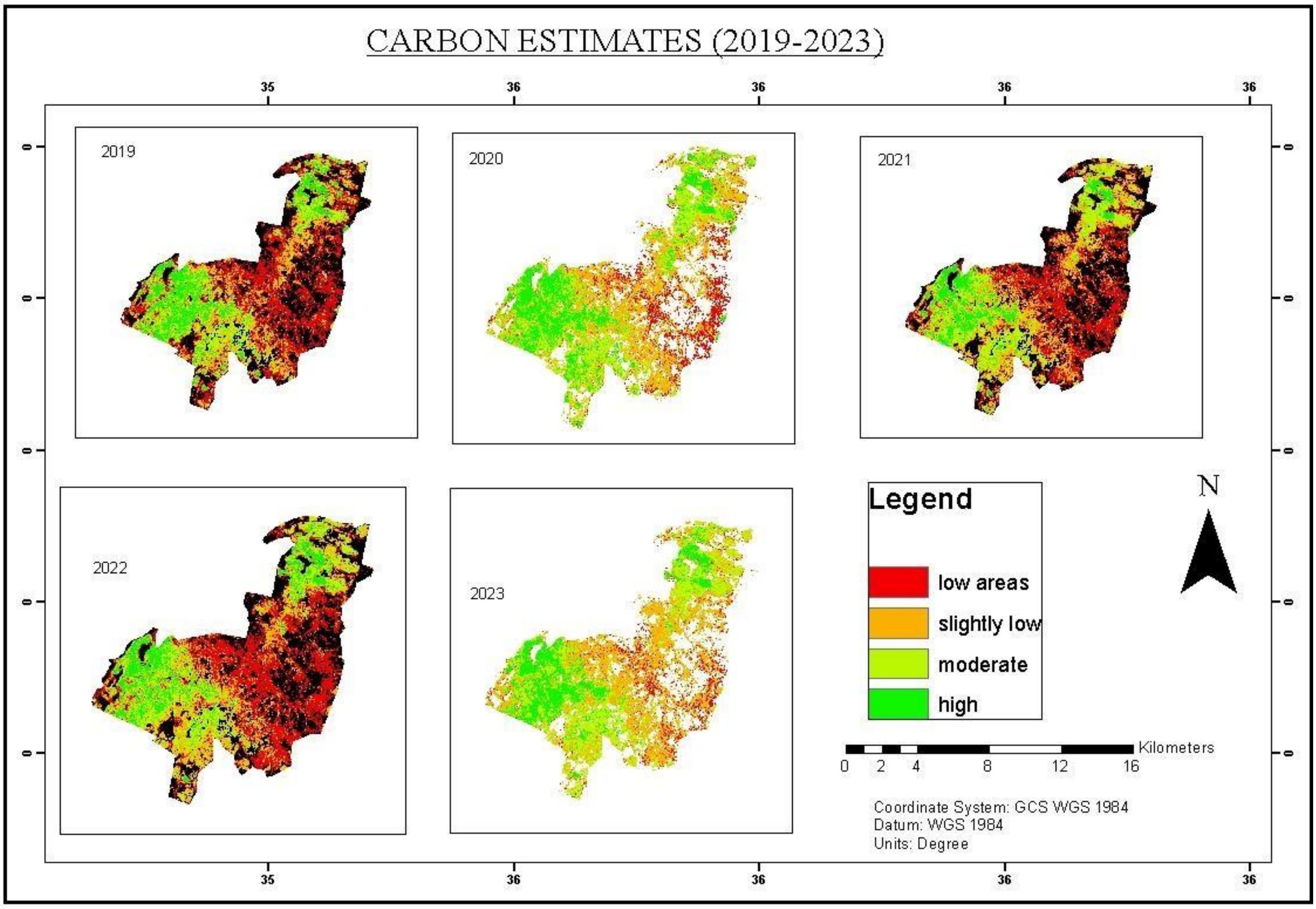

Figure4. 12 A map of quantified carbon estimates and its distribution in the study area for the study period between 2019 to 2023

Figure 4.12: represents the carbon estimates for the year 2019 to 2023.The high areas representing high carbon content was located near the mountainous areas which implied that these areas were always undisturbed from human activities hence the high number of carbon content. Mountainous regions often host diverse and undisturbed ecosystems with varied vegetation types, including dense forests, alpine meadows, and montane shrub lands. These ecosystems tend to accumulate substantial biomass over time, contributing to elevated carbon storage capacities (Ruankawe, et al. (2007)). Additionally, the cooler temperatures and unique microclimates characteristic of higher elevations can promote slower decomposition rates, allowing organic matter to persist in the soil and vegetation for longer periods, further enhancing carbon retention. Luoto (2017) noted that the cooler temperatures and specific

microclimates in higher elevations reduce decomposition rates, allowing organic matter to accumulate and persist for extended periods.

Correlation analysis between biomass and carbon

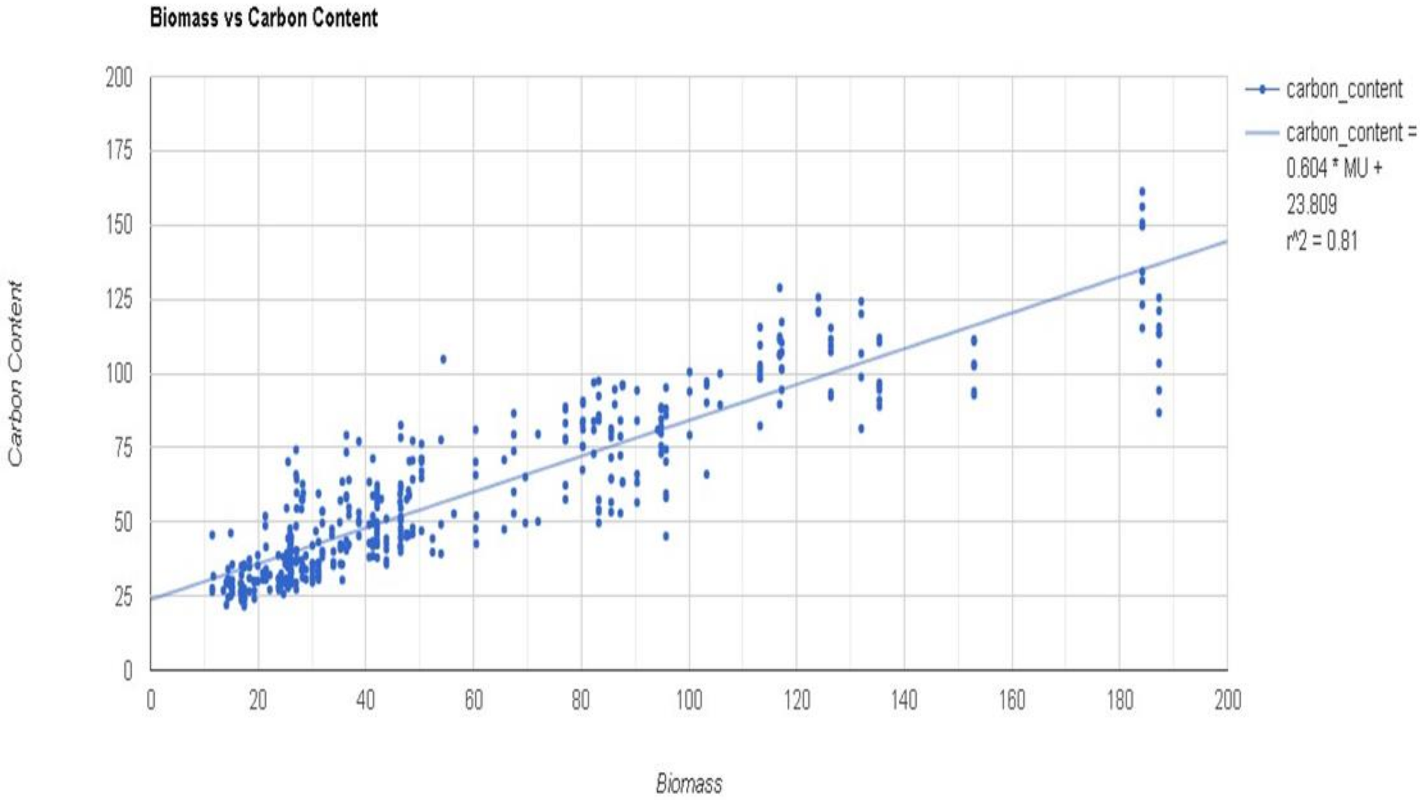

Figure4. 13 A graph of correlation analysis between the biomass estimated and the carbon sequestration

The analysis of the Figure 4.13: shows a strong positive correlation between biomass and carbon content. This correlation implies that as forests accumulate more biomass, they also sequester and store larger amounts of carbon, contributing positively to carbon sequestration efforts (Saatchi et al.'s (2011) his study indicated that areas with higher biomass tend to store more carbon, emphasizing the critical role of biomass accumulation in enhancing carbon sequestration.

4.4.1 Times series Trend of carbon sequestration

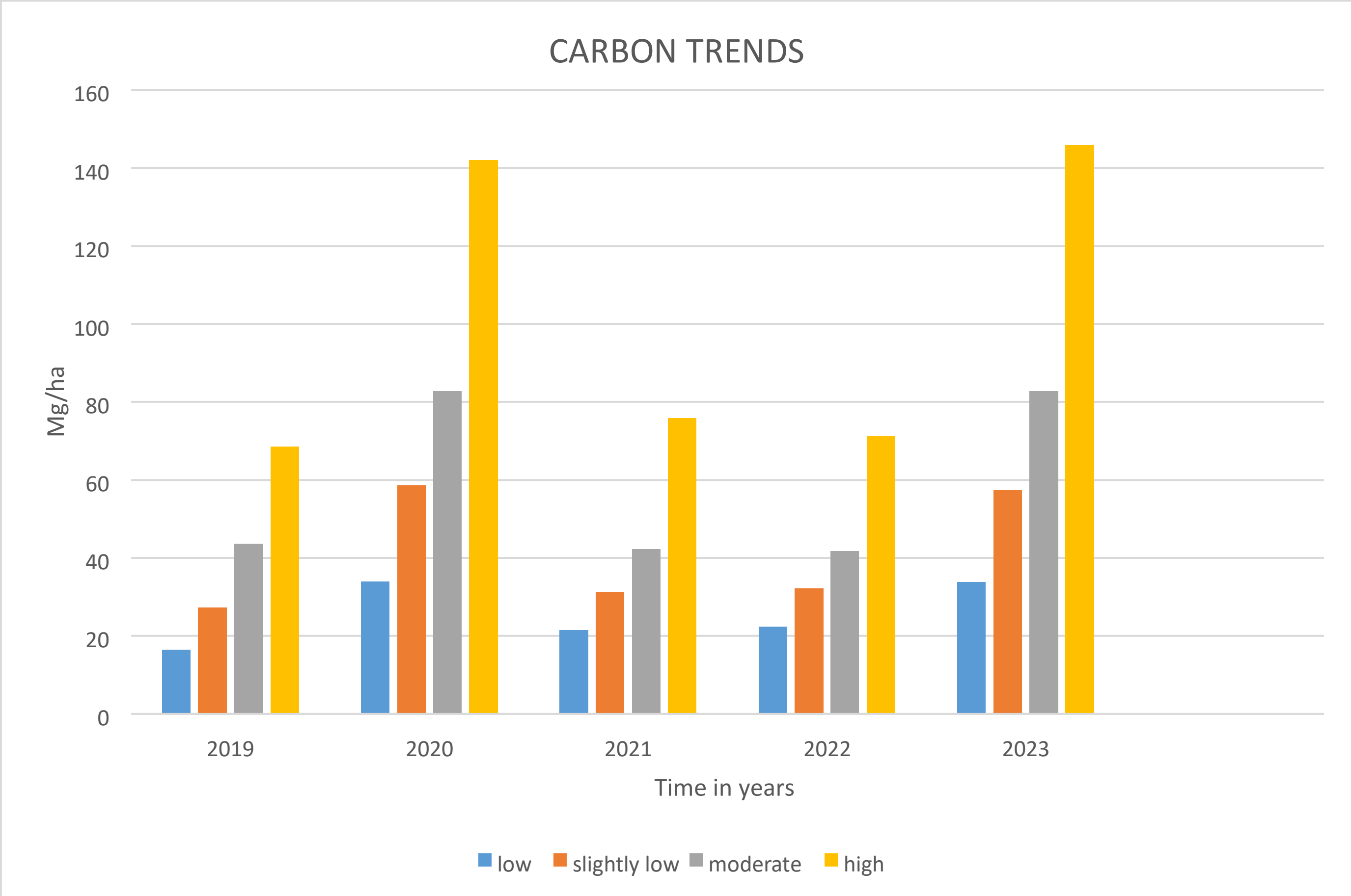

Figure4. 14 A graph of carbon sequestration trends between the years 2019 to 2023 classified into four classes in a hierarchical manner

Figure 4.14: shows a fluctuating carbon content over the years with a notable higher content in the years 2020 and 2023 compared to low carbon content for the years 2019,2021 and 2022 this was due to high biomass accumulation for in the respective years. Higher carbon content in 2020 and 2023 suggests periods of enhanced vegetation growth and productivity, likely due to favorable environmental conditions such as optimal rainfall, suitable temperatures, and reduced anthropogenic disturbances. Conversely, the lower carbon content observed in 2019, 2021, and 2022 indicates periods of reduced biomass accumulation, possibly caused by adverse environmental factors, such as extreme weather events, droughts, or increased land disturbances. This pattern emphasizes the dynamic relationship between environmental conditions, biomass production, and carbon sequestration, highlighting the importance of continuous monitoring and management of ecosystem health to maximize carbon storage capabilities. Understanding these variations helps in identifying key factors that influence carbon dynamics, providing valuable insights for developing effective strategies to enhance carbon sequestration and mitigate climate change impacts the results aligns with the finding by

Pan et al.'s (2011) who linked the fluctuations in carbon content to environmental conditions and biomass accumulation, additionally (Pugh et al. (2019)) also reported that biomass and carbon content are significantly influenced by forest management practices and natural disturbances.

4.5 Discussions

The analysis from the factors affecting biomass distribution revealed that Land Use Land Cover (LULC), Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Digital Elevation Model (DEM), and rainfall significantly influence biomass distribution, Higher NDVI and EVI values were recorded during the wet season months of April to August, indicating healthy vegetation growth during this period ((Pettorelli et al., 2005)). However, a declining trend in EVI values was observed from 2019 to 2023, suggesting potential stress conditions affecting the vegetation. Vegetation health is a key determinant of biomass accumulation, as stressed or unhealthy vegetation will have reduced biomass production ((Xu et al., 2020)). Additionally mountainous regions showed consistently higher biomass levels compared to lower elevation areas, this was supported by the fact that slope became the most significant predictor variable followed by band 11 (Luoto et al., 2017). This is likely due to the undisturbed nature of the dense forests found at higher elevations. Altitude affects various environmental factors like temperature, precipitation, and soil characteristics, which in turn impact vegetation growth and biomass accumulation (Körner, 2007). Rainfall patterns played a significant role in biomass distribution, with higher rainfall amounts received during the months of April, May, and August with a mean annual rainfall of 1589mm per year moisture availability is essential for plant growth and biomass accumulation, while lower rainfall or drought conditions can stress vegetation and reduce biomass levels ((Ali et al., 2019). The LULC analysis results showed lower vegetation cover in 2019 and 2022 compared to 2020 factors such as deforestation, land degradation, or extreme weather events can lead to reductions in vegetation cover and biomass (Achard et al., 2002). The study employed machine learning techniques, specifically Random Forest regression, to estimate above-ground biomass (AGB), the predicted biomass values showed a strong positive correlation with observed and validation data, demonstrating the effectiveness of the model with higher biomass concentrations in forested regions and lower values in areas dominated by non-vegetation areas or bare areas ((Baccini et al., 2012). The study revealed fluctuations in biomass levels over the years, with notable increases in 2021 followed by relatively stable or slightly decreasing values, attributed to factors like land use changes and natural disturbances, an average of 152Mg/ha of biomass per year was estimated. This could be attributed to factors such as improved rainfall patterns, land management practices, or natural regeneration processes, contributing to increased biomass levels and healthier vegetation cover (Pan et al., 2011). Carbon content was estimated by applying a conversion factor of 0.47 (Dubayah et al., 2022; Duncanson et al., 2022). to the biomass values, as the study area was predominantly forested. The highest carbon content was found in the undisturbed mountainous regions, emphasizing the importance of protecting these areas for carbon sequestration (Lewis et al., 2009). The findings suggest that any changes in the forest structure in terms of its disturbances whether due to forest disturbances directly impacts the biomass of the area and hence significantly impact the region's carbon sequestration capacity. Further analysis showed strong correlation between biomass and carbon content (Dixon et al., 1994).

CHAPTER 5: CONCLUSION & RECOMMENDATIONS

5.1 Overview

This chapter deals with the study conclusion, and recommendations that are obtained from the results of the Corresponding objectives of the project study.

5.2 Research Findings Summary

The study's main objective was to assess the effects of biomass on carbon sequestration in the study area from 2019, 2020, 2021, 2022 and 2023. All the data processing was done on Google Earth Engine with the help of the Data Catalog. The study was based on estimating the biomass using the available GEDI to get the biomass values and consequently the carbon content using machine learning techniques. Among the various factors identified to impact biomass distribution were climatic conditions, such as moderate temperatures and adequate rainfall which tend to support lush vegetation with higher biomass levels. Soil characteristics, topographical features such as elevation, slope, and aspect can create microclimatic variations that influence biomass patterns within a landscape. However, some of the indices were of great significance in determining biomass included; Normalized difference fraction index, Advanced Vegetation Index, and normalized difference vegetation index. Finally, the carbon stocks was estimated using the biomass values obtained using the carbon content conversion factor of about 0.47, and correlation analysis between biomass and carbon done. It was evident that high biomass and carbon content were recorded in the mountainous areas since the ecosystem there remain undisturbed hence also the high carbon content. The results of the corresponding objectives were produced and values were classified.

5.3 Conclusions

Vegetation health, as indicated by indices like NDVI, EVI, and NDFI, directly influences biomass distribution by reflecting the vigor and density of plant growth. Higher vegetation health values typically correlate with increased biomass due to more active photosynthesis and biomass production as observed in (Figure 4.1, 4.2, 4.3, 4.4 and 4.5). Adequate rainfall and optimal temperatures often lead to higher biomass accumulation by promoting favorable conditions for plant growth and productivity as seen mainly during the months of May to August when the rainfall received is higher as seen from (Figure 4.6). Biomass was high in 2021 and 2022, drop down in 2020 and 2019, and slightly increased afterward in 2023 till today as seen from (Figure 4.8 and 4.9). The slight decrease biomass in the Kedowa londiani forest has led to low carbon sequestration (Figure 4.12). The results demonstrated a strong correlation analysis between biomass and carbon content (Figure 4.13). It has contributed to climate change and afterward caused drought. The results from the map and graphs show that areas with much change in biomass and carbon content values and that the low areas of carbon and biomass were mostly based on the following areas; Quarrying areas, Bare lands Areas next to the road, and settlements such as Londiani Centre and along the forest margin as shown in (Figure 4.14). The remaining percentage of the forest should be kept safe and secure for future generations to combat the effects of climate change and effects of carbon sequestration. The study revealed also the strong correlation between biomass and carbon content. There is a need for sustainable forestry management practices that prioritize reforestation efforts in areas affected by deforestation due to the supply of wood fuels to factories such as KTDA in tea estates this can be reduced by encouraging alternative energy sources and promoting efficient use of existing resources, such as promoting renewable energy options for tea processing, can reduce the reliance on wood fuel.

5.4 Recommendations

Based on the findings unlike Lidar data, forest managers should consider using GEDI data for estimating the aboveground biomass of the forest to give information regarding the live and dead trees on the earth and the amount of carbon sequestration in a given geographical area. Legislation and policy frameworks should be revisited to hold the forest managers for accounting activities such as over-logging and Quarrying activities that have been evidenced to affect the forest canopy cover negatively also future scholars should consider developing a web application to assess to assess and estimate biomass and carbon content.

To meet emerging biomass and carbon information needs, it's essential to collect new biomass data and develop a framework to integrate existing data and equations. Future research should focus on creating a web application for assessing and estimating biomass and carbon content.

Considering future climate changes, it’s crucial to study variations in the allometric forms of species across different climatic and soil gradients. Developing integrated biomass equations that account for a broader range of measurable tree dimensions will ensure accurate carbon sequestration estimates.

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APPENDICES

Biomass estimation

https://code.earthengine.google.com/e8ff92475a64d58438d103f5a2f609a5

Land use land cover

https://code.earthengine.google.com/3ad8aaeb5a3560891cc5b488888f670d