KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY, KUMASI, GHANA

GEOSPATIAL-BASED MODELLING OF WOODY VEGETATION PATTERNS AND ABOVEGROUND BIOMASS IN THE SALOUM DELTA, SENEGAL: A PATHWAY TO OPTIMAL LAND RESTORATION

By

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DOCTOR OF PHILOSOPHY IN CLIMATE CHANGE AND LAND USE

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DECLARATION

I hereby declare that this submission is my own work towards the PhD in Climate Change and Land Use and that, to the best of my knowledge, it contains no material previously published by another person, nor material which has been accepted for the award of any other degree of the University, except where due acknowledgement has been made in the text.

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ABSTRACT

The interplay of climate and anthropogenic pressures has led to significant vegetation degradation in many regions, leading to land degradation and affecting ecosystem services. While evidence of land degradation is apparent, some areas also show promising signs of regreening, offering both challenges and opportunities for restoration. The Saloum Delta exemplifies these dynamics, yet there is a lack of detailed understanding of its vegetation patterns, particularly woody tree vegetation, which have implications for managing the landscape. A spatially detailed assessment is critical to reconcile these contrasting trends and inform sustainable management strategies for optimal land restoration. The first objective assessed woody cover dynamics from 2002 to 2022. A random forest algorithm (RF) was used to classify images in the Google Earth engine. Post-classification analysis, such as change detection, fragmentation, and connectivity analysis, was done using R software. The second objective assessed the environmental drivers of the spatial distribution of the woody cover and related habitat suitability. Species Distribution Models (SDM) were applied using GPS coordinates of the woody tree covers as occurrence data and ten environmental variables. Ensemble model with Maxent, General Linear Model (GLM) and RF were used. Using allometric equations and machine learning, the third objective estimated the aboveground biomass (AGB) of the different woody tree covers. AGB estimation integrated ground inventory data from 138 plots with Sentinel-2 imagery from the dry and wet seasons. The machine learning models included Random Forest (RF), K-Nearest Neighbor (K-NN), Super Vector Machine (SVM) and XGB (Gradient Boosting Model) to predict the AGB. First, the spatiotemporal analysis revealed that Mangroves dominate both Protected Forests (PF) and Outside Protected Forests (OPF), with significant gains from “Water” and “No Woody Cover.” Plantations in OPF showed progressive expansion, highlighting land-use shifts outside protected areas. Pattern analysis indicated increased connectivity and reduced fragmentation for Mangroves and Close Woodlands in PF. In contrast, Open Woodlands in OPF showed dynamic fragmentation patterns with increased small patches in Plantations. The assessment of woody tree spatial drivers reveals key environmental predictors, such as salinity and bulk density for Mangroves, rainfall and salinity for Close Woodlands, burn area index for Open Woodlands, and rainfall and proximity to villages for Plantations with spatial patterns highlighting their suitability for optimising their coverage. Mangroves accounted for the smallest gap between the actual and suitable coverage, with a gap of 3.47%. Strong gab still existed for the other woody trees, with 5.49, 6.03 and 6.41% for Close Woodlands, Open Woodland and Plantations, respectively. Lastly, the AGB estimation of the woody cover revealed that Close Woodlands had the highest biomass density (295.08 Mg/ha), followed by Open Woodlands, Plantations, and Mangroves. Seasonal variability influenced predictions, with wet-season Sentinel-2 imagery yielding more accurate results. Random Forest models provided the highest accuracy ($R^2 = 0.83$, RMSE = 47.20). The findings filled the identified gap by employing advanced geospatial analyses. They helped understand woody vegetation patterns, further suitable areas, and biomass potential, supporting future land management strategies for optimising land restoration and policy regreening.

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LIST OF ABBREVIATIONS

AFOLU - Agriculture, Forestry, and Other Land Use
AGB - Aboveground Biomass
AGC - Aboveground Carbon
AI - Aggregation Index
AUC - Area Under the Curve (model performance metric)
BMBF - German Federal Ministry for Education and Research
CCLU - Climate Change and Land Use
COR - Correlation Coefficient (model performance metric)
CPT - Captain
CSV - Comma-Separated Values
CV - Coefficient of Variation
DBH - Diameter at Breast Height
ED - Edge Density
ERA5-Land - ECMWF Reanalysis 5 for Land (climate data source)
EVI - Enhanced Vegetation Index
GLCM - Gray Level Co-occurrence Matrix
GLM - Generalized Linear Models (statistical modeling technique)
GNDVI - Green Normalized Difference Vegetation Index
GPS - Global Positioning System
$GtCO_2eq\ yr^{-1}$ - Gigatonnes of Carbon Dioxide Equivalent per Year
HydroSHEDS - Hydrological data and maps based on SHuttle Elevation Derivatives at multiple Scales
IPCC - Intergovernmental Panel on Climate Change
IRD - Institut de Recherche pour le Développement
IREF - Inspection Régionale des Eaux et Forêts
K-NN - k-Nearest Neighbor
KNUST - Kwame Nkrumah University of Science and Technology
LPI - Largest Patch Index
LT - Lieutenant
LULC - Land Use and Land Cover
Maxent - Maximum Entropy Modeling (species distribution modeling technique)
METE - Ministry of Environment and Ecological Transition
MODIS - Moderate Resolution Imaging Spectroradiometer (satellite-based data)
NDVI - Normalized Difference Vegetation Index
OECD - Organisation for Economic Co-operation and Development
OPF - Outside Protected Forests
PA - Patch Area
PADEC - Programme d'Appui au Développement Communautaire
PAFRAC - Perimeter-Area Fractal Dimension
PASA - Senegal-German Agricultural Development Project
PBA - Pixel-Based Approach
PCA - Principal Component Analysis
PF - Protected Forests
R - A statistical programming language
R^2 - Coefficient of Determination

REDD+ - Reducing Emissions from Deforestation and Forest Degradation, plus conservation, sustainable forest management, and enhancement of forest carbon stocks
RF - Random Forest (modeling technique)
RMSE - Root Mean Square Error
SAVI - Soil-Adjusted Vegetation Index
SDM - Species Distribution Models
SE - Standard Error
SS - Sudanian Savanna
SSA - Sub-Saharan Africa
SSZ - Sudano-Sahelian Zone
SVM - Support Vector Machine
TSS - True Skill Statistic (model performance metric)
UCAD - Université Cheikh Anta Diop
UNCCD - United Nations Convention to Combat Desertification
UNFCCC - United Nations Framework Convention on Climate Change
VI - Vegetation Index
VIF - Variance Inflation Factor
WASCAL - West African Science Service Centre on Climate Change and Adapted Land Use
XGB - XGBoost (Extreme Gradient Boosting)

DEDICATION

I dedicate this PhD research work to:

My Mother for her endless love,

My Father for his support,

My wife for her patient support,

My daughter, whose presence fills my life with joy and inspiration,

My Brothers and Sisters.

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CHAPTER 1 : GENERAL INTRODUCTION

1.1. BACKGROUND

Woody vegetation, particularly trees, is critical in maintaining ecosystem balance. These vegetation systems contribute to biodiversity, provide essential ecosystem services such as carbon sequestration, soil stabilization, and water regulation, and support local livelihoods (Sinare & Gordon, 2015). The importance of woody vegetation has been extensively documented, highlighting its pivotal role in mitigating climate change impacts and fostering sustainable land-use practices (Kebebew & Ozanne, 2024). The preservation and restoration of woody vegetation are essential for ecological balance and addressing broader agro-environmental challenges (Mbawine & Dzekoto, 2023). These ecosystems present unique challenges in areas where balancing conservation efforts with sustainable resource use is crucial (Wei et al., 2018).

However, woody vegetation ecosystems are increasingly under pressure from climatic and anthropogenic stressors (Barrio & Rapini, 2023; Kapuka et al., 2022). Climate change exacerbates extreme weather conditions, alters precipitation patterns, and contributes to desertification, all threatening vegetation health and growth (Hailu, 2023; Pal et al., 2023). Concurrently, human activities such as agricultural expansion, urbanization, and unsustainable resource extraction further degrade these ecosystems (Fanday & Tchobsala, 2024; Makunga et al., 2017). The combined effects of these stressors are accelerating vegetation decline, underscoring the urgent need for comprehensive strategies to mitigate these impacts and promote ecosystem resilience (Nguyen et al., 2023).

Global initiatives underscore the urgency of addressing land degradation and vegetation loss. The United Nations Convention to Combat Desertification (UNCCD) advocates for achieving land degradation neutrality, aiming to balance land degradation with sustainable restoration practices (Lebel et al., 2024). Similarly, the G20 Land Initiative sets an ambitious goal of reducing degraded land by 50% by 2040 (G20 Global Land Initiative, 2023). The United Nations Framework Convention on Climate Change (UNFCCC) emphasizes the importance of afforestation and reforestation in achieving the global goal of limiting warming to below 2°C (UNFCCC, 2011). These frameworks highlight the critical role of vegetation restoration in combating climate change and achieving Sustainable Development Goals (SDGs). Specifically, this framework aligns with SDG 13 (Climate Action), SDG 14 (Life Below Water), and SDG 15 (Life on Land) by promoting ecosystem restoration, enhancing resilience to climate impacts, and supporting the balance between sustainable resource use and conservation (SDG, 2015).

Early intervention is critical to limit further vegetation decline and to support the recovery of degraded ecosystems (Cheng & Li, 2024). This approach requires integrating innovative approaches that combine scientific insights with practical solutions (Ruhana et al., 2024). Optimizing restoration efforts involves addressing current vegetation challenges and anticipating risks and opportunities.

Leveraging advanced tools and technologies is central to achieving effective restoration outcomes. Geographic Information Systems (GIS), in particular, play a critical role in identifying vulnerable areas, mapping suitable restoration zones, and designing targeted intervention strategies (Nizamani et al., 2023; Salimi et al., 2024). GIS enables researchers and policymakers to analyze spatial patterns, monitor changes over time, and prioritize areas for action based on evidence. By supporting data-driven decision-making, GIS and other innovative technologies enhance the precision and efficiency of restoration efforts, paving the way for sustainable land management and ecosystem recovery (Chatrabhuj et al., 2024; Nasr & Orwin, 2024).

1.2. PROBLEM STATEMENT AND JUSTIFICATION

Woody vegetation is a basis of ecosystem sustainability, particularly in regions experiencing rapid environmental and socio-economic changes. In the Sahel, the combined impacts of climate change, erratic rainfall patterns, prolonged droughts, and human activities such as deforestation and unsustainable land use have contributed to severe vegetation degradation, soil erosion, and declining water resources (IRD, 2015; Karlson & Ostwald, 2016). However, despite historical degradation, evidence suggests that parts of the Sahel have experienced a greening trend since the severe droughts of the 1970s and 1980s, presenting new opportunities for ecological restoration (Herrmann et al., 2014; Hickler et al., 2005; Li et al., 2004).

In West Africa, rapid land-use changes, particularly agricultural expansion and forest degradation have significantly altered vegetation cover and ecosystem functionality (Herrmann et al., 2020; Souverijns et al., 2021). Like other Sahelian regions, Senegal has witnessed substantial declines in forest formations, characterized by reduced woody cover, lower species density, and shifts in ecosystem structure (Diop et al., 2011). While some areas show signs of regreening, the broader trend of land degradation remains a concern (Herrmann et al., 2013, 2014).

The Saloum Delta Biosphere Reserve and Ramsar Site exemplify these ecological challenges. This biologically diverse landscape harbours a rich assemblage of woody species. Yet, it faces ongoing degradation due to late-season fires, overgrazing, and resource exploitation, particularly in areas such as the Fathala Protected Forest (Kaly et al., 2021). Studies employing a "terroir" approach have also revealed differences in woody species richness and composition between traditional communities and reference sites, further illustrating the interplay between cultural practices and vegetation dynamics (E. Faye et al., 2014). Moreover, a focused study of one area of Saloum, such as Kaffrine, has documented a progressive loss of biodiversity and shifts in community structure over several decades, emphasizing the vulnerability of woody vegetation to overexploitation and climatic stress (Sarr et al., 2013). Investigations within community-managed forests and ethnobotanical surveys further emphasize that local perceptions and traditional uses of woody species are critical; local stakeholders often report declines in large, culturally valued trees (Mohamed Mahamoud et al., 2008). Despite these threats, a localized increase in woody vegetation ecosystems has been emphasized by some studies (Andrieu et al., 2020; Fent et al., 2019).

Ground-based inventories and ethnobotanical studies have informed these woody vegetation trends and generated rich datasets on species composition, regeneration rates, and local use (Lykke, 2000; Sambou et al., 2008; Sarr et al., 2013). These data often remain separate from geospatial analyses. A nuanced, geospatially driven assessment is needed to reconcile these opposing trends and guide sustainable management strategies.

Existing geospatial studies in the Saloum Delta have predominantly relied on satellite-derived indices, such as NDVI, to capture overall vegetative productivity. Still, they are insufficiently sensitive to woody vegetation's structural and compositional nuances (Solly et al., 2022). This failed to capture the intricate spatial and structural variations within woody vegetation (Faye et al., 2022; Tine et al., 2020) and their relative contribution to carbon sequestration. Consequently, this disconnect limits the capacity to produce comprehensive maps that distinguish between different woody vegetation types, structural attributes and carbon sink potential. As a result, actionable spatial products for identifying areas requiring reforestation, conservation, or sustainable interventions are still lacking.

This study aims to bridge these knowledge gaps by employing advanced geospatial analyses to assess woody vegetation dynamics in the Saloum Delta. The research will provide critical insights for conservation planning, carbon budgeting, and land restoration by generating a comprehensive understanding of spatial and structural vegetation changes. Ultimately, the findings will contribute to optimizing restoration efforts in a region where balancing conservation and sustainable resource use remains a persistent challenge.

1.3. AIM, OBJECTIVES AND RESEARCH QUESTIONS

1.3.1. Aim

This study aims to investigate the Saloum Delta woody tree vegetation hotspot for optimum land restoration, carbon sinks, and policy implementation.

1.3.2. Specific Objectives

Objectives of this study were to:

- Assess the dynamic of the woody cover and related patterns (fragmentation/connectivity) from 2002 to 2022;
- Assess the environmental predictors of the spatial distribution of woodland communities and related habitat suitability;
- Model aboveground biomass/carbon stock using allometric equation and machine learning algorithm.

1.3.3. Research Questions

- How has the spatial pattern of woody tree covers (extent, fragmentation, and connectivity) changed between 2002 and 2022?
- What are the key environmental predictors influencing the distribution of woody tree covers, and where further suitable areas could be found?
- What is the aboveground biomass potential of woody tree covers and their spatial distribution?

1.4. PRESENTATION OF THE STUDY AREA

1.4.1. Location and Size

The Saloum Delta is primarily located in the Foundiougne department within the Fatick region, positioned between latitudes 13°40'30" and 14°12'00" North and longitudes 16°49'30" and 16°07'30" West (Figure 1.1). This area spans 2,959 km² and had an estimated population of 224,659 in 2002. It includes the Saloum or Gandoul Islands, which cover 950 km². The region is traversed by three major rivers, the Saloum, Diombos, and Bandiala, which flow into the Atlantic Ocean at Sangomar Point. Foundiougne experiences a Sudanian-Sahelian climate characterized by a dry season from November to May and a rainy season from June to October. The region's annual rainfall is highly variable, with prolonged droughts occurring mainly from the 1970s onward.(Tine et al., 2020).

The Saloum River and its tributaries cross the area, giving it a fragile environment influenced by coastal dynamics. The climate is Sudanian-Sahelian, with a dry season from November to May and a rainy season from June to October. Annual rainfall ranges between 500 and 1,000 mm, with an average yearly temperature above 28°C. Rainfall patterns over the decades show significant variability, notably with severe droughts in the 1970s and 1980s, followed by improved rainfall from the 1990s onward (Tine et al., 2020).

The region faces heightened vulnerability to recurring droughts, which have led to a reversal of the salinity gradient, with salt concentrations reaching as high as 130 ‰ upstream. This shift has altered the structure and distribution of aquatic species. Once abundant in freshwater, the estuary now has ecosystems severely affected by increasing salinity, threatening the survival of local species (Nalivata et al., 2017).

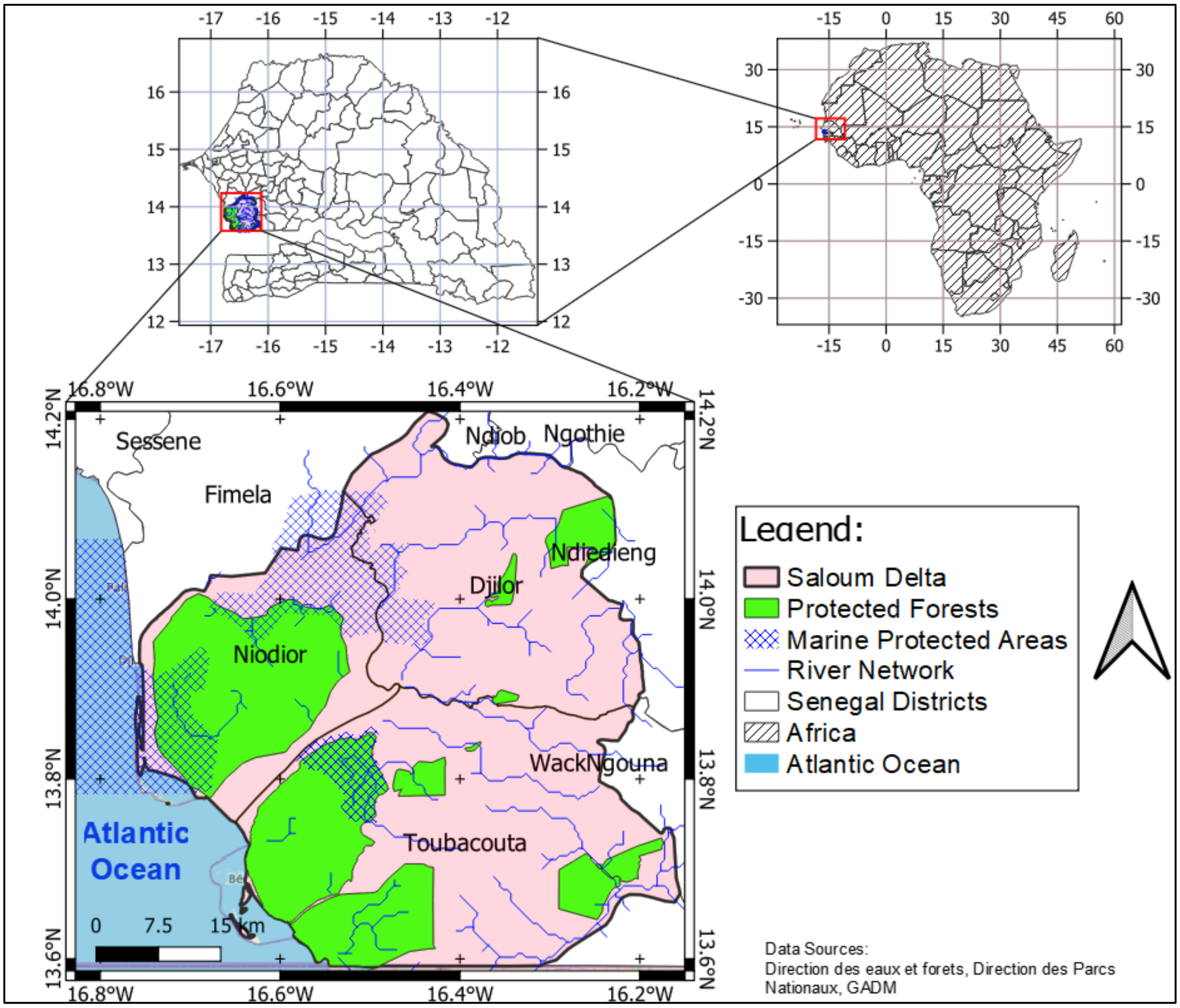


Figure 1.1: Map of the study area

1.4.2. Vegetation

The natural region of Sine-Saloum consists of four main vegetation types: wooded steppe, shrub and wooded savanna, forested islets, and Mangroves. Among the 43 species found here, spanning 34 genera and 23 families, the Mimosaceae and Combretaceae families are the most prominent. Notable species include *Combretum glutinosum*, *Feretia apodanthera*, *Guiera senegalensis*, and *Acacia seyal*. While medicinal species are few, *C. glutinosum* (24.3%), *F. apodanthera* (22.8%), and *G. senegalensis* (16%) show relatively high natural regeneration rates, in contrast to *A. seyal*, which has a low rate (5.8%). The vegetation structure mainly comprises shrubs under 5 meters, making up 80% of the total abundance. (Mohamed Mahamoud et al., 2008). The mangroves are low in species diversity, dominated by *Rhizophora racemosa* (52.11%), *R. mangle* (30.20%), and *Avicennia africana* (18.20%) (A. Diop et al., 2024).

1.4.3. Soil

The region has three types of soils: sandy, clay and sandy-clay. The sandy soils, which comprise 30 to 80% of the area, are suitable for cultivation, particularly peanuts and millet. The clay soils cover 10 to 30% of the region and are used for maize, rice, and vegetable farming. The sandy-clay soils are less commonly used for most crops (ANDS, 2013).

1.4.4. Climate Overview and Hydrography

The region experiences a tropical Sudanian climate featuring both Sahelo-Sudanian and Sudanian-Sahelian variations. Coastal areas, particularly in the Foundiougne and Fatick departments, are also influenced by a maritime climate. This climate gives the region a Sudanian-Sahelian-type environment, characterized by alternating seasons: a rainy season from June–July to October, followed by an extended dry season lasting 8 to 9 months. The predominant winds are the maritime and continental trade winds (also known as the Harmattan), easterly winds that blow from February to May. The monsoon winds from the southwest, and the rainy season starts around mid-June. This pattern is shaped by the general wind circulation across West Africa, where Senegal falls under the monsoon influence at the end of the dry season. These winds move gradually northward until August and then retreat southward more quickly. They significantly impact rainfall distribution, temperature patterns, and the wind regime. Regarding temperatures, annual minimum averages range from 21°C to slightly above 24°C from December through late February, while annual maximum averages range from 35°C to over 42°C from March to June (ANSD, 2021).

Water resources in the region consist of surface and groundwater sources. Surface water includes the perennial rivers of Sine, Saloum, and the Gambia, along with their tributaries located in the Foundiougne department, such as the Bandiala, Soundougou, Nianing-Bolong, and Diomboss rivers. There are also temporary water bodies, including seasonal streams and ponds. Groundwater resources include aquifers from the Maastrichtian, Paleocene, Eocene, and the Continental Terminal formations (ANSD, 2021).

1.4.5. Human Population and Socio-economic Activities

The region's economy is primarily driven by agriculture, livestock, and fishing, although tourism is also emerging as a promising sector for economic development. Agriculture is the dominant activity, occupying 50% of the regional land area and employing nearly 90% of the active population (ANSD, 2014). Around 26% of lowland areas are used for rainfed rice cultivation and vegetable farming. Agricultural production is extensive, focusing on subsistence crops (millet, rice, maize, and cowpea) and cash crops (peanut, sesame, watermelon, and other vegetables and fruits). Crop diversification is supported by a rainfall range of 400-600 mm in Gossas to over 1000 mm in Foundiougne (ANSD, 2021).

Fishing mainly occurs in the Saloum Delta Biosphere Reserve, encompassing continental, amphibious (three island groups), and maritime areas along a 65 km coastline. This deltaic region includes marine and river-lagoon zones with a 70 km front, rich in fish, crustaceans, and molluscs. An extensive hydrographic network, a vast mangrove forest, and diverse aquatic and terrestrial ecosystems enhance the region’s fishing potential. Technical support from the government and NGOs and development partnerships focusing on sustainable fishing, especially in the Saloum Delta, are key to strengthening this sector (ANSD, 2021).

Tourism holds significant potential and is essential to the region's economy. The area boasts a variety of attractive sites, including numerous waterways and "bolongs" (tidal channels), the Saloum Islands, the Saloum Delta National Park, as well as various historic sites and monuments (ANSD, 2021).

1.5. THESIS ORGANISATION

The thesis write-up is organised into the following chapters:

- Chapter 1: This Chapter captures the background information, the problem statement and justification, the aim, objectives and research questions, and how the thesis is organised.
- Chapter 2: This Chapter presents the definition of woody trees, their importance in carbon sequestration, their environmental pressures and management implications, the main woody trees taken into account in this study and the review of the methods used for assessing woody vegetation.

- Chapter 3: This Chapter assesses the spatiotemporal change of woody tree vegetation and pattern analysis.
- Chapter 4: This Chapter predicts the spatial distribution of the woody tree cover and associated environmental predictors.
- Chapter 5: This Chapter assesses ground and remote sensing-based estimation of the Saloum Delta woody aboveground biomass using allometric equations and machine learning.
- Chapter 6: This Chapter summarises findings, conclusions and recommendations.

CHAPTER 2 : LITERATURE REVIEW

2.1. INTRODUCTION

Woody vegetation, primarily made up of trees and shrubs, represents a significant portion of terrestrial plant life, supporting biodiversity, carbon cycling, and ecosystem stability. Unlike herbaceous plants, woody vegetation exhibits secondary growth, characterized by lignified tissues that provide strength and resilience, allowing these plants to grow taller and live longer (Niklas, 1994). This structural integrity has led to woody vegetation's dominance in various ecosystems, from dense tropical rainforests to sparse woodlands and shrublands, each hosting unique species adapted to local conditions (Johnson & Miyanishi, 2008).

Woody vegetation encompasses plant species that develop wood through secondary growth, enabling them to attain significant height and structural stability. The composition of wood primarily includes lignin and cellulose, which strengthen the plant's tissues, allowing it to thrive in various environmental conditions (Spicer & Groover, 2010). This characteristic not only promotes individual growth but also supports the development of complex, layered ecosystems. The vegetation structure, including factors such as canopy height and density, varies considerably among landscapes dominated by woody plants, contributing to the ecological diversity found in forests, savannas, and shrub-dominated ecosystems (Poorter et al., 2024).

Forests and woodlands, characterized by a continuous canopy formed by trees, are the most recognized types of woody vegetation. In these environments, trees grow in dense clusters that influence essential factors like light availability, moisture retention, and soil composition. Conversely, shrublands and savannas combine woody and herbaceous plants, resulting in unique ecosystems that support a wide array of species by maintaining ecological gradients in light and moisture (Lambin & Meyfroidt, 2011).

The exploration of woody species in ecosystems has garnered significant attention in recent years, particularly regarding their ecological roles, interactions with disturbances, and implications for biodiversity and ecosystem functioning.

2.2. DEFINITION OF TREES

A tree is generally defined as a long-lived woody plant that grows to a substantial height and size. It is distinguished by a strong, self-supporting main trunk and branches that typically emerge some distance above the ground. This definition emphasizes three key elements: significant size, classification as a woody perennial species, and a distinct structural form with a single main stem and elevated branching (Diederich, 2014).

Various definitions of trees exist across different contexts (Lund, 2015):

- The Turkey Forest Law No. 6831 defines trees as plants at least 8 meters tall, with crowns and wooden stems, regardless of age or diameter.
- According to the (IPCC, 2006), "trees outside forests" include all trees located outside forested areas and other wooded lands, such as those in stands smaller than 0.5 hectares, agricultural lands (e.g., agroforestry systems, orchards, or home gardens), urban environments, along roads, or scattered throughout the landscape.
- The USA Federal Code (1985) describes a tree as a woody plant with a single, erect perennial stem, at least 7.5 cm in diameter at breast height (DBH) at maturity, a crown of foliage, and a height of at least 5 meters when mature.
- In Ghana (1999), Osei Kofi, Forestry Dept.- Letter 7 May 99, defines a tree as a tall, long-living plant with a thick central wooden stem or trunk from which branches bearing leaves grow.

While the specifics may vary, the essential characteristics of a tree consistently highlight its height, woody nature, and structural form.

2.3. WOODY TREE BIOMASS AND CARBON SEQUESTRATION

Woody biomass serves as a significant indicator of ecosystem health, contributing to primary productivity and carbon sequestration, which are vital for mitigating climate change (Dada et al., 2024). In African savannas, woody vegetation influences biomass dynamics by interacting with climatic factors like rainfall and disturbance regimes (fire, herbivory). In semi-arid regions, such as South Africa's Lowveld savannas, ongoing fuelwood harvesting has implications for both biomass and ecosystem structure (Sankaran, 2019). Also, LiDAR techniques allow scientists to assess biomass and carbon storage across different canopy layers, contributing to a better understanding of sub-canopy dynamics and fuelwood sustainability (Mograbi et al., 2015).

Woody tree vegetation plays a central role in the carbon cycle, as it is one of the primary reservoirs for carbon storage (Stephenson et al., 2014). Trees and shrubs capture atmospheric carbon dioxide (CO_2) during photosynthesis, incorporating it into their biomass. This process helps offset greenhouse gas emissions, contributing to climate change mitigation (Díaz et al., 2019). The carbon stored in woody vegetation is not only significant in terms of quantity but also in its longevity. Unlike non-woody plants decompose relatively quickly, woody vegetation retains carbon over extended periods, especially in forested ecosystems with high biomass density (Houghton & Nassikas, 2017).

Recent studies have examined the carbon sequestration potential of different types of woody vegetation across various ecosystems. For instance, in temperate and tropical forests, the density and height of trees result in higher biomass and, thus, more significant carbon storage potential (Friedlingstein et al., 2022). Additionally, savanna ecosystems with moderate tree cover contribute considerably to carbon storage while balancing carbon sequestration and biodiversity (Abreu et al., 2017; Mohammed et al., 2016; Nero et al., 2024). However, the intensity of land use, fire regimes, and grazing practices can alter the carbon balance, making it essential to consider these factors when managing woody vegetation (Mograbi et al., 2015).

Remote sensing technologies, particularly Light Detection and Ranging (LiDAR) and satellite-based assessments have enhanced the accuracy of biomass and carbon stock estimates (Borsah et al., 2023; Knapp et al., 2018). LiDAR, for example, enables detailed three-dimensional mapping of vegetation structure, capturing information on canopy height, density, and even sub-canopy layers (Li et al., 2024). This technology allows scientists to monitor carbon sequestration rates over time and assess how natural and anthropogenic disturbances impact biomass and carbon storage (Borsah et al., 2023).

Woody tree vegetation in West Africa, especially in the Sahelian and Sudanian zones, plays a significant role in carbon sequestration, soil protection, and microclimate stabilization. A study by Grieco et al. (2024) (Figure 2.1) witnessed the large amount of carbon pools in different LULCs in Ghana. In Senegal, for example, woody tree vegetation in areas like the Saloum Delta contributes extensively to carbon storage and helps maintain biodiversity (Gallup et al. 2019). This region’s mangrove ecosystems, among the densest in West Africa, offer high carbon storage per unit area, helping to mitigate regional climate impacts (Manga et al. 2022).

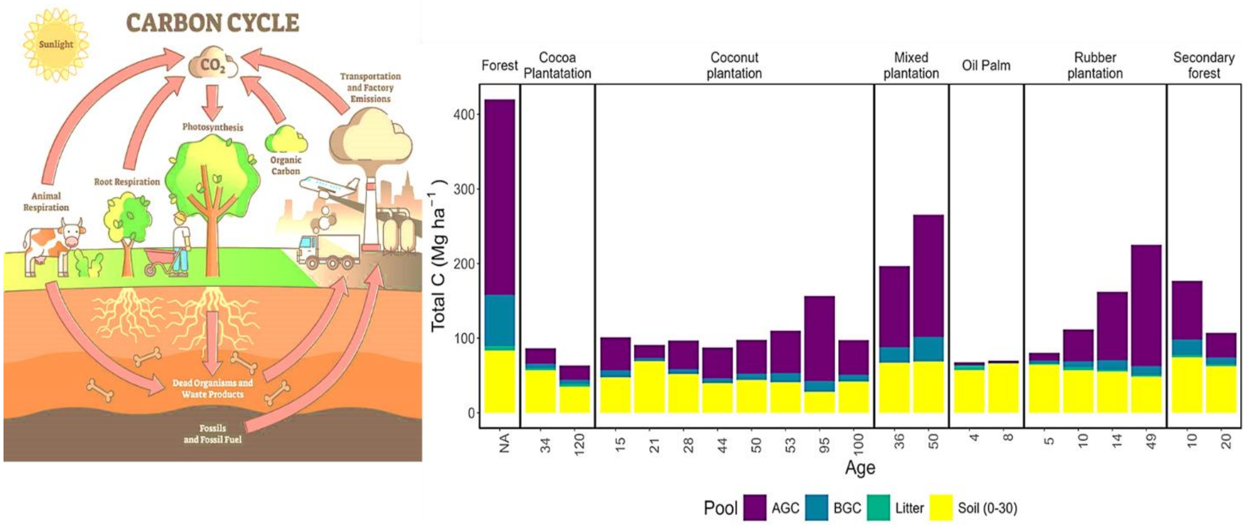


Figure 2.1: Carbon stock potential of different LULC

Source: Modified picture from (Grieco et al., 2024).

The biomass distribution across different types of woody vegetation in Senegal and West Africa varies widely, mainly due to environmental gradients and human pressures, including land conversion, overgrazing, and fuelwood collection (Woomer et al., 2004). For instance, savannas in Senegal and Burkina Faso exhibit a range of woody biomass levels, reflecting variations in rainfall, soil type, and fire frequency (Brandt et al., 2014; Straaten et al., 2019). Studies have shown that biomass levels are higher in protected areas where human activities are restricted (Nicol et al., 2023). This points to the importance of conservation zones and sustainable management practices in maintaining and enhancing biomass for carbon storage.

2.4. ADAPTATION TO ENVIRONMENTAL PRESSURES AND MANAGEMENT IMPLICATIONS

Studies highlight how woody vegetation responds to environmental changes, including climate variability, human activity, and natural disturbances (Figure 2.2). Subtropical forests with high woody plant diversity demonstrate resilience and adaptive ability to recover post-disturbance, as shown by their species composition and biomass changes over time (Hlásny et al., 2021). This adaptive capacity highlights the importance of management practices that conserve woody vegetation for long-term ecosystem sustainability (Nawaz et al., 2023).

Woody vegetation exhibits various adaptive responses to environmental pressures such as climate change, land-use changes, and fire (Stroh et al., 2018). For instance, in fire-prone savannas, trees often develop thick bark, which protects their vital tissues, enabling them to survive periodic burns (Huntley, 2023). Additionally, some species resprout from roots or basal buds, allowing them to recover rapidly after disturbances (Wilgen, 2009). These adaptations contribute to the resilience of woody ecosystems in environments where fire and herbivory are regular occurrences (Case & Staver, 2017).

The sustainability of woody vegetation is highly contingent on land management practices. Unsustainable harvesting, mainly for fuelwood, poses a significant threat in many developing regions where it is a primary energy source (Abanikannda & Dantani, 2021). Research shows excessive wood extraction can lead to localized vegetation depletion, impacting biodiversity and ecosystem services (Ranius et al., 2018). In South Africa, for example, the extensive use of live wood for fuel has led to the degradation of communal rangelands, prompting calls for sustainable management practices that balance human needs with ecological health (Seware, 2015).

Effective woody vegetation management should consider adaptive strategies incorporating community involvement, sustainable harvesting practices, and restoration efforts (Moyo et al., 2021). Approaches like community-based resource management (CBRM) and the establishment of protected areas can help mitigate the negative impacts of resource extraction, providing pathways for both conservation and livelihood support (Robinson et al., 2021). Additionally, restoration efforts, such as afforestation and reforestation, have shown potential for enhancing carbon storage and restoring ecosystem services, especially in degraded landscapes. Such efforts also provide opportunities for climate mitigation, as restored forests contribute significantly to carbon sequestration while providing habitat for diverse species (Díaz et al., 2019).

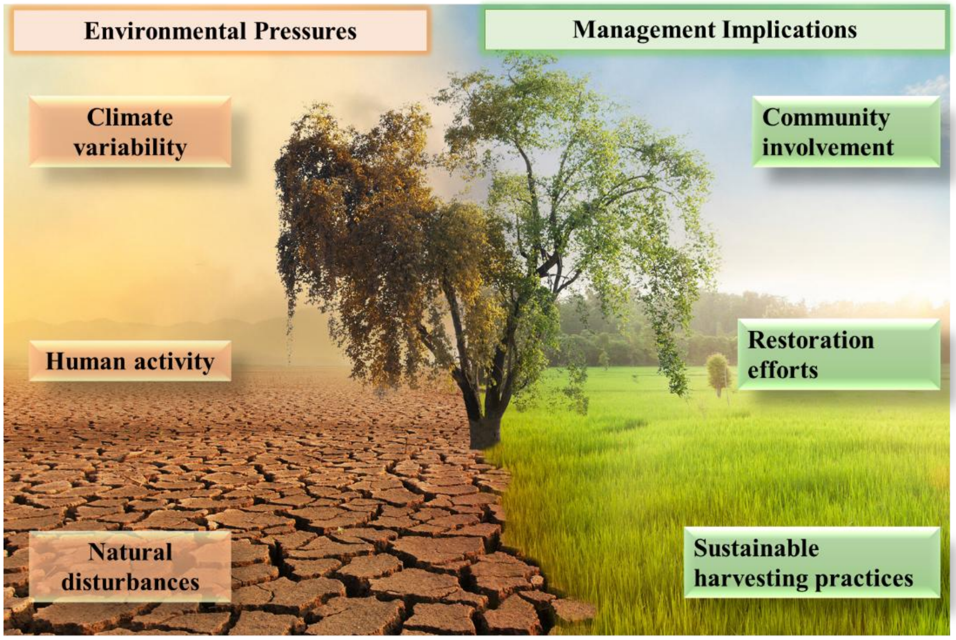


Figure 2.2: Main existing interaction between trees, environmental stress and management

Source: Modified picture from https://bgr.com/science/climate-change-is-making-it-harder-for-trees-to-breathe/

2.5. WOODY TREE COMMUNITIES IN SALOUM DELTA

2.5.1. Mangroves

The mangroves in the Saloum Delta are an essential socio-economic and ecological resource, comprising primarily Rhizophora racemosa (52.11%), Rhizophora mangle (30.20%), and Avicennia africana (18.20%), with smaller contributions from Conocarpus erectus and Laguncularia racemosa (Diop et al., 2024; Kauffman & Bhomia, 2017). These species provide critical habitats for fish, molluscs, and crustaceans, supporting local fisheries that produce over 15,000 tons of seafood annually (Gallup et al., 2020). Additionally, mangroves act as physical barriers against coastal erosion, while their dense root systems stabilize sediments and mitigate storm surges (Diop et al., 2024).

From a socio-economic perspective, mangroves are heavily relied upon for fuelwood, particularly dead wood from Rhizophora species, which is preferred for its high burning efficiency and durability, especially for cooking and fish smoking (Gallup et al., 2020). Beyond fuel, mangrove ecosystems support oyster harvesting, honey production, and other subsistence activities vital for the livelihoods of coastal communities (Gallup et al., 2020; Diop et al., 2024). Local communities, such as the Serere Niominka, view mangroves as spiritual and cultural assets, further reinforcing their importance (Gallup et al., 2020).

Regarding climate mitigation, the Mangroves in the Saloum Delta serve as significant carbon sinks, with carbon stocks averaging 463 Mg C ha^{-1}, predominantly stored in soils (Kauffman & Bhomia, 2017). This storage capacity highlights their role in global climate change mitigation efforts. However, these ecosystems face significant threats from overexploitation, salinity variations caused by climate change, and reduced freshwater inflow due to upstream human activities (Diop et al., 2024; Kauffman & Bhomia, 2017).

To ensure sustainability, community-based management and large-scale reforestation programs have been initiated, often supported by international organizations and NGOs (Gallup et al., 2020). Such initiatives are critical to maintaining the ecological functions and socio-economic benefits mangroves provide while mitigating their degradation.

2.5.2. Close and Open Woodland Forests

The woody vegetation in the Saloum Delta provides vital resources, including firewood, non-timber forest products, and medicinal plants, which are integral to the local economy (Sambou, 2015). Species such as *Acacia seyal* and *Balanites aegyptiaca* dominate the region, being sources of firewood and fruits. These species contribute significantly to household incomes (Sambou, 2015). However, the degradation of woody vegetation has heightened the reliance on remaining resources, causing overexploitation and threatening sustainability (Kaly et al., 2021).

Forests in this region also serve as agricultural and grazing land. Encroachment of agriculture into forested lands has led to the transformation of savanna ecosystems, affecting biodiversity and increasing soil erosion risks (Sambou, 2015). The interplay between agricultural expansion and forest resource use has created a complex socio-economic dynamic that requires participatory resource management to mitigate conflicts (Kaly et al., 2021).

Participatory management approaches have been proposed to balance local needs with conservation efforts. Local governance reforms, such as the 1998 Forest Code, aim to empower communities to manage resources sustainably (Sambou et al. 2008).

2.5.3. Plantations/Agroforestry

Agroforestry practices in Senegal's Saloum region have been the subject of various scientific studies, highlighting their significance in enhancing biodiversity, improving soil fertility, and supporting local livelihoods (Sambou et al., 2017). Research indicates that farmers are crucial in conserving tree diversity within agroforestry landscapes (Olatujoye et al., 2025). Protecting and managing trees on their farms contributes to preserving various species, which is vital for maintaining ecosystem services and resilience against environmental stresses (Mahmud et al., 2021). A study focusing on West Africa, including regions like Saloum, found that such farmer-managed systems support a diverse range of tree species, underscoring the importance of local knowledge and practices in biodiversity conservation (Sambou et al., 2017).

Additionally, the salinization of arable land poses a significant challenge to agriculture in the Saloum region (Thiam et al., 2021). Studies have assessed various technologies and practices to curb soil salinization and restore productivity. Agroforestry systems, through strategically planting salt-tolerant tree species, have been identified as a viable approach to rehabilitate salt-affected soils, enhancing food security and supporting sustainable livelihoods (Sene et al., 2024).

In summary, scientific research underscores the multifaceted benefits of agroforestry in the Saloum region, including biodiversity conservation, soil restoration, and socio-economic development. The active participation of local farmers in managing and adopting agroforestry practices is pivotal to the success and sustainability of these systems.

In addition to cashew cultivation, mango farming is prevalent in the Saloum region. The area contributes to Senegal's overall mango production, which has been experiencing fluctuations. For example, during the 2022-2023 season, Senegal exported approximately 16,000 tonnes of mangoes, a decrease from previous years. Factors such as pest infestations, particularly fruit flies, have impacted yields. The Saloum region and others like Casamance and Niayes are integral to the country's mango supply chain (Wahome, 2024).

Furthermore, agroforestry practices in the Saloum region often incorporate cashew trees to combat bushfires. The dense canopy and fire-resistant properties of cashew trees make them effective natural firebreaks, protecting other crops and maintaining soil fertility. Farmers in areas such as Sokone have implemented cashew Plantations to safeguard their orchards, which include mango and orange trees, from the devastating effects of bushfires (FARM RADIO.FM, 2022).

Cultivating mangoes and cashews in the Saloum region is integral to local agricultural practices, providing economic benefits and contributing to environmental management strategies.

2.6. WOODY COMMUNITIES AND CLIMATE ADAPTATION/MITIGATION

Woody vegetation in the Saloum Delta can be categorized into four groups: Mangroves, Close Woodlands, Open Woodlands, and Plantations (Figure 2.3). The woody vegetation in Saloum acts as a significant carbon sink, with variations in tree density and biomass influencing carbon storage capacity. Deforestation and land-use changes result in carbon emissions, undermining mitigation efforts (Kaly et al., 2021; Sambou, 2015). Agroforestry practices and afforestation programs under frameworks like REDD+ (Reducing Emissions from Deforestation and Forest Degradation) are suggested as strategies to enhance carbon sequestration (Sambou, 2015). Persistent droughts and climate stress have exacerbated woody vegetation decline, transitioning ecosystems from dense forests to savanna or shrubland (Kaly et al. 2021; Sambou et al. 2008). Climate change adaptation measures are crucial, focusing on species with higher drought resistance and restoring degraded lands (Kaly et al., 2021). Though the annual deforestation rate is relatively low (0.09% in some cases), it contributes to cumulative emissions over time. Sustainable land-use practices are essential to curb these trends (Sambou, 2015).

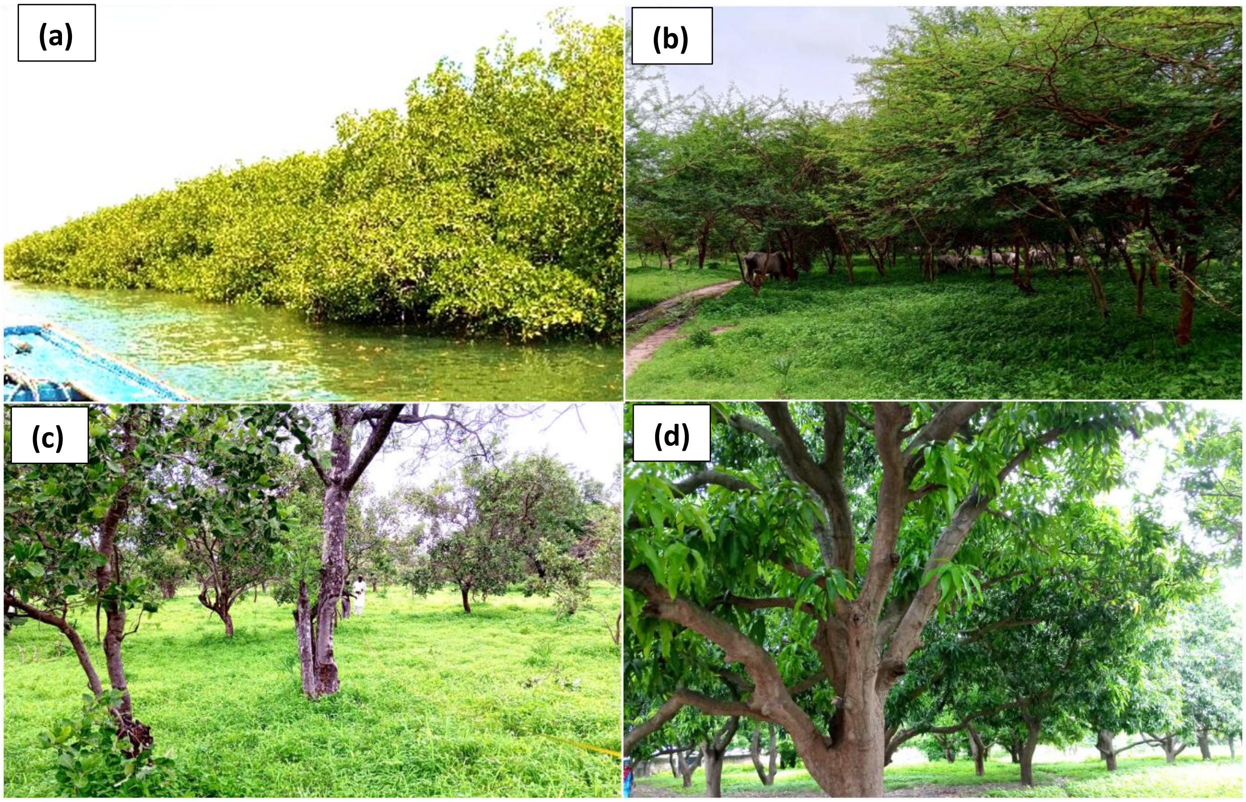


Figure 2.3: Different communities of woody cover types in the study area

(a):; (b): Close Woodlands communities of Acacia seyal species; (c): Open Woodlands; (d): Mango Plantations

2.7. TECHNIQUES FOR WOODY TREE VEGETATION ASSESSMENT

2.7.1. Remote Sensing Techniques

Remote sensing has revolutionized woody vegetation assessment by allowing large-scale monitoring of biomass, canopy structure, and changes over time (Almeida et al., 2025). High-resolution satellite imagery and LiDAR (Light Detection and Ranging) are among the most widely used technologies (Reutebuch et al., 2005). LiDAR, in particular, has become invaluable for assessing canopy height, tree density, and under-canopy vegetation in complex ecosystems. This technology generates precise three-dimensional vegetation models, enabling researchers to estimate biomass accurately, even in areas with dense forest cover (Mazlan et al., 2023).

In addition to LiDAR, multispectral and hyperspectral imaging are used to detect plant health, species composition, and biomass. These tools capture data across different wavelengths, allowing scientists to identify specific vegetation types and monitor stress indicators like chlorophyll content or water stress. This tool is handy in assessing woody vegetation health in response to climate stressors like drought, a growing concern in dry regions of Africa (Wei et al., 2023). Figure 2.4 shows common research area that can be related to woody vegetation and remote sensing:

- Monitoring and management efforts aim to integrate ground-based national inventory data with remotely sensed data to enable large-scale mapping of forest parameters such as standing volume, mean and dominant height, and forest types. Field data often include measurements like stem position and diameter at breast height (DBH), which help approximate age classes (Fassnacht et al., 2024).
- Forest disturbances, including wildfires, logging, and pest or pathogen outbreaks, are assessed over spatial and temporal scales that are challenging to capture through field surveys. This research area often involves quantifying the long-term effects of forest disturbances (Stahl et al., 2023).
- The investigation of leaf traits focuses on examining small-scale leaf characteristics, such as chlorophyll content, and linking these to remotely sensed parameters. This information can then be extrapolated to larger scales, aiding in assessing vegetation conditions (Moreno-Martínez et al., 2018).
- Biodiversity and habitat studies leverage remote sensing data of forests as covariates for modelling species- or taxa-specific habitats. This area is closely tied to ecological research (Cavender-Bares et al., 2020).
- Forest structure studies explore vertical and horizontal structures, such as canopy heights and structural complexity, which can serve as proxies for diversity or habitat quality. Techniques like synthetic aperture radar (SAR) or lidar are frequently employed in this domain (Li et al., 2024).
- Phenology research examines the timing of leaf emergence and senescence, marking the start and end of the growing season, respectively (Guan et al., 2014).
- Forest type and cover investigations classify tree species, monitor forest cover, and track changes over time (Appiah et al., 2021).

- Biomass and productivity research addresses forest growth and increment, often about soil health or management practices. This information is valuable for understanding available biomass for harvest and informing forest management strategies (Moore et al., 2018).

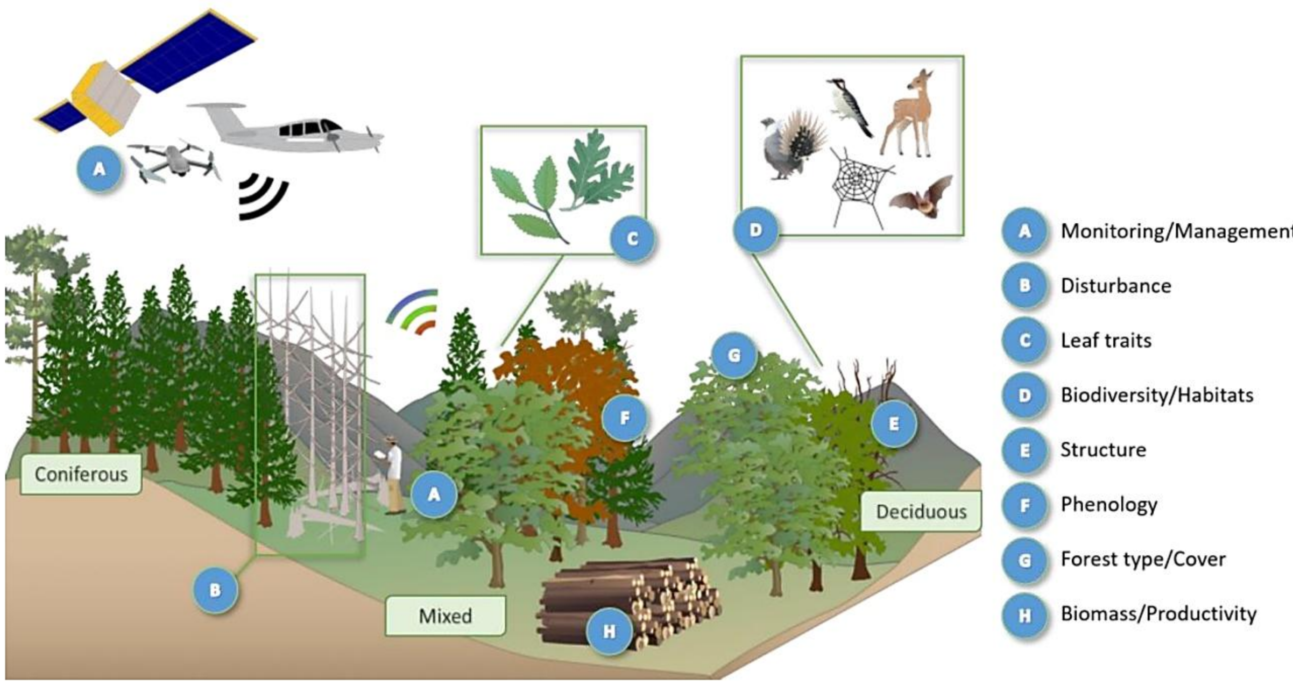


Figure 2.4: Common research areas for remote sensing of forests

Adapted graphic elements from (Coleman et al. 2024)

2.7.1.1. Google Earth Engine

Remote Sensing (RS) systems have gathered vast amounts of data for decades, making it impractical to manage and analyze them using standard software packages and desktop computing resources. To address these challenges, Google developed Google Earth Engine (GEE), a cloud computing platform for efficient big data analysis. This platform enables large-scale geospatial data processing and long-term environmental monitoring (Amani et al., 2020). Google Earth Engine (GEE) is a cloud-based geospatial analysis platform for processing large-scale remote sensing and geospatial datasets (Gorelick et al., 2017). It integrates petabytes of satellite imagery and provides an extensive application programming interface (API) for various environmental, ecological, and climate studies (Tamiminia et al., 2020). The following review explores key applications and challenges associated with GEE.

Applications of Google Earth Engine:

GEE has been widely used in land use and land cover classification studies (Ganjirad & Bagheri, 2024). Researchers utilize machine learning algorithms such as Random Forest, Support Vector Machines (SVM), and Deep Learning for LULC classification. Gorelick et al. (2017) demonstrated the efficiency of GEE in mapping global LULC changes using Landsat imagery. Another study by (Liu et al., 2024) leveraged GEE for detecting urban expansion using Sentinel-2 and Landsat imagery.

GEE has played a significant role in forest cover change detection, deforestation monitoring, and biomass estimation. Global forest loss monitoring is done in GEE, processing over 650,000 Landsat images (Hansen et al., 2013). In addition, aboveground biomass in tropical forests is also assessed using Sentinel-1 and Sentinel-2 datasets (Jiang et al., 2022). GEE enables monitoring of climate change effects, such as temperature variations, drought assessments, and carbon stock evaluations (Rodrigues de Almeida et al., 2023).

Challenges and Limitations:

GEE has some limitations, such as:

- **Internet Dependency**: As a cloud-based platform, GEE requires a stable internet connection, which may limit accessibility in remote areas (Amani et al., 2020).
- **Processing Limitations**: Users encounter computational quotas and limitations on specific functions, especially for complex models (Amani et al., 2020).
- **Data Gaps and Resolution Issues**: Some regions may have limited high-resolution data availability, affecting spatial accuracy (Amani et al., 2020).

2.7.2. Limitations of Remote Sensing Techniques

While remote sensing has transformed large-scale vegetation assessment, it is not without limitations. One major challenge is satellite imagery's spatial and spectral resolution, which may not always be sufficient to capture fine-scale variations in canopy structure or detect smaller shrubs and understory vegetation (Tuanmu et al., 2010; Yang et al., 2023). For example, in dense tropical forests or complex landscapes, vegetation layers below the canopy can be obscured, resulting in underestimating total biomass or missing data on understory species (Yang et al., 2023).

LiDAR, though highly effective for structural analysis, is costly and limited in availability, especially in resource-constrained regions. Its applications in West Africa, where it can provide invaluable insights into savanna and forest structure, are often limited by access to technology and funding (Houndjo et al. 2024). Additionally, while machine learning techniques have improved remote sensing data analysis, these models depend on high-quality, labeled training data, often scarce in tropical and subtropical regions like West Africa (Potter et al., 2023). Finally, the interpretation of remote sensing data is affected by cloud cover and atmospheric interference, a common issue in tropical regions, which reduces the temporal frequency and quality of usable imagery (Hashim et al., 2014; Prudente et al., 2020).

2.7.3. Species Distribution Models

Species Distribution Models (SDMs) have become integral tools in understanding and predicting the spatial distribution of species under varying environmental conditions (Barker & MacIsaac, 2022; Goicolea et al., 2024; Tong et al., 2023). These models are widely applied in biodiversity conservation, forest management, and climate change mitigation, among other fields. For example, SDMs have been used to analyze tree diversity in Senegalese agroforestry systems, revealing how anthropogenic factors shape and sustain biodiversity (Ndao et al., 2022). Similarly, they have been employed to predict the impacts of climate change on tree species in data-scarce regions, leveraging high-resolution remote sensing and topographical data (Ahmadi et al., 2023).

Methodologically, advancements in machine learning, such as Random Forests and Boosted Regression Trees, have significantly improved SDM accuracy by addressing the complexities of non-linear ecological processes (Yu et al., 2020). Ensemble modelling, which combines outputs from multiple algorithms, further enhances robustness, particularly for rare or poorly sampled species (Ahmadi et al., 2023). Multi-scale approaches integrating climate and land-use variables have also emerged as critical for refining predictions and ensuring ecological relevance (Fournier et al., 2017).

Despite these advancements, SDMs face data limitations, model transferability, and validation challenges. Researchers increasingly use high-resolution satellite imagery and proxy indicators to overcome these issues while employing rigorous validation frameworks that include expert assessments (Boyd et al., 2023). Recent trends involve integrating correlative and mechanistic models to account for dynamic species-environment interactions and using genetic data to enhance predictions (Franklin, 2023).

Applications of SDMs span diverse ecosystems, from cold-water coral habitats, where ensemble models aid in conservation planning, to riparian forests, where hydrological variables are integrated to guide forest management (Tong et al., 2023). These case studies highlight the versatility of SDMs in addressing complex ecological questions while emphasizing the need for methodological rigour and interdisciplinary approaches (Vasconcelos et al., 2024). As SDMs evolve, they offer valuable insights into theoretical and applied ecology, fostering more effective conservation and management strategies in the face of global environmental change (Vasconcelos et al., 2024).

Inadequate data on species occurrences and environmental variables remains a significant hurdle. Proxy indicators and high-resolution satellite imagery have shown promise in overcoming these gaps (Sallmannshofer et al., 2021). Ensuring that models perform well across different spatial and temporal contexts is critical. Studies emphasize the need for rigorous validation frameworks using metrics like AUC and expert assessments (Boyd et al., 2023).

2.7.4. Emerging Application of SDM: From Individual Species to Communities

2.7.4.1. Conceptual Framework

SDMs are rooted in ecological niche theory, which posits that environmental interactions determine species distributions. While traditionally applied to individual species, the principles can be extended to communities by modelling the collective habitat preferences or occurrence of multiple species within a specific ecological context (Zurell, 2020). Community-level distributions can be forecasted by combining the habitat suitability predictions of individual species (Sanguet et al., 2022). This process entails a model capturing the common environmental needs of all species within the community. For example, a study on mangrove communities demonstrated how SDMs could be used to map suitable habitats based on the collective distributions of multiple mangrove species (Rodríguez et al., 2020).

2.7.4.2. Scientific Support Justification

SDMs utilize georeferenced biodiversity observations alongside environmental data (e.g., climate, land cover). Integrating data on multiple species and their respective environmental tolerances makes it possible to assess the overall suitability of habitats for entire communities rather than single species (Vogel et al., 2023). Traditional SDMs predict the potential distribution of individual species based on their environmental preferences. When applied to communities or vegetation types, SDMs are often "stacked" to infer broader ecological patterns (Vogel et al., 2023). Community-level approaches, however, integrate interactions among species and shared environmental drivers. These models better account for co-occurrence patterns and biotic interactions, making them particularly suited for analyzing vegetation types as cohesive units under changing environmental conditions (Maguire et al., 2016; Bonthoux et al., 2013). Studies comparing SDMs for individual species versus communities (e.g., CLMs) suggest that while SDMs might be less accurate for novel climates, they perform well in environments with known ecological conditions (Maguire et al., 2016). This approach supports their utility in predicting established vegetation types, primarily focusing on environmental constraints rather than species-specific interactions (Maguire et al., 2016).

SDMs for communities often involve multivariate approaches, like ordination or clustering, to define vegetation types based on species composition. The selected community traits can then be linked to environmental variables in SDMs to predict their potential niches across landscapes (Durbecq et al., 2020; Porfirio et al., 2014).

2.7.4.3. Relevance of Environmental Drivers and Application in Ecological Communities

SDMs can be adapted to predict the occurrence of ecological communities by integrating species-level data into composite indices or by treating the community as a single "species" defined by shared traits or environmental requirements. This approach aligns with conservation efforts where preserving entire habitats is critical (Porfirio et al., 2014).

Ecological communities, like mangroves or woodlands, are influenced by similar environmental factors that drive species distributions, such as climate, soil properties, and hydrology. Identifying these shared drivers can enable the modelling of community-level distributions using SDMs. Studies often identify the major environmental factors that correlate with species assemblages to guide conservation and restoration efforts (Durbecq et al., 2020; Porfirio et al., 2014)

2.7.4.4. Exploring SDM on Woody Communities-Based Classification and Inventory

Predicting vegetation classes as "functional communities" leverages the idea that species within these classes share ecological requirements and responses to environmental gradients. For example, mangroves are defined by their tolerance to saline conditions, making them a coherent ecological unit suitable for SDM applications (Chiou & Blair, 2021; Maguire et al., 2016). Research has demonstrated the application of SDMs to define potential reference communities in degraded ecosystems, such as identifying suitable sites for grassland restoration based on environmental compatibility. Similar methods can be applied to woody vegetation types, ensuring that environmental suitability is assessed for the entire community rather than individual species (Durbecq et al., 2020).

2.7.5. Integrative Approaches for Biomass Assessment

2.7.5.1. Field-Based Assessments

Field-based assessments of woody vegetation often involve measuring attributes like diameter at breast height (DBH), tree height, species composition, and canopy cover (Mercker & Yang, 2022). These metrics provide essential data on biomass, growth rates, and ecosystem structure. Innovations in field protocols now emphasize integrating tree characteristics with environmental variables, allowing for a more comprehensive understanding of how factors like soil type, elevation, and climate impact vegetation (Chauvier et al., 2021; Rahman et al., 2021). For instance, research in West African landscapes has shown that soil moisture and nutrient availability influence the density and distribution of woody species, with significant implications for managing vegetation in semi-arid regions (Tiawoun et al., 2022).

Allometric models, which relate tree dimensions to biomass, remain a staple of field-based woody vegetation assessments (Nam et al., 2016; Ganamé et al., 2021). Recent studies have refined these models to improve accuracy across different vegetation types, including tropical savannas, mangroves, and dry forests (Chave et al., 2014; Prance, 2006). Research has also explored species-specific models, which account for the unique growth patterns and wood density of particular tree species, enhancing biomass estimation accuracy (Hossain et al., 2019; Mulatu et al., 2024; Ganamé et al., 2021).

2.7.5.2. Limitations of Field-Based Assessments

While highly accurate and essential for obtaining ground-truth data, field-based assessments face several limitations. One significant limitation is their resource-intensive nature; collecting data in the field requires substantial time, labour, and financial resources, especially in remote or difficult-to-access areas. In West Africa, logistical challenges such as limited infrastructure and seasonal weather conditions, like heavy rains, can further complicate fieldwork, often restricting data collection to certain seasons and limiting the overall spatial coverage (Shaffer et al., 2018). Like heavy rains, seasonal weather patterns often restrict data collection to specific periods and limit overall spatial coverage. For instance, significant floods have affected data collection in Sierra Leone, impacting over 220,000 people in the last 15 years (Brown et al., 2022).

Additionally, field-based methods rely on allometric equations to estimate biomass from tree measurements like DBH and height. While these equations are widely used, they can introduce errors when applied to diverse species with varying wood densities, growth forms, or ecological conditions, especially in biodiverse regions like tropical West Africa. The accuracy of these models may also vary based on tree age, height, and structural variability, indicating that a single model may not suit all vegetation types without adjustments (Vorster et al., 2020). Research on reducing error in biomass estimates emphasizes the importance of model selection and calibration, noting that choosing an allometric equation can substantially impact the accuracy of biomass predictions (Picard et al., 2015).

In the context of West Africa, studies have developed species-specific allometric models to improve biomass estimation accuracy. For example, research on AGB-based allometric equations in the tropical woodlands of Ghana underscores the necessity of locally developed models tailored to specific species and ecological conditions (Aabeyir et al., 2020).

These findings suggest that while allometric equations are valuable tools for biomass estimation, their application requires careful consideration of species-specific and regional factors to minimize errors, particularly in diverse ecosystems like West Africa.

2.7.5.3. Combining Field Data with Remote Sensing

Recent research underscores the value of integrating field-based data with remote sensing to enhance the accuracy of woody vegetation assessments (Reinke & Jones, 2006). Field measurements provide essential ground-truth data that improve the calibration of remote sensing models, particularly for biomass estimation. This combined approach has proven effective in landscape-scale studies, enabling detailed assessments of species diversity, carbon stock, and structural characteristics across heterogeneous landscapes (Galidaki et al., 2017). For instance, a study focusing on the African savanna demonstrated that integrating remote sensing and geostatistics allowed for more accurate estimations of woody vegetation, highlighting the benefits of combining these methodologies (Adjorlolo & Mutanga, 2013). Additionally, research on bush encroachment mapping in Africa employed a multi-scale analysis with remote sensing and GIS, calibrated with field data from surveys and experts in Southern and Eastern Africa (Graw et al., 2016). This integrative approach facilitated the detection of woody vegetation across the continent, illustrating the effectiveness of combining field data with remote sensing techniques.

These integrative approaches have been applied in various African ecosystems, including savannas and mangrove areas, where remote sensing data alone might miss fine-scale variations in biomass and species diversity. By combining field-based data with remote sensing, researchers can achieve more comprehensive and accurate assessments of woody vegetation, which is crucial for effective ecosystem management and conservation efforts.

2.7.5.4. Machine Learning

Machine learning (ML) and artificial intelligence (AI) are increasingly applied in woody vegetation assessments to analyze large datasets from remote sensing and automate the identification of species and canopy structures (Raihan, 2023). For instance, deep learning algorithms can process complex image data to classify vegetation types, identify individual trees, and predict biomass more accurately than traditional models (Ma et al., 2024). A study demonstrated that deep learning-based 3D point cloud regression significantly improved forest biomass estimation (Oehmcke et al., 2021).

In West African ecosystems, such as the Sahel-Sudan-Guinea region, machine learning has been employed to map and monitor changes in vegetation greenness over time, providing valuable insights into habitat dynamics and conservation needs (Zeng et al., 2024). Research utilizing explainable machine learning techniques has analyzed the nonlinear evolution of vegetation greenness and its climatic drivers in this region, enhancing the understanding of vegetation dynamics (Zeng et al., 2024).

2.7.5.5.Challenges and Future Directions

Despite significant advancements, woody vegetation assessment faces several challenges, particularly in regions with limited access to high-quality remote sensing data or field resources. Refining allometric models for understudied tropical species remains a priority to improve biomass estimation accuracy. Additionally, integrating socioeconomic factors into vegetation assessment frameworks is crucial, as human activities like logging and agricultural expansion significantly impact woody vegetation in many regions (Chirwa et al., 2024).

Future directions point towards increasing collaboration between remote sensing scientists, ecologists, and local communities to create robust and locally adapted woody vegetation monitoring programs. Enhanced accessibility to satellite data and the development of low-cost remote sensing technologies are expected to broaden the applications of these assessments, allowing for better-informed management and conservation decisions (Löhr et al., 2024).

Integrating ecosystem services and life cycle assessment frameworks can also provide a more comprehensive evaluation of the socio-environmental impacts of human activities on woody vegetation (Taelman et al., 2024).

CHAPTER 3 : SPATIOTEMPORAL CHANGE OF WOODY VEGETATION AND PATTERN ANALYSIS

3.1. INTRODUCTION

Woody tree vegetation plays a crucial role in ecosystems, offering stability and impacting various ecosystem aspects like soil water storage, evapotranspiration, soil stability, erosion, and carbon storage, which reflects ecosystem health (Fazan et al., 2020). Livelihoods in Savannah are supported by woody vegetation due to the provision of wildlife habitats and ecosystem services (Kibet et al., 2021). Significant factors like soil degradation, land use, erosion (water and wind), and salinization are recognized to lead to woody vegetation loss (Tülay & Başkan, 2022). Wood vegetation pattern and their dynamics affect in return biodiversity and ecosystem services (Sinare & Gordon, 2015a).

Climate change threatens major woody species in Africa, impacting woody vegetation patterns (Kapuka et al., 2022). Besides the conservation and biodiversity aspect, protecting trees is crucial for mitigation due to their high carbon storage capacity (Mildrexler et al., 2023). Tree planting is also considered an effective mitigation, storing more carbon than alternative vegetation (Kirschbaum et al., 2024). Trees outside forests make a substantial input to woody cover and woody biomass. Their contribution is vital for assessing the overall impact of woody vegetation on carbon stock and climate mitigation efforts (Kapuka et al., 2022).

In Senegal, forests are typically located in the central and southern regions, with a decline in coverage observed in the last decades (MEDD, 2015). In 2005, the forest area was approximately 9.7 million hectares, but by 2010, it had declined to 8.5 million hectares (MEDD, 2015). According to data from Global Forest Watch, from 2002 to 2023, Senegal lost 8 ha of primary humid forests, representing 0.17% of its total tree cover loss during the same period.

The decrease in plant formations noted in the 1980s was further affirmed during the subsequent decade from 1980 to 1990 (Brandt et al., 2017). Historical reports, cartographic studies, targeted surveys, and recent observations have shown a gradual decline in plant resources (Dendoncker et al., 2020; Solly et al., 2020; Badji et al., 2014). Despite their protected status, forest reserves have been affected by degradation. Certain reserves have seen a decrease in their initial area, a notable decline in biodiversity, and a reduction in the density of the woody species (Sambou et al., 2008; Touré et al., 2019).

In the Saloum region, human activities have significantly altered the composition and structure of vegetation, particularly in the Peanut Basin (Andrieu & Alexandre, 2010). While some assessments have indicated a decline in vegetation across the entire Saloum, there are instances of potential regreening. For example, the Delta may be experiencing regreening due to Cashew cultivation initiated by the Senegal-German project (PASA) initiate in 1979 (Coly, 2016). Mangrove revegetation has also been observed in the Saloum estuary (Andrieu, 2018; Andrieu et al., 2020; Carré et al., 2022).

An accurate understanding of the distribution and changes in woody plant populations in steppes is ecologically significant (Cheng et al., 2023). Field observation has been used for vegetation monitoring (Thimonier et al., 2011). The main challenges with this approach were the significant expenses in terms of human labour and materials and uncertainties when extrapolating samples (Hao et al., 2020). The rapid progress in remote sensing technology for earth observation has empowered researchers to nowadays monitor and map the temporal and spatial patterns of woody plant distribution for both local and global scales (Fundisi et al., 2022; Strnad et al., 2023). The advancements in remote sensing technology present a promising alternative for monitoring and mapping the distribution of woody plants, potentially addressing the constraints associated with traditional ground-based surveys.

Research on landscape fragmentation, particularly the structural characteristics of LULC at class and patch levels in the Saloum region, has not received adequate attention. While numerous studies have concentrated on LULC changes (Silva et al., 2017; Tine et al., 2020), there is a notable lack of studies that examine the interplay between landscape structure and LULC changes in diverse landscapes that include both protected areas and their adjacent environments (Matyukira & Mhangara, 2023). A lack of this critical information prevents policymakers from designing appropriate interventions, such as land restoration initiatives and REDD+ strategies, to address key ecological and socio-economic challenges effectively. This gap indicates a need for further investigation into how these structural characteristics influence ecological dynamics in such heterogeneous landscapes.

This paper focuses on assessing the dynamic and pattern of woody trees in the Saloum Delta, an area characterised by complex vegetation communities that have been sparsely documented, and their present dynamics are not thoroughly understood. Although recurrent climate, mitigation and conservation efforts may have significantly affected woody vegetation. The objective here is to assess the extent and trends in how spatial patterns of woody tree landscapes have been shaped in the Saloum Delta, to promote optimal landscape management for carbon sequestration and support effective policy implementation.

3.2. METHODOLOGY

The most effective approach for spatially assessing extensive woody vegetation cover is using Earth Observation (EO) technologies (Symeonakis et al., 2016). Numerous research endeavours have used Landsat data to monitor woody cover or access its dynamic (Arévalo et al., 2023; Avitabile et al., 2012; Chen et al., 2021).

3.2.1. Data Acquisition

3.2.1.1. Woody Cover Classes

The study takes into account the main woody tree covers existing in the landscape study, which are the following: “Mangroves”, “Close Woodlands”, “Open Woodlands”, “Plantations”. In addition to these woody cover classes, two relevant classes without trees have been defined: “No Woody Cover”, and “Water” (Table 3-1 and Figure 3.1).

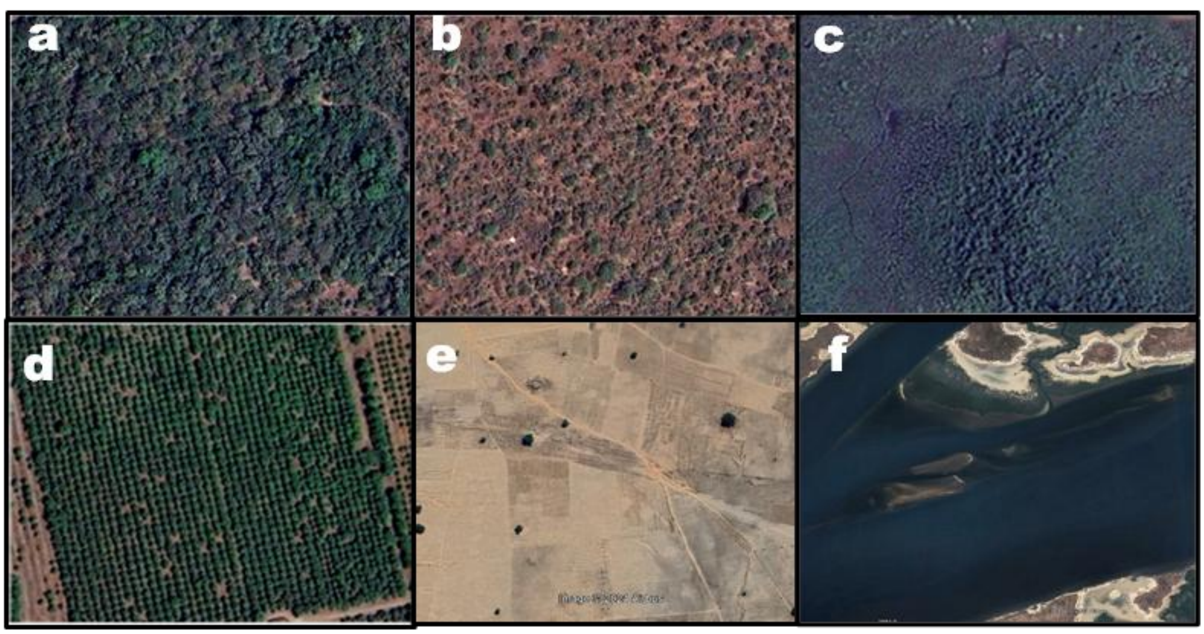


Figure 3.1: High-resolution orthophoto of different woody vegetation cover in the study area with Close Woodlands (a), Open Woodlands (b), Mangroves (c), Plantations (d), No tree cover (e) and Water (f). Source: Google earth Pro 02/06/2023.

Table 3-1: Definitions of the land cover types identified in the study area

Land cover types	Definition	Abbreviation
Mangroves	Mangroves are forests and shrublands composed of salt-tolerant trees and shrubs found in the intertidal zone of sheltered tropical and subtropical coasts (Alongi, 2002).	MG
Close Woodlands	A Close Woodlands, alternatively called a closed forest, denotes a wooded area where the canopy of trees extends over more than 80% of the ground surface. This extensive coverage of tree crowns creates a thick canopy, which restricts light penetration to the forest floor. (ABARES, 2020).	CW
Open Woodlands	Open Woodlands are characterized by relatively low tree density, with widely spaced trees and an open canopy, allowing significant sunlight penetration to the ground. Crown cover is less than 80% (ABARES, 2020).	OW
Plantations	A forest stand is created through deliberate planting or seeding as part of afforestation or reforestation initiatives, typically serving a specific purpose, such as timber production, fruit cultivation, or the generation of other forest-derived products (FAO, 2001).	PT
No Woody Cover	Areas with little to no tree vegetation cover, often characterized by bare land, agricultural land, mad, rock, or other substrates with minimal plant growth	NWC
Water	Waterbody	WT

3.2.1.2. Landsat Images Collection

The Landsat images are precious for biodiversity assessment due to their extensive history of ongoing surveillance and moderate spatial precision (Hackman et al., 2020). The study leveraged Tier 1 surface reflectance imagery from the Landsat satellite constellation, accessed through the Google Earth Engine (GEE) platform, as it offers the most precise representation of surface characteristics.

This study analysed 30-meter spatial resolution satellite imagery from Landsat-5, 7 and 8. Multi-temporal Landsat images for 2002, 2007, 2017, and 2022 were examined. Image classification was conducted on the GEE platform, using only images with a cloud percentage of less than 10% for accuracy (Ermida et al., 2020; Faisal et al., 2021). Table 3-2 provides details of the image collection, including satellite name, number of images collected with less than 10% cloud cover, and the mean cloud percentage (CCP). After retrieving the Landsat images, the data was spatially filtered using the study area's shapefile. A temporal filter was also applied to select images from the chosen dates (January to December). The mask function was applied for insufficient data (such as clouds, shadows, and saturated pixels).

Table 3-2: Landsat image collection for the different study periods

Year	Sensor	Number of images<10%	Mean CCP
2002	LANDSAT/LE07/C02/T1_L2	26	1.23
2007	LANDSAT/LT05/C02/T2_L2	2	0
2007	LANDSAT/LE07/C02/T1_L2	31	1.9
2017	LANDSAT/LC08/C02/T1_L2	32	3.04
2022	LANDSAT/LC08/C02/T1_L2	32	0.33

3.2.1.3. Ground Truthing Sample Collection

The sample for the image classification was obtained from Google Earth Pro (GE) and combined with GPS field coordinates, as shown in Figure 3.2. Four thousand eight sampling points were used, with 301 points from the GPS and 3707 points from Google Earth Pro (Table 3-3). The training samples were selected based on ease of access or availability. For each woody cover class, several samples were chosen based on the accessibility of the cover type within the study area. The high-resolution orthophotos in Google Earth Pro allow us to review previous years, helping to maintain consistent sample sets for classification across all years.

3.2.1.4. Feature Selection

Additionally, two spectral indices, namely Normalized Difference Water Index (NDWI) and Normalized Difference Vegetation Index (NDVI), derived from the Landsat 5, 7, and 8 surface reflectance images, were employed as features (Table 3-4). NDWI helps distinguish water bodies from other land cover types, making it particularly useful in areas where the proximity of vegetation and water may cause misclassification. NDWI is especially relevant in environments with mangroves, wetlands, and other water-vegetation interfaces (Hariyono et al., 2023). NDVI is essential for identifying and quantifying vegetation, especially in studying woody vegetation, as it can indicate biomass, canopy density, and vegetation vigour. NDVI is critical for distinguishing vegetated land cover types from non-vegetated areas (Le et al., 2022). The DEM was also used to differentiate aquatic vegetation like mangroves from other vegetation (Tolentino et al., 2021). Six surface reflectance bands (Blue, Green, Red, Near-infrared, SWIR-1, and SWIR-2) were used in this study. These bands allow for accurate analysis of vegetation structure, health, and cover changes, which are key components for studying woody vegetation.

Table 3-3: Sampling points from the remote and in-situ (GPS) collection

Class	MG	CW	OW	PT	NWC	WT	Total
GPS	---	60	46	36	159	---	301
Google Earth Pro	60	78	340	69	3111	49	3707
Total	60	138	386	105	3270	49	4008

Table 3-4: Indices used for the image classification

Index	Equation	Reference
NDVI	$\frac{\boldsymbol{NIR-Red}}{\boldsymbol{NIR+Red}}$	Tucker 1979
NDWI	$\frac{\boldsymbol{Green-NIR}}{\boldsymbol{Green+NIR}}$	McFeeters 1996

3.2.2. Image Processing

Once all remotely sensed scenes suitable for a specific land use/cover study have been identified, the first crucial step is to merge these datasets. Two widely applied composition methods are commonly used for land cover classification with multi-temporal Landsat images. One method involves creating a composition of time series data using all the available cloud-free Landsat images (Hermosilla et al., 2018; Zhu & Woodcock, 2014). The other method is the temporal aggregation approach, which uses metrics such as mean, median, and min/max derived from time series images (Hu, 2019; Richards & Belcher, 2019). This study used a median filter to merge the image collection. The median is used because it provides a robust measure of central tendency, which helps reduce the influence of outliers (such as clouds or shadows) compared to using a simple mean (Boateng et al., 2012). This use ensures the final composite image better represents the true surface reflectance for each year. Landsat composites were obtained for each year 2002, 2007, 2017, and 2022 and subsequently used to classify the images.

3.2.3. Classification of the Landsat Images

The classification was run on 65% of the samples. The Random Forest classifier (parametrised with 120 trees) was employed for the image classification. This classifier was chosen since it is widely utilized in land-cover classification tasks (Noi et al., 2020). The number of decision trees chosen showed good performance in previous studies. Each additional tree increases processing time and memory requirements, especially in Google Earth Engine, where large datasets and extensive image collections like Landsat are used. The classification workflow is provided below (Figure 3.3).

3.2.4. Accuracy Assessment

The classification accuracy was assessed using 35% of the samples. All post-classification and testing procedures were conducted in QGIS 3.18.3. Various tasks were performed to refine the classification results further. These tasks included preparing map layouts, reclassifying land cover classes, and estimating pixel values for all classes (Gilbert & Shi, 2023). Overall accuracy, user and producer accuracy, kappa coefficient (Mathewos et al., 2022), and area calculations were determined in R using the following equations.

$$\text{OA}\ (\%) = \frac{1}{N}\sum_{k=1}^{r} n_i \times 100 \quad (1)$$

$$\text{UA}\ (\%) = \frac{X_{kk}}{X_{k+}} \times 100 \quad (2)$$

$$\text{PA}\ (\%) = \frac{X_{kk}}{X_{+k}} \times 100 \quad (3)$$

$$\text{KC} = \frac{N\ \sum_{k=1}^{r} X_{kk} - \sum_{k=1}^{r}(X_{k+} . X_{+k})}{N^2 - \sum_{k=1}^{r}(X_{k+} . X_{+k}} \times 100 \quad (4)$$

$$\text{Area}\ (A_k) = \text{P}_k \times\ 0.0009[\text{km}^2] \quad (5)$$

$$\text{Area in percent} = \frac{A_k}{\sum_k A_k} \times 100 \quad (6)$$

$$\text{Percentage change between time intervals} = \left(\frac{A_k,\text{t}_2 - A_k,\text{t}_1}{A_k,\text{t}_1}\right) \times\ 100 \quad (7)$$

OC = Overall Accuracy; UA = User accuracy; PA = Producer accuracy; KC = Kappa Coefficient; N = Total number of observations; X_{kk} = Pixels correctly classified for class k; X_{k+} = Total pixels classified as class k (row total in the confusion matrix); X_{+k} = Total actual pixels in class k (column total in the confusion matrix); $A_k t_1$= Area of class k at time t_1; $A_k t_2$= Area of class k at time t_2. P_k = Pixel count for a class k; Ax = Area calculated from pixel count of a class k.

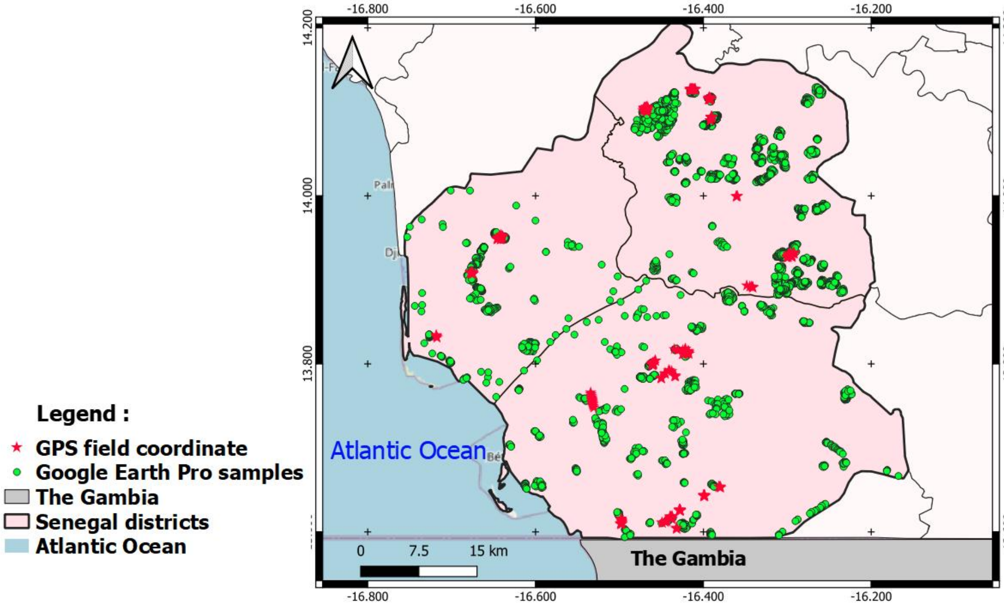


Figure 3.2: Spatial distribution of the ground truthing samples

3.2.5. Change matrix

Change matrix were formulated in R software to examine shifts in land cover values over time. A transition matrix was generated by cross-tabulating the pixel values from both rasters. A matrix was produced, where rows represent the original classes (Woody cover in 2002), and columns represent the new classes (Woody cover in 2022). Each cell in the matrix indicates the number of pixels transitioning from one class to another. To process the statistics inside and outside the protected forest, the data partitioning was done using the protected forest boundaries from the forestry service (Direction des Eaux et Forets). R software was used to evaluate the origin and destination of each land cover value, shedding light on the transitions between different land cover categories (Daou et al., 2023). The Chord diagram was used to visualise the transition, using the circle package available in R software.

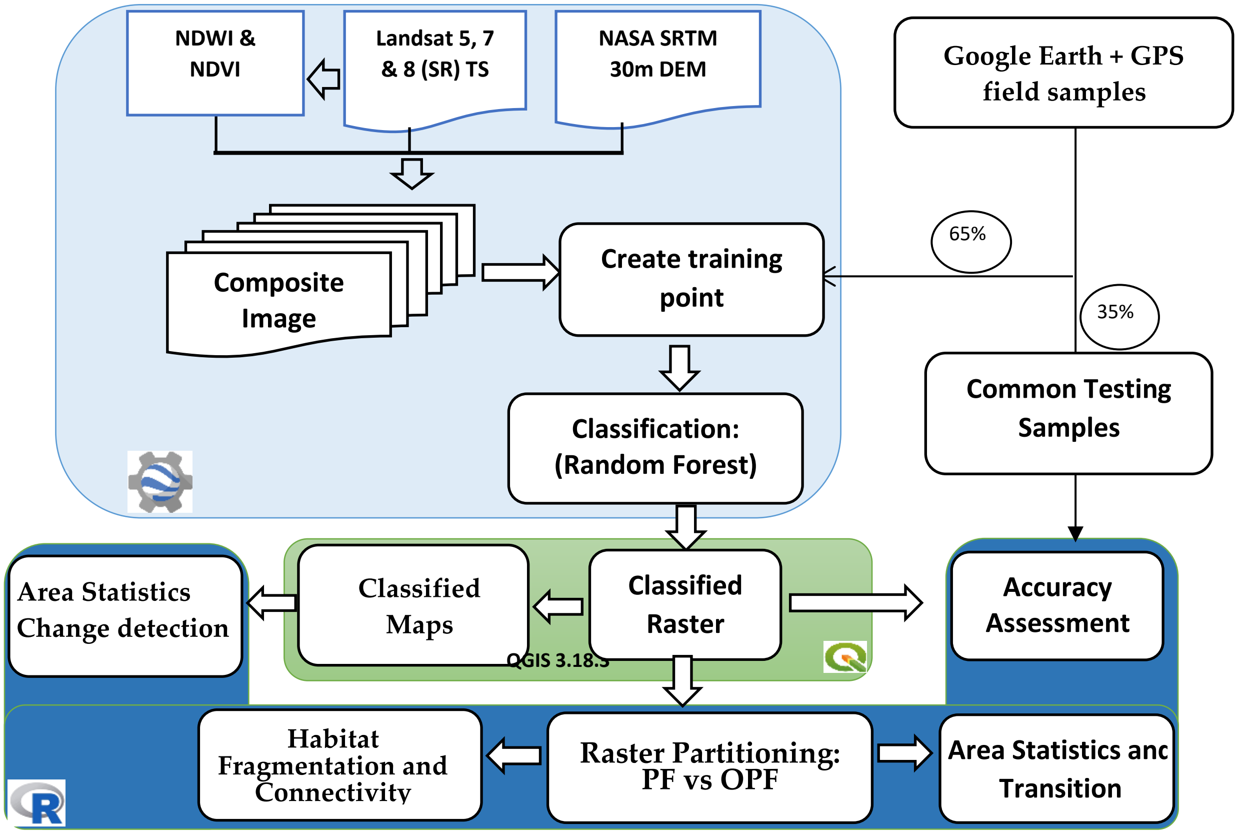


Figure 3.3: Schematic workflow used for the classification and pattern analyses

3.2.6. Fragmentation and Connectivity Analysis

Assessing fragmentation and connectivity patterns of woody vegetation provides critical insights into habitat integrity, biodiversity conservation, and ecological processes influenced by spatial structure (Gallé et al., 2022). R's landscape metric package was used to assess the fragmentation/connectivity pattern of the woody cover. It contains several metrics to evaluate landscape structure and fragmentation (Kumar et al., 2018). The metrics were chosen based on reviewing the commonly used ones in landscape restoration studies (Rosa et al., 2017; Sertel et al., 2018; Kumar et al., 2018). Four class-level metrics and one patch-level metrics were used, as shown in Table 5. The largest patch index (lpi), edge density (ed), perimeter-area fractal dimension (pafrac), and aggregation index (ai) were calculated to assess woody vegetation structure at the class level.

For spatial visualisation of the pattern, the patch area metric (pa) was mapped using R software's show() function. Patch metrics offer insights into landscape patches' configuration and spatial distribution (Song et al., 2021). By integrating the patch areas maps, researchers can identify specific areas of concern, determine the factors driving fragmentation, and develop targeted conservation and land management strategies. This approach aims to mitigate ecological impacts and enhance landscape resilience within the Saloum region. It also helps in assessing the potential resilience of these ecosystems to climate change, as larger, contiguous patches of vegetation are often more resistant to disturbances (Gould et al., 2008). The output map of the patch area metric provided by R software comes as an image; the 2022 coverage map was used as a reference to target the concerned coverage spatially.

Table 3-5: Class level Landscape metrics used in this study

Metrics	Explanation	Formulas
Largest Patch Index (lpi)	lpi measures the proportion of the largest forest patch relative to the total forest area, indicating the dominance of a single contiguous patch within the landscape	lpi $=(\frac{Amax,x}{AT}) \times 100$
Edge Density (ed)	The total length of edges (boundaries) per unit area in the landscape reflects how fragmented or "edgy" a landscape is. Higher edge density indicates more fragmentation.	ed $= \frac{Ex}{AT}$
Perimeter Area Fractal (pafrac)	Reflects the complexity of patch shapes, approaching 1 for simple shapes and increasing with more complex, fragmented patches.	pafrac $= \frac{2\ln(0.25\times P)}{\ln(A)}$
Aggregation Index (ai)	Quantify the degree of spatial aggregation or clumping of patches within a landscape	ai $= \frac{g_x}{Max(g_x)} \times 100$
Patch Area (pa)	pa at the patch level indicates the size of individual habitat patches within a landscape. Larger pa values generally represent more substantial habitat areas	pa $= \frac{A_y}{10000}$

A= Area of the patch [m²]; Amax,x = Area of the largest patch in class x; AT = Total area of the entire landscape; Ex = Total edge length of all patches in class; P= Perimeter of the patch; is the number of like adjacencies for class x (i.e., the number of cell edges where a cell of class ii is adjacent to another cell of the same class); Max()= maximum possible number of like adjacencies for class x, given its proportional abundance and assuming a completely aggregated (clumped) distribution.; = area of an individual patch y in square meters.

3.3. RESULTS

3.3.1. Spatial Observation of the Woody Tree Classes

The result of the woody cover map (Figure 3.4) showed a spatial distribution of woody cover in the landscape study. Mangroves, Close Woodlands, and Open Woodlands experience some dynamics within the landscape. Plantations show a significant increase, mainly in the southern part of the study area. The overall accuracy was 94.85%, 97.32%, 97.74, and 97.18 for 2002, 2007, 2017 and 2022, respectively (Table 3-6).

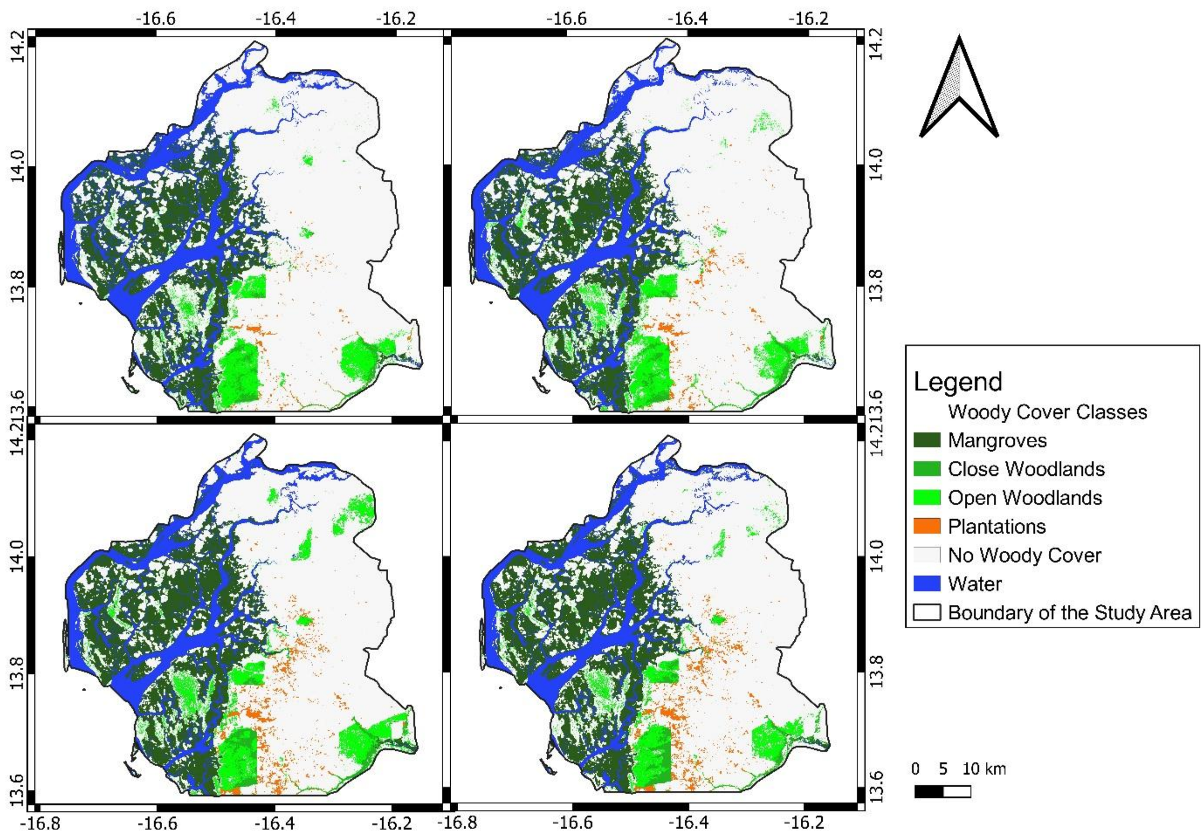


Figure 3.4:Woody tree cover map in the study landscape

Table 3-6: Accuracy assessment of the image classification

YEARS	OVERALL ACCURACY	KAPPA	AVERAGE USER	AVERAGE PRODUCER
2002	94.85	83.14	0.97	0.90
2007	97.32	91.66	0.98	0.94
2017	97.74	93.02	0.98	0.96
2022	97.18	91.16	0.98	0.95

3.3.2. Area Statistics and Percentage Coverage

The results of the area statistics (Figure 3.5) show that during the initial study period in 2002, except for No Woody Cover (60.04%), the woody cover landscape was dominated by Mangroves 548.29 km^2 (18.47%). Open Woodlands covered 5.03% (149.21 km^2) of the area, followed by Close Woodlands at 1.23% (36.54 km^2). In the subsequent study period in 2007, Mangroves remained the dominant LULC class, accounting for 18.69% (554.65 km^2), followed by Open Woodlands 5.62% (166.81 km^2), Close Woodlands 1.30% (38.54 km^2), and Plantations 0.95% (28.05 km^2). In the year 2017, Mangroves occupied 21.09% of the study area, followed by Open Woodlands 6.91% (205 km^2), Plantations 1.94% (57.58 km^2), and Close Woodlands 1.67% (49.56 km^2). In the final study period, Mangroves still dominated with 21.17 % (628.43 km^2), followed by Open Woodlands at 4,95% (147.02 km^2), Plantations at 2.11% (62.61 km^2) and Close Woodlands at 1.83% (54.31 km^2).

3.3.3. Comparison Analysis Within and Outside Protected Forests

3.3.3.1. Area Statistics

The area statistic differences between Protected Forests (PF) and the area outside of Protected Forests (OPF) (Figure 3.6) show that the woody cover is more dominant by Mangroves on both sides, with percentage coverage ranging from 39% to 43% in PF and from 9 to 11% OPF. Open Woodlands PF experienced a significant increase from 4.93% in 2002 to 5.11% in 2017 and a slight decrease in 2022 with 3.18% of the coverage. In contrast to OPF coverage, Plantations has a significant dynamic from 0.80% to 3.03%.

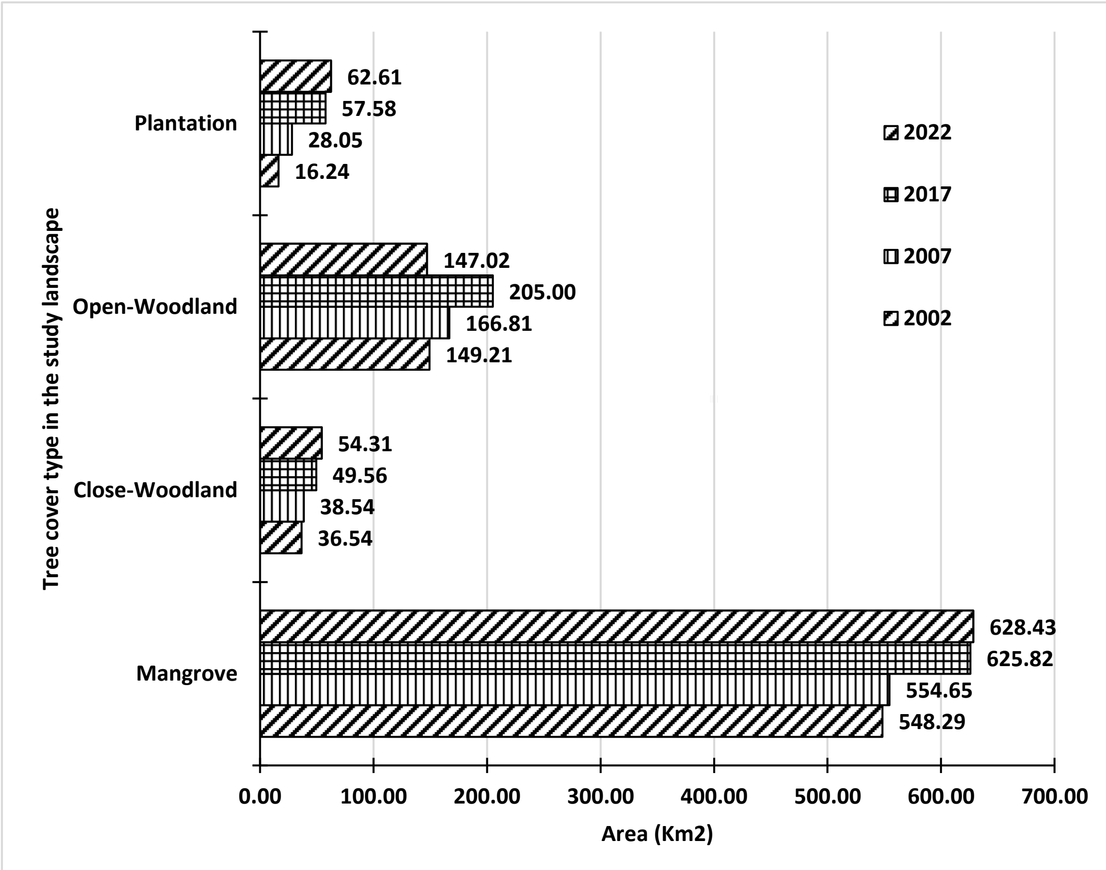


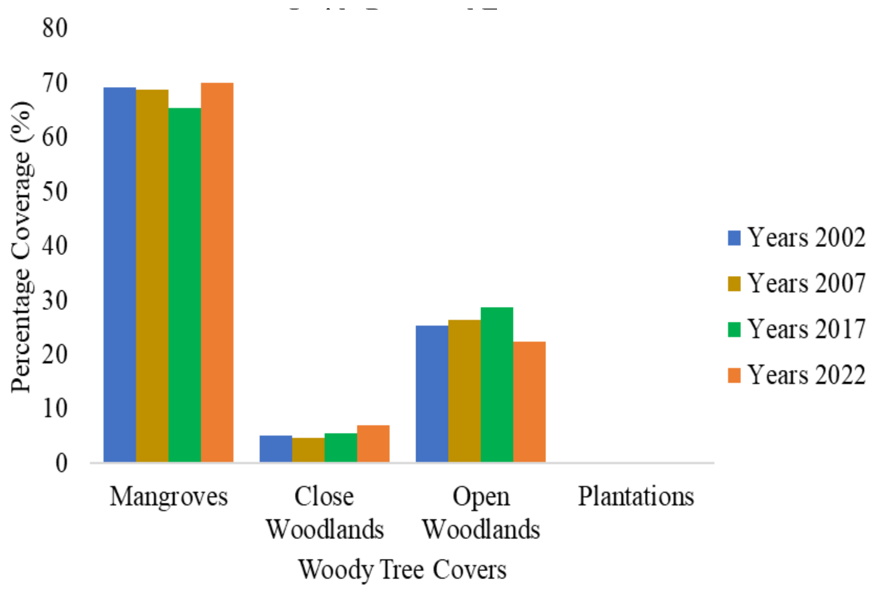
Figure 3.5: Woody tree cover distribution of the study landscape

3.3.3.2. Transition Analysis

Analysis of the transition matrix by a Chord diagram (Figure 3.7) shows that Mangroves PF is mainly gaining area from Water with 12.71 and 13.43%, respectively, for the period 2002-2007 and 2007-2017and from No Woody Cover with 7.79% of its coverage for the period 2007-2017. Open Woodland's PF gain from No Woody Cover with 11.50, 22.67 and 6.73%, respectively. Vice-versa, No Woody Cover also gained 20.15, 14,37 and 32.15% of its coverage from Open Woodlands. Open Woodlands are subjected to significant conversion with No Woody Cover and slight conversion with Close Woodlands with both gain and loss over the study period.

Mangroves OPF gain mainly from No Woody Cover, with 2.01 % of its coverage during the 2007-2017 study period. Results show an increase of Plantations which gain progressively from No Woody Cover over the study period with 1.01, 2.07 and 1.07% respectively.

Results show a slight gain in Open Woodlands from No Woody Cover during the 2002-2007 study period and a slight gain from Close Woodlands during the 2007-2017 study period.



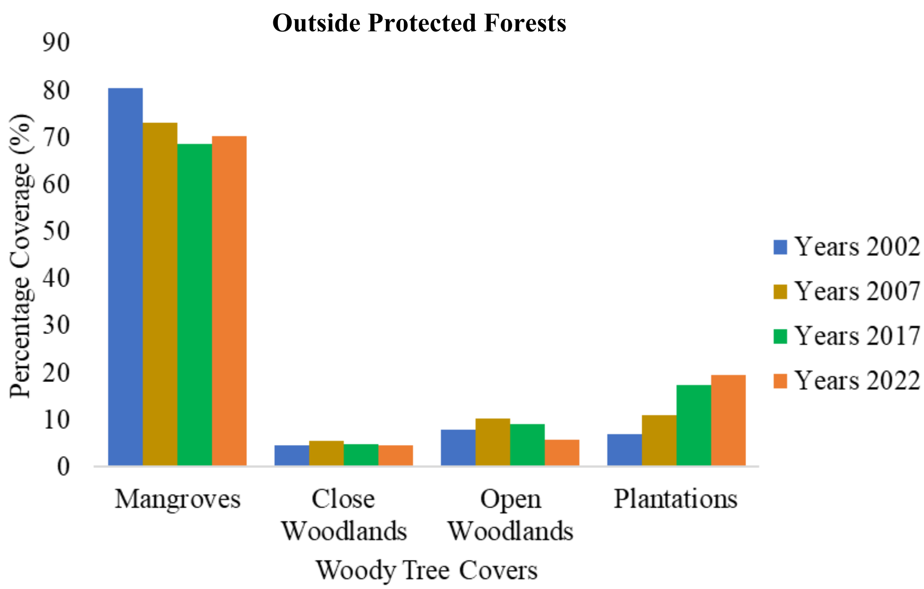


Figure 3.6: Woody coverage inside and outside protected forests

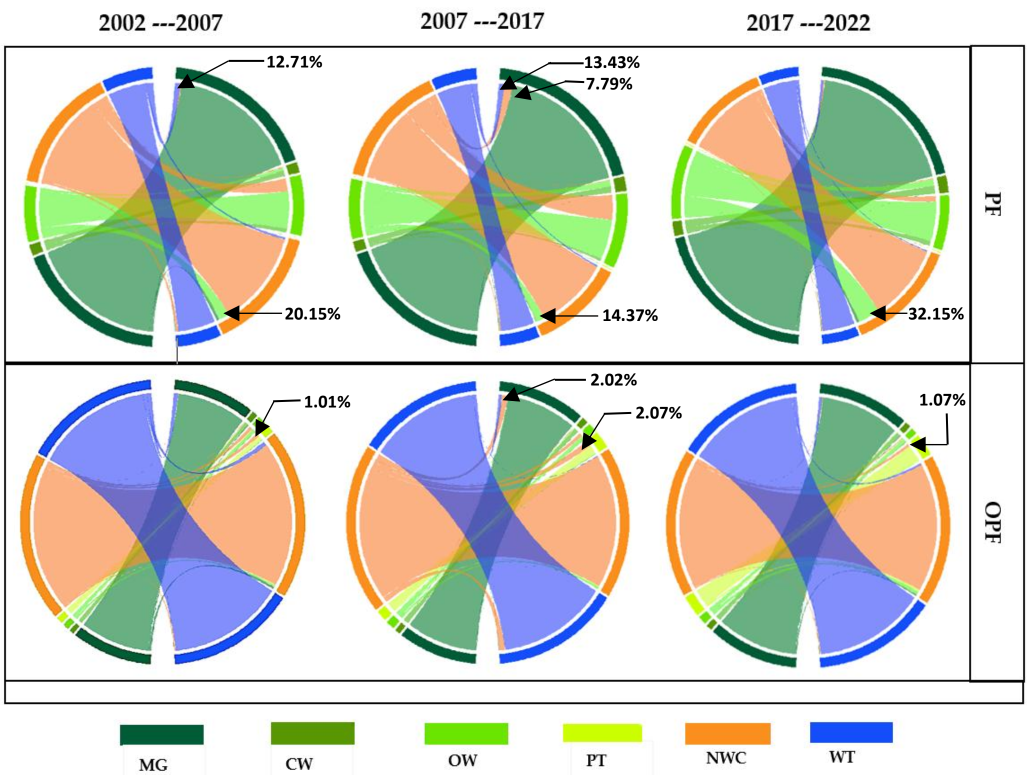


Figure 3.7: Chord diagram of woody vegetation conversion from 2002 to 2022

NWC OPF has been rescaled to its half value, allowing a better visualisation of the other classes

3.3.4. Landscape Metrics Analysis

3.3.4.1. Pattern Inside Protected Forests

Figure 3.8 shows that the largest patch index (lpi) in Mangroves PF strongly increased from 2002 to 2022. Edge density (ed) showed a strong decrease over this period, indicating reduced fragmentation. The perimeter area fractal dimension (pafrac) declined from 2002 to 2022, except for a peak observed in 2007, suggesting the Mangroves's shape has become less irregular over time. The aggregation index (ai) showed a strong increase throughout the study period, shifting from a fragmented, dispersed landscape to a more clustered and connected one.

Close Woodlands PA's largest patch index (lpi) significantly increased from 2007 to 2022. Edge density (ed) decreased strongly between 2002 and 2017, reflecting reduced fragmentation but slightly increased from 2017 to 2022, indicating a minor rise in fragmentation. The perimeter area fractal dimension (pafrac) decreased from 2002 to 2017, with a slight increase in 2022, indicating that while the Close Woodlands shape became more regular by 2022, it was less regular during the earlier period. The aggregation index (ai) showed a strong increase over the study period, indicating a shift from a fragmented to a more connected landscape.

Open Woodlands PA's largest patch index (lpi) strongly decreased from 2002 to 2022. Edge density (ed) strongly increased from 2002 to 2017, indicating more significant fragmentation, followed by a slight decline from 2017 to 2022, showing a reduction in fragmentation. The perimeter area fractal dimension (pafrac) strongly increased from 2002 to 2007, with a slight decrease afterwards until 2022, suggesting a more regular shape from 2002 to 2007, followed by a less regular one. The aggregation index (ai) showed alternating trends: an increase from 2002 to 2007, a decrease from 2007 to 2017, and another increase from 2017 to 2022. This reflects alternating phases of fragmentation and cohesion.

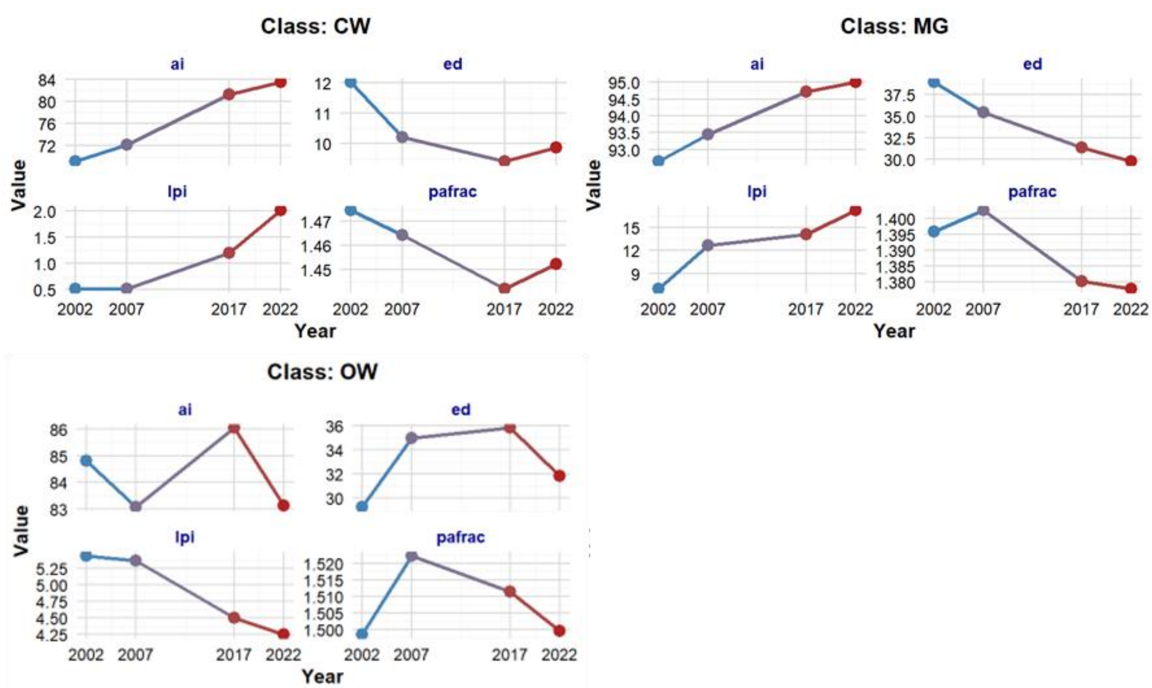


Figure 3.8: Pattern analysis from 2002 to 2022 in Protected Forests classes

3.3.4.2. Pattern Outside Protected Forests

Figure 3.9 shows that in Mangroves, the largest patch index (lpi) strongly increased from 2002 to 2017, followed by a slight decrease in 2022. Edge density (ed) strongly decreased throughout the study period, indicating reduced fragmentation. The perimeter area fractal dimension (pafrac) showed a slight increase from 2002 to 2022, with a notable decrease in 2017, suggesting that the Mangrove's shape became less regular. A slight increase in 2022 suggests a more regular shape at that point. The aggregation index (ai) strongly increased during the study period, shifting from a fragmented, dispersed landscape to a more clustered and connected one.

In Close Woodlands areas (CW), the largest patch index (lpi) showed a slight increase in 2007, followed by a significant decrease in 2022. Edge density (ed) slightly declined in 2017 but strongly increased in 2022, indicating increasing fragmentation. The perimeter area fractal dimension (pafrac) firmly declined from 2002 to 2017, indicating a less regular shape. However, an increase in 2022 suggested a more regular shape had emerged. The aggregation index (ai) strongly increased from 2002 to 2017, reflecting a shift toward a more clustered and connected landscape but slightly decreased from 2017 to 2022, indicating ongoing fragmentation.

In Open Woodlands areas (OW), the largest patch index (lpi) strongly increased in 2007 and decreased in 2022. Edge density (ed) increased strongly up to 2017, indicating greater fragmentation, followed by a strong decrease in 2022, reflecting reduced fragmentation. The perimeter area fractal dimension (pafrac) increased from 2002 to 2007, suggesting a more regular shape, but subsequent declines and increases were observed in 2017 and 2022, respectively. The aggregation index (ai) slightly increased in 2007, indicating more connected areas, while the perimeter area fractal dimension (pafrac) declined in 2017 before slightly increasing again in 2022.

In Plantations areas, the largest patch index (lpi) strongly increased from 2002 to 2022. Edge density (ed) also strongly increased throughout the study period, indicating progressively more fragmentation. The perimeter area fractal dimension (pafrac) strongly declined from 2002 to 2007, suggesting a less regular shape, with a slight increase observed in 2022. The aggregation index (ai) strongly increased during the study period, shifting from a fragmented, dispersed landscape to a more clustered and connected one.

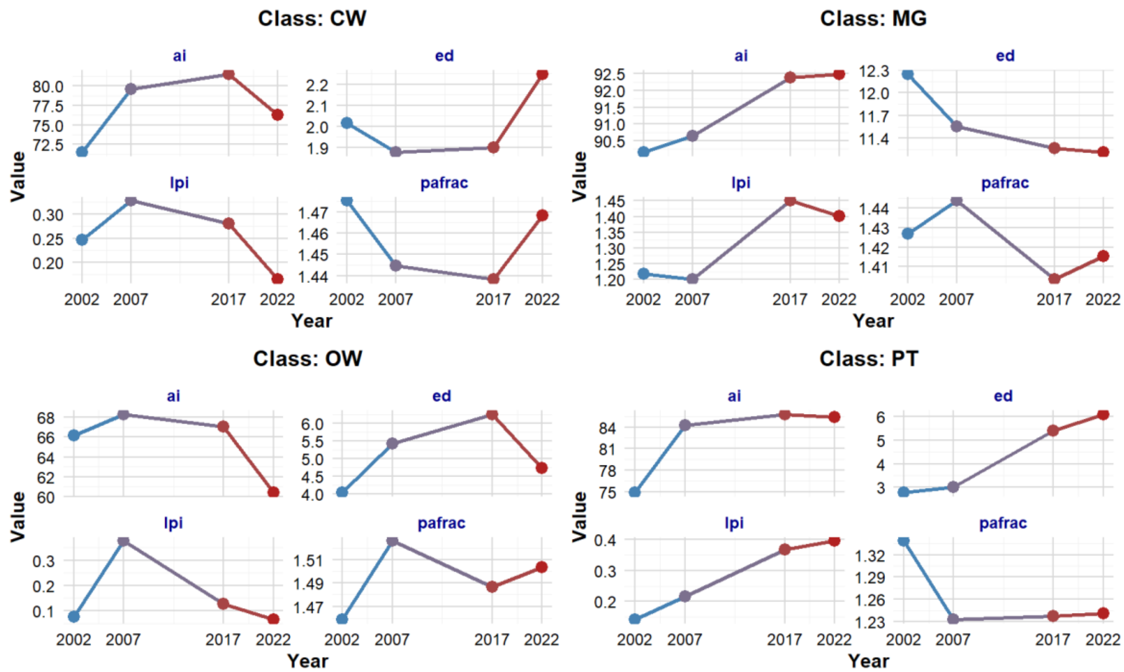


Figure 3.9: Pattern analysis from 2002 to 2022 Outside Protected Forests classes

3.3.4.3. Spatial Visualisation of the Patterns

Spatial pattern analysis for habitat connectivity using patch area metrics between 2002 and 2022 (Figure 3.10) reveals that the largest Mangroves patch in PF was located in the northern part of its coverage. An increase of that largest patch has been progressively noticed north-eastward across the study period. In OPF, the largest mangrove patches were mainly observed in the eastern part of its coverage. From 2002 to 2022, an increase in the largest patch was noticed northward, with a decrease observed in 2017. Plantations are mainly found in OPF, with a significant increase in the minor patches across the study period. The Plantations patches were mostly progressing eastward.

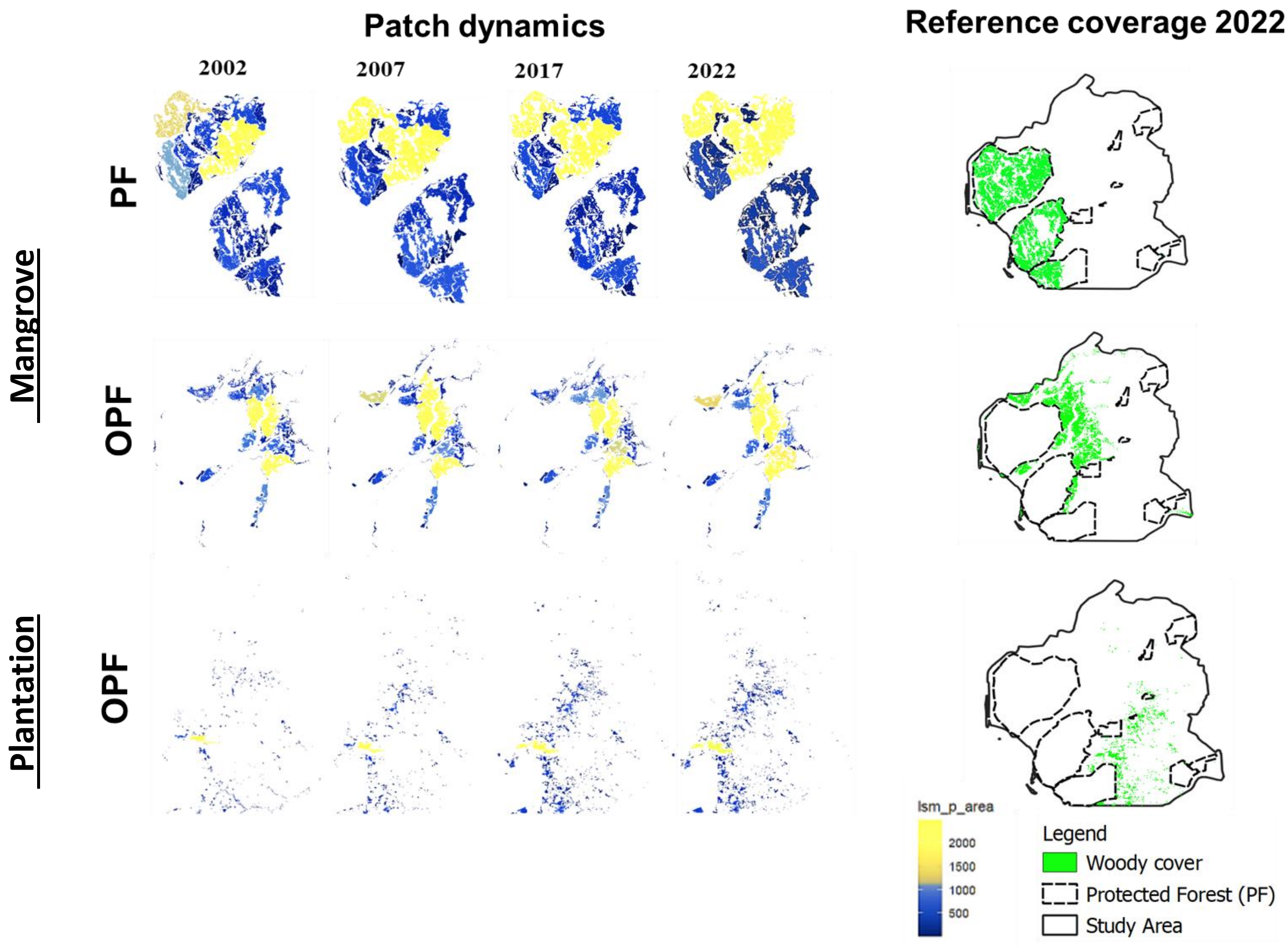


Figure 3.10: Patch area dynamic for most significant changes

3.4. DISCUSSION

Our findings show a slight increase in the Close Woodlands from 2002 to 2022. The Open Woodlands increased till 2017, and a decrease was observed in 2022. A significant area of Close Woodlands (12 km^2) has been converted to Open Woodlands and vice versa from Open to Close Woodlands (23 km^2). Previous studies highlighted an extremely dynamic Sahel vegetation affected by human use and climatic situations (Sambou et al., 2016). In recent decades, numerous studies have demonstrated a persistent degradation of Sahelian and Soudano-Sahelian woody vegetation attributed to agricultural practices and climatic factors (Gonzalez et al., 2012). Conversely, some studies have reported an increase in the density of woody trees (Hiernaux et al., 2009; Nyamekye et al., 2018). However, higher density in the woody vegetation in central Senegal and these increases were limited to the shrub landscape (Herrmann and Tappan, 2013). Dendoncker et al., (2020) illustrated a decrease in woody plant density in the Ferlo (Senegal) following the major droughts of the 1970s–1980s, with a slight recovery in more recent years. Although the declining trends in woody vegetation density and cover observed from 1965 to 2008 have halted in the last decade (2008–2018).

While specific research indicates a decline in closed woodland regions, alternative studies emphasize a rise in Open Woodlands, grass/shrub land, and agricultural areas. These shifts illustrate the fluctuating landscape of land cover across Africa, shaped by various factors such as land management techniques, climate fluctuations, and human interventions (Andrew et al., 2023). Brandt et al. (2018) revealed that in the semi-arid Sahel region, agricultural practices in farmland areas contribute to the growth of woody vegetation around villages. In contrast, on average, adjacent savannah areas typically exhibit lower levels of woody vegetation coverage. The depletion and looming disappearance of woodlands and pastures between villages in Senegal's groundnut basins underscores the challenges confronting these ecosystems due to human activities (Badji et al., 2014).

Mangroves have increased in the study area and during the specific period of our study, mainly toward the northern part of the locality. Over time, the quality and coverage of the mangrove ecosystems within the Saloum Delta have shown improvement, partly due to initiatives like mangrove protection measures and development projects (Dieye et al., 2013). Studies have shown that between 1988 and 2018, mangrove forest areas experienced a notable overall increase of 51.21% across The Gambia, Saloum, and lower regions (Kauffman & Bhomia, 2017). Moreover, research concentrating on the utilization and management of mangroves in the Saloum Delta highlights their economic and ecological importance to local communities. The study emphasizes the significance of implementing sustainable practices and engaging the community in preserving and optimising mangrove resources (Gallup et al., 2020). First assessments in previous research indicated a concerning decline in the mangrove ecosystems of the Saloum estuary, marked by a notable reduction of 34.8% between 1972 and 2010 (Dieye et al., 2013). An assessment from 1979 to 2019, combining remote sensing and field botany, showed that the dynamic is a regeneration of the mangroves fringe along the tidal creeks, which suffered from drought. These changes are primarily attributed (95%) to spontaneous regeneration, thus more related to environmental fluctuations than human factors (Andrieu, 2021).

Our findings show that Plantations is significantly increasing from 2002 to 2022. High Plantations densities, yields, and the socioeconomic aspects of cashew cultivation have also been reported (Oumar et al., 2018). The Saloum Delta is experiencing regreening due to Cashew cultivation initiated by the Senegal-German project (PASA) in 1979 (Coly, 2016).

Patterns comparison between the PF and OPF show differences. In both PF and OPF, more cohesive landscapes have been noticed in Mangroves. This ecosystem is well-suited to the low-oxygen conditions found in waterlogged mud and tends to flourish in the upper portion of the intertidal region. This specialized adaptation allows Mangroves to form dense, cohesive stands in coastal areas. While mangroves overgrowth can result in a more uniform landscape structure, it also promotes the development of cohesive patches (Shih et al., 2019). Species interactions and environmental gradients are crucial in driving mangrove forest dynamics, underscoring the importance of trait plasticity in shaping community structure and function (Olagoke, 2016).

Results have shown that in Open Woodlands, there is an alternating trend of fragmentation and cohesion. While fire can initially lead to fragmentation by creating patches of varying ages and compositions, it can also enhance cohesion over time. The regeneration of vegetation after fire can result in a more homogeneous landscape, as similar species establish in the burned areas, potentially increasing the overall connectivity of the woodland (Bernardie et al., 2021; Arshad et al., 2022). In addition, drier climates tend to produce more dispersed vegetation, which may appear more fragmented than moister climates (Gould et al., 2008).

Our results have shown that Close Woodlands OPF, particularly in 2017 and 2022, shows fragmentation and complex patch shapes. Close Woodlands can become fragmented due to urbanization, agriculture, and infrastructure development, resulting in patches of different sizes and shapes (Rivas, 2022).

Our findings show that continuous small patches characterise the Plantations despite increased connectivity. Research indicates that Plantations often exhibit a range of patch sizes, with empirical distributions typically showing increasing variation with patch size (Song et al., 2021).

3.5. CONCLUSION

This study concludes that Mangroves cover increased, primarily in the northern area, reflecting successful conservation efforts and natural regeneration. Close Woodlands showed modest gains, while Open Woodlands expanded until 2017 but then declined, pointing to environmental pressures and human impact. Protected Forest (PF) and Outside Protected Forest (OPF) areas revealed differing trends. PFs exhibited more cohesive Mangroves structures with large, connected patches, indicating ecosystem resilience in managed areas. OPF areas, however, showed greater fragmentation in Open and Close Woodlands, due to land-use pressures like agriculture and urbanization. Plantations, notably cashews and mango, saw a significant rise, especially in OPFs, contributing to regreening. Landscape metrics (LPI, ED, PAFRAC, AI) indicated reduced fragmentation and higher connectivity in PF Mangroves, whereas Open Woodlands displayed alternating patterns of fragmentation and cohesion. These results underscore the importance of additional protected areas in maintaining landscape connectivity in Mangrove areas. The disturbance in PFs shows limitations in the management and would require a clear understanding of the drivers. The rising fragmentation in OPF areas suggests a need for sustainable land management to balance ecological health with socioeconomic benefits. Continued conservation and community-led management could enhance resilience in the Saloum Delta, promoting REDD+ policy and supporting biodiversity and local livelihoods.

CHAPTER 4 : PREDICTING SPATIAL DISTRIBUTION OF THE WOODY TREE COVER AND ASSOCIATED ENVIRONMENTAL DRIVERS

4.1. INTRODUCTION

Woody covers are essential ecosystems, providing critical services such as carbon sequestration, biodiversity conservation, and livelihood support (Sinare & Gordon, 2015a). However, these ecosystems are increasingly threatened by deforestation, land degradation, and climate change (Emmanuel & Williams, 2017; Grieco et al., 2024). Global initiatives like REDD+ (Reducing Emissions from Deforestation and Forest Degradation) emphasise preserving and restoring forest landscapes while promoting sustainable land management (Panwar et al., 2022; Salvini et al., 2016). In this context, understanding the environmental factors driving vegetation patterns is crucial for effective planning and intervention.

Soudano-sahelien zone has a dynamic interplay of climate variability, human activities, and ecological processes (Gonzalez, Tucker, and Sy 2012; Cheng et al., 2023). This context demands a comprehensive, data-driven approach to inform land restoration strategies zones. The assessment and monitoring of forest ecosystems rely increasingly on advances in geospatial technologies and ecological modelling (KOMBATE et al., 2023; Xue et al., 2019). Remote sensing tools, Geographic Information Systems (GIS), and predictive modelling techniques have revolutionized our ability to map vegetation patterns, monitor changes over time, and assess the underlying environmental drivers (Dimobe et al., 2015; Matyukira & Mhangara, 2024; W. Zhang et al., 2019).

The Saloum Delta in Senegal, a UNESCO World Heritage Site, is an ecologically and socioeconomically significant region characterized by diverse habitats, including Mangroves, savannas, and woodland ecosystems (Diop, 1998; Sambou, 2015). Woody tree cover in this delta is vital for maintaining ecological balance, supporting local communities, and contributing to global carbon storage. However, environmental and anthropogenic pressures, such as changing climate patterns, land use changes, and resource extraction, threaten these ecosystems (Dia, 2012). Predicting the spatial distribution of woody cover and associated environmental drivers is key to identifying suitable or priority conservation and land restoration areas.

Species Distribution Models (SDMs) offer powerful tools for understanding and predicting the spatial patterns of vegetation in response to environmental variables (Fournier et al., 2017; Tong et al., 2023). SDMs use statistical and machine learning approaches to correlate species occurrences or vegetation presence with environmental factors (Srivastava et al., 2019) such as climate, soil properties, and topography. These models are instrumental in identifying the key drivers of distribution, determining the area suitability, forecasting future scenarios under changing conditions, and supporting land management strategies (Srivastava et al., 2019). For regions like the Saloum Delta, SDMs can provide critical insights into the drivers of the main woody cover and their related area suitability, facilitating targeted actions for optimum restoration and alignment with REDD+ objectives.

In this study, we apply SDMs to predict the environmental drivers and associated spatial distribution of woody tree cover in the Saloum Delta. By integrating spatial data and ecological modelling, this research seeks to inform optimum land restoration and enhance the effectiveness of future REDD+ initiatives in the region. The findings will contribute to sustainable land management, improved carbon stock pools, and the conservation of the Saloum Delta's ecosystems.

4.2. METHODOLOGY

4.2.1. Data Input

4.2.1.1. Occurrence Data

SDM usually require data on species occurrence to determine their ecological niche or suitability (Franklin, 2023). In this study, we didn't focus on a single species but the ecological community. An ecological community is a group or association of populations of two or more species occupying the same geographical area simultaneously (Aoki, 2012). So, our assumption relied on the fact that each woody cover type refers to a particular ecological community, as previous studies have included plant communities as a class of LULC (Sharma, 2022). Then, the occurrence of each woody cover was extracted randomly using the classified woody cover raster 2022 combined with ground truthing GPS coordinates and coordinates of the plot inventory. Therefore, the sampled points represent the occurrence of the ecological community defined by the land cover type, not individual species. In each woody vegetation class, we selected 100 points to represent species occurrence, which were considered as the distributional data.

4.2.1.2. Environmental Variables

We selected ten environmental variables grouped into five categories such as climate data (temperature and rainfall); soil chemical parameters (salinity and soil organic carbon); soil physical parameters (Coarse Fragment and Bulk Density); anthropogenic activities (Distance to Built-up, Distance to Road) and Other natural features (Burn Area Index, Distance to River). Details of the environmental variables are presented in Table 4-1.

The relevance of climate data is that climatic conditions directly influence woody cover. Temperature and precipitation dictate the physiological processes of plants, including photosynthesis, respiration, and water use efficiency (Amissah et al., 2014). These variables influence soil moisture and nutrient availability, indirectly affecting woody cover (Seghieri et al., 2009).

Soil chemical parameters were used because nutrient availability in the soil is vital for plant growth and survival (Mussa et al., 2016). Salinity was considered because the Saloum Delta has been experiencing salt-affected land (Descroix et al., 2020; Thiam et al., 2021).

The chosen soil physical parameter is important because the physical properties of soil determine water infiltration, retention, and root penetration (Richards et al., 2024). Soil compaction or erosion can reduce habitat suitability for woody species.

Human interventions can directly or indirectly modify woody cover through land use changes, deforestation and settlements (Aide et al., 2019).

Proximity to natural features, such as Distance to Rivers, provides ecological niches and affects resource availability. Burn area index, for instance, leads to a critical change in woody cover (Straaten et al., 2019).

4.2.2. Model Processing

Woody tree cover occurrence data and predictor variables were integrated into a modelling framework. Occurrence data for woody tree covers, including geographic coordinates of woody tree covers from fieldwork ground truthing and inventory, was prepared and reformatted into a spatial data format compatible with environmental rasters (Bracken et al., 2022).

Environmental predictors (Table 4-1) were prepared to ensure spatial uniformity across datasets. All raster data was resampled to align with the extent and resolution of rainfall and temperature datasets (Díaz-Pacheco et al., 2018). This step was critical to address ERA5-Land data gaps, particularly along the coastal areas, and maintain consistency for analysis. Data cleaning processes, which filtered out missing values, were done. Background data (pseudo-absence) was generated by randomly sampling the study area to support robust model training. This approach is a common practice in species distribution modelling (Descombes et al., 2022)

Machine learning algorithms were applied to model species distributions, including Random Forest, Generalized Linear Models, and Maximum Entropy. These algorithms have been widely recognised for handling complex ecological data (Chollet et al., 2023; Zhang & Li, 2017; Zhao et al., 2022). Advanced cross-validation techniques like subsampling and bootstrapping enhanced model reliability (Tsamardinos et al., 2018). Computational efficiency was improved through parallel processing techniques (Tian & Zhao, 2015).

Model performance was evaluated using metrics like correlation coefficients, area under the curve (AUC), and true skill statistics (TSS), which are standard for assessing species distribution models (Dubos et al., 2022). The relative importance of environmental predictors was assessed to identify key drivers of woody tree distributions (Gomez & Cassini, 2015; Rueda et al., 2021)

Predicted habitat suitability maps were generated for the study area and visualized through plots to illustrate further suitable areas for each woody tree cover. Area statistic calculations were done to compare the actual coverage of the woody tree cover (2002), the suitable coverage from the model prediction, and the gap between the two. The workflow is presented in Figure 4.1.

Table 4-1: Environmental predictors used in this study

Environmental variables	Data	Resolution	Sources
Climatic Data	Temperature	11.1 Km	ERA5-Land
	Precipitation data	11.1 Km	ERA5-Land
Soil Chemical parameters	Salinity	30m	Dehni and Lounis (2012)
	Soil organic carbon (dg/kg)	250m	Soilgrids.org
Soil Physical parameters	Coarse fragments (cm3/dm3)	250m	Soilgrids.org
	Bulk density (cg/cm3)	250m	Soilgrids.org
Human activities	Distance to road		GRIP4
	Distance to Built-up	10m	World Settlement Footprint (WSF)
Other data	Burn Area Index	500m	MODIS
	River network		HydroSHEDS

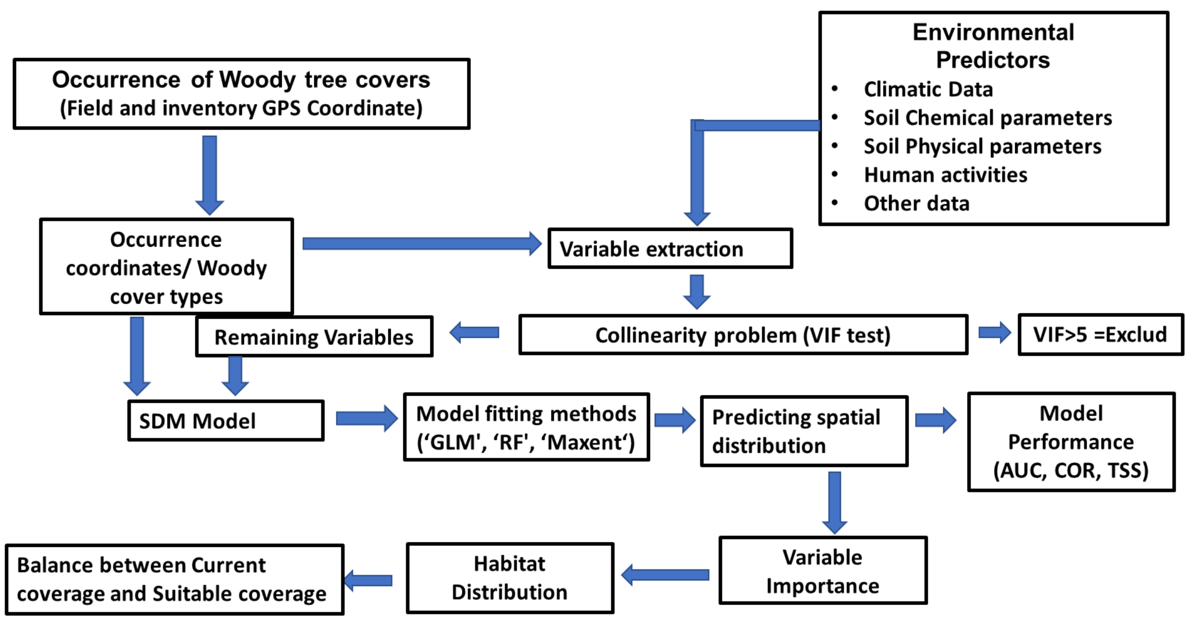


Figure 4.1: Workflow of the model prediction

4.3. RESULTS

4.3.1. Model Performance

The model results highlight the differences in performance across the three methods: Random Forest (RF), Generalized Linear Model (GLM), and Maxent when applied to various vegetation types (Table 4-2). For Mangroves, RF shows the highest performance with an AUC of 0.86 and a COR of 0.50, combined with a relatively low Deviation of 0.43. Maxent matches RF in AUC at 0.86 but demonstrates greater instability with a Deviation of 0.71. GLM, on the other hand, shows weaker performance, with a lower COR of 0.39 and a higher Deviation of 0.54.

For Close Woodlands, RF and Maxent achieve the highest AUC values of 0.97, with TSS scores of 0.87, indicating excellent model accuracy. RF exhibits superior reliability with the lowest Deviation of 0.24. GLM, while slightly behind in performance, achieves an AUC of 0.95 and a COR of 0.67 but shows greater variability with a Deviation of 0.32.

In the case of Open Woodlands, RF outperforms the other methods, achieving an AUC of 0.94, a COR of 0.65, and a TSS of 0.81, highlighting its effectiveness. Maxent follows closely with an AUC of 0.92 but is less stable, as reflected by a Deviation of 0.55. GLM showed an AUC of 0.90, a COR of 0.47, and a higher Deviation of 0.39.

For Plantations, RF continues to excel with an AUC of 0.94, a COR of 0.66, and a TSS of 0.79, underscoring its reliability. While maintaining a decent AUC of 0.91, Maxent showed a higher Deviation of 0.56. GLM is the weakest performer, with lower metrics across all categories, including an AUC of 0.89, a COR of 0.47, and a notable Deviation of 0.44.

Across all vegetation types, the Random Forest (RF) performs better than the other models. Maxent achieves good results regarding AUC and TSS but is less dependable due to more significant variability. Generalized Linear Models (GLM) tend to perform poorly, indicating that they may not be well-suited for these datasets and vegetation types.

Table 4-2: Model evaluation using the AUC, COR, and TSS

	Methods	AUC	COR	TSS	Deviation
Mangroves	RF	0.86	0.5	0.59	0.43
	GLM	0.84	0.39	0.59	0.54
	Maxent	0.86	0.4	0.6	0.71
Close Woodlands	RF	0.97	0.77	0.87	0.24
	GLM	0.95	0.67	0.78	0.32
	Maxent	0.97	0.73	0.87	0.27
Open Woodlands	RF	0.94	0.65	0.81	0.31
	GLM	0.9	0.47	0.7	0.39
	Maxent	0.92	0.52	0.77	0.55
Plantations	RF	0.94	0.66	0.79	0.34
	GLM	0.89	0.47	0.66	0.44
	Maxent	0.91	0.51	0.73	0.56

4.3.2. Variable Importance

The Figure 4.2 shows the relative importance of the drivers in predicting the woody cover distribution. The analysis reveals that the most critical drivers for Mangroves are Salinity, followed by Bulk Density and Coarse Fragments. Salinity is the primary factor in Close Woodlands, followed by Rainfall and Burned Areas. Salinity and Burned Areas are identified as the key drivers for Open Woodlands. In Plantations areas, the dominant factors are Rainfall, Distance to Built-up areas, and Salinity.

Predictors such as Temperature, Distance to Rivers, and Distance to Built-up areas exhibit the lowest contributions in predicting the distribution of Mangroves and Close Woodlands. In Open Woodlands, Temperature and Distance to Rivers are identified as the least influential factors. For Plantations areas, Soil Organic Carbon and the Burn Area index show the lowest contributions to the prediction.

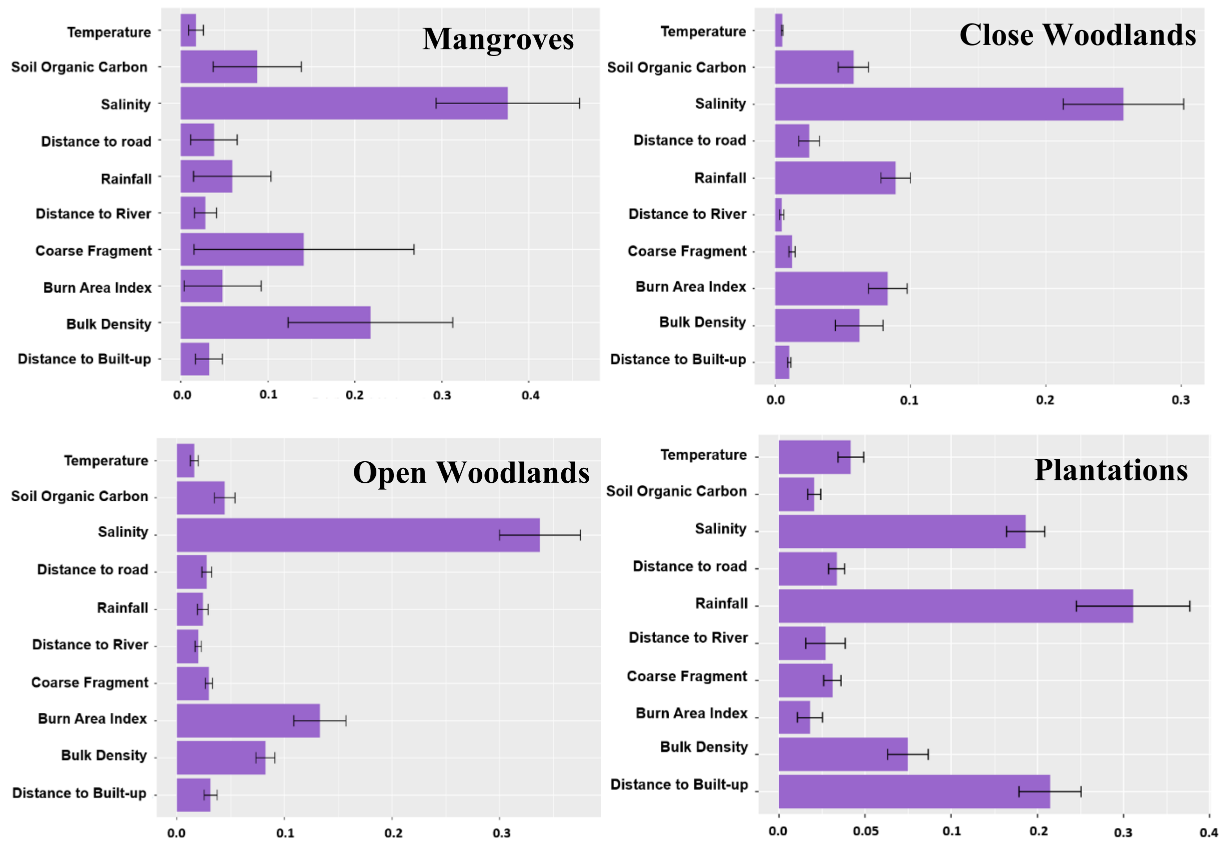


Figure 4.2: Variable importance of the woody cover drivers

4.3.3. Environmental Range Suitable for Woody Tree

Figure 4.3 illustrates the habitat suitability, indicating that Mangroves thrive within an environmental range characterized by the lowest Salinity Index (600 and 800) and a low to medium Bulk Density (0 and 60 g/cm³).

Salinity and Rainfall emerged as the key factors influencing distribution in Close Woodlands areas. The suitable environmental range is observed at the lower end of the Salinity Index (600–800) and the highest Rainfall range between (0.6 to 0.7m).

Salinity and the Burn Area Index were identified as significant drivers for Open Woodlands habitats. These areas exhibit suitable conditions within a low Salinity Index range of 600 to 800 and a low to medium Burn Area count of 50 to 300.

In Plantation zones, Rainfall and Built-Up areas were the main influencing factors. Habitat suitability for Plantations is within the highest Rainfall range between 0.65 to 0.7m and the closest distance to Built-Up between 0 and 10000m.

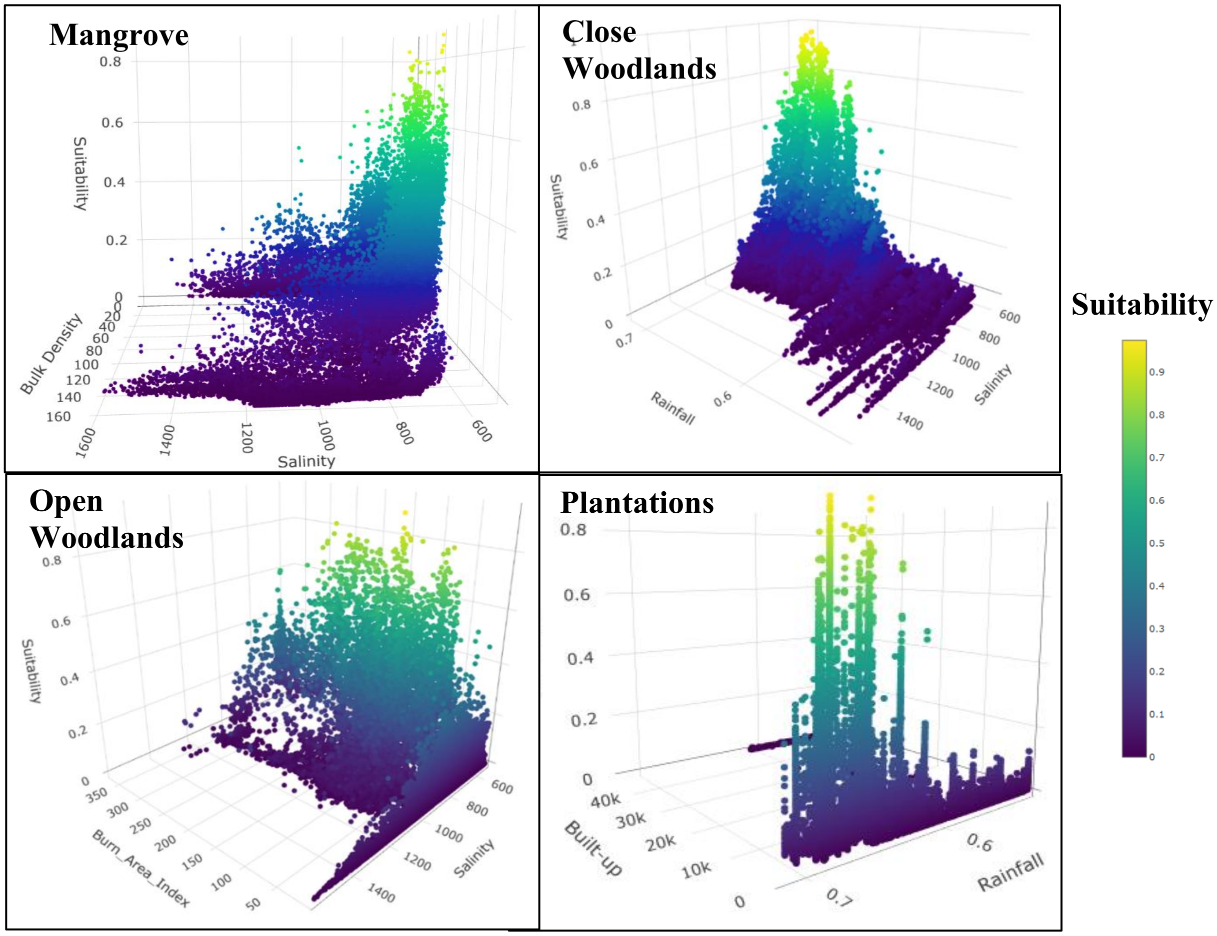


Figure 4.3: Habitat suitability from two main drivers in different woody cover

4.3.4. Habitat Distribution

The suitability of woody communities across the study area is illustrated in Figure 4.4. For Mangroves, the results indicate that their distribution aligns closely with the regions of maximum suitability. However, there is a notable absence of Mangroves along the northern edge of the study area, as reflected in the 2022 coverage data. For Close Woodlands, the highest suitability is observed within the protected areas, closely corresponding to their actual coverage. Additionally, the suitability extends beyond the boundaries of the protected forests, indicating a broader potential habitat. For Open Woodlands, the results suggest a significant overlap with the coverage of Close Woodlands, albeit in different high-suitability zones. These areas are particularly associated with regions where burn scars are more prevalent.

Lastly, the Plantations suitability is markedly lower than its actual coverage. Suitable areas for Plantations are predominantly located in the southeastern part of the study area, mainly outside the protected forest regions.

Results of comparison analysis between the current woody tree coverages in 2022 and the predicted suitable coverage for optimum restoration of the woody cover show a smaller gap for Mangroves compared to other woody tree covers. It can be observed from Figure 4.5, that in 2022, Mangroves cover 21.1% of the area, while the predicted suitable coverage is 24.57% with a gap of 3.47%. For the other woody covers, differences between current and predicted coverages were 5.49, 6.03 and 6.41% for Close Woodlands, Open Woodlands and Plantations, respectively.

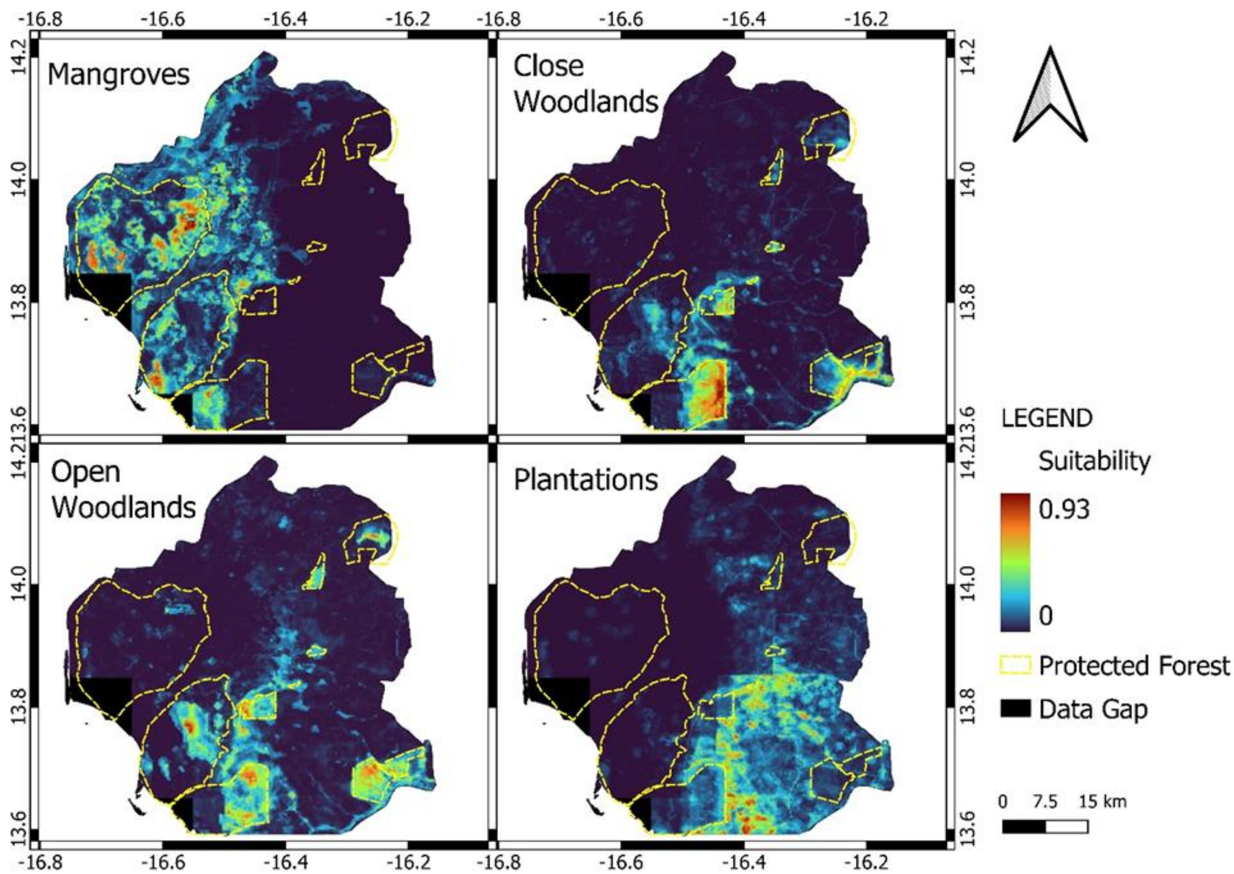


Figure 4.4: Map prediction of the habitat distribution in different woody cover

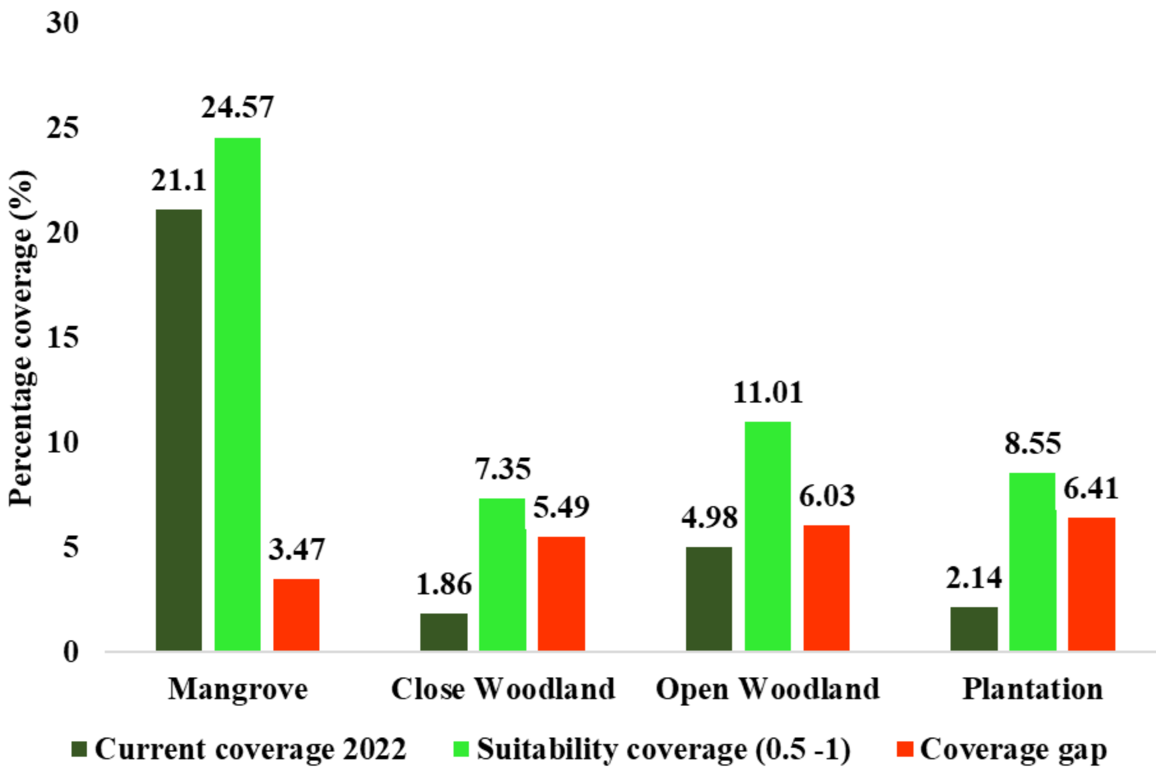


Figure 4.5: Comparison between current coverage and predicted suitable coverage

4.4. DISCUSSION

The variable importance analysis reveals that salinity is a predominant driver influencing the distribution of all vegetation types studied. This finding aligns with research emphasizing the critical role of salinity in shaping coastal and estuarine ecosystems, particularly Mangroves (Barik et al., 2018). For Mangroves, additional significant factors include bulk density and coarse fragments, underscoring the importance of soil physical properties in mangrove ecology (Dittmann et al., 2022).

In Close Woodlands and Plantations, rainfall emerges as a key determinant, highlighting the dependence of these vegetation types on water availability (Spracklen et al., 2018). The significance of burnt areas in Open Woodlands points to the influence of fire regimes on vegetation dynamics, a relationship extensively explored in ecological studies (Doherty et al., 2022). Evidence suggests that many areas within the forest zone of West Africa may have experienced frequent fires, particularly in the dry forest regions (Dahan et al., 2023; Mbow et al., 2000).

Interestingly, variables such as Temperature, Distance to Rivers, and Distance to Road exhibit minimal contributions across most vegetation types. This observation is consistent with context-specific environmental filtering, where the relative importance of environmental variables varies depending on the specific ecological and geographical context (Wallis et al., 2021).

The ecological niche analysis provides further insights into the favourable environmental ranges for each vegetation type. Mangroves, for instance, thrive within a salinity index range of 600 to 800 and a bulk density between 0 and 60. This finding is consistent with studies indicating that mangroves are adapted to specific salinity ranges and soil conditions (Barik et al., 2018).

Close Woodlands prefer lower salinity levels and moderate rainfall, while Open Woodlands are associated with specific salinity ranges and annual burnt count, reflecting their adaptability to fire regimes (Veenendaal et al., 2018). The research found that nearly 99.82% of the total settlement area has been identified as suitable for home gardens (Singh et al., 2022). Plantations show suitability within particular rainfall ranges and proximity to villages, indicating potential influences from human activities and related to their adaptation practices.

The maximum coverage pattern of Mangroves aligning with areas of maximum suitability remains a valuable ecological asset. Previous studies have shown a significant increase in Mangroves coverage, particularly in the northern region of the study area. This increase indicates that, despite the high salinity levels characteristic of this region, mangrove regeneration has been notably successful. Such resilience highlights the importance of conserving and promoting Mangroves habitats, which are crucial for coastal protection and biodiversity.

For Close Woodlands, the areas of highest suitability are predominantly located within protected areas. This suitability suggests that conservation efforts within these areas have had a positive impact, but it also underscores the need for continued and enhanced management strategies. Prioritizing the expansion and formation of Close Woodlands should take precedence, especially considering its ecological importance. This prioritization may need to come at the expense of Open Woodlands, which is heavily influenced by burn scars and other disturbances. Addressing the factors driving the expansion of Open Woodlands, particularly those linked to fire, will be crucial for achieving a balanced and sustainable landscape that supports diverse woody communities.

Our findings show the suitability of Plantations mainly on the South-Eastern side of the study area. Most regions in the Saloum Delta are salt-affected areas. Cropland yield collapsed in recent years, leaving the place to Plantations with more resistant trees. The implementation of cashew Plantations not only enhances environmental resilience but also contributes to economic development. In the 1970s, initiatives like the Senegalese-German Cashew Project facilitated the financial viability of cashew cultivation in the Sokone area. This dual benefit underscores cashew trees' value in ecological conservation and livelihood improvement (FARM RADIO.FM, 2022).

4.5.CONCLUSION

This study highlights the critical environmental drivers influencing the spatial distribution of woody tree cover in the Saloum Delta. By employing species distribution models (SDMs) such as Random Forest (RF), Generalized Linear Model (GLM), and Maxent, we demonstrated that RF consistently outperforms the other methods across all vegetation types in terms of AUC, COR, and stability. While Maxent shows promise in predictive accuracy, its higher variability suggests limitations in its reliability for certain vegetation types. GLM, on the other hand, exhibits weaker performance, emphasizing the importance of model selection in ecological studies.

The analysis of variable importance underscores the role of salinity as a key driver for Mangroves and woodland ecosystems. At the same time, rainfall is critical for Close Woodlands and Plantations. Other factors, such as bulk density and the burn area index, also significantly determine habitat suitability for specific vegetation types. Conversely, predictors like temperature and distance to rivers contribute minimally across most vegetation types, indicating their limited influence in this context.

Ecological niche analysis further refines our understanding by defining environmental ranges within which different vegetation types thrive. Mangroves are primarily influenced by salinity and bulk density, while Close Woodlands depend more on a combination of salinity and rainfall. Open Woodlands and Plantations exhibit unique environmental requirements, with the burn area index and proximity to built-up areas playing pivotal roles.

These findings have significant implications for conservation and management strategies in the Saloum Delta. The prominence of salinity as a key driver suggests the need to develop adaptive management strategies to address salinity as a key driver of landscape change by prioritizing the use of resilient tree species and salt-tolerant plants, such as Eucalyptus spp. and Tamarix spp.(Thiam et al., 2021). These efforts should focus on restoring degraded areas, enhancing ecosystem resilience, and promoting sustainable land-use practices to mitigate the impacts of salinity on biodiversity and livelihoods. Maintaining appropriate soil conditions and mitigating saltwater intrusion are crucial for Mangroves' conservation. In Open Woodlands, implementing effective fire management practices is essential to sustain ecological balance.

CHAPTER 5 : GROUND AND REMOTE SENSING-BASED ESTIMATION OF THE SALOUM DELTA WOODY ABOVEGROUND BIOMASS USING ALLOMETRIC EQUATIONS AND MACHINE LEARNING

5.1. INTRODUCTION

According to the International Panel on Climate Change (IPCC), aboveground biomass (AGB) encompasses all living biomass above the soil, including stems, branches, bark, foliage, seeds, and stumps. AGB in forests is a vital element of the global carbon cycle and is crucial in climate change mitigation (Kalimantan, 2017). Forest biomass significantly influences carbon and water cycles within terrestrial ecosystems, making its spatial estimation vital for understanding terrestrial carbon dynamics and enhancing forest management practices (Kafy et al., 2023). This role is underscored by its importance in addressing scientific and operational challenges (Mitchard, 2018).

In Africa, deforestation rates in savannahs and woodlands often exceed those in tropical rainforests (Wei et al., 2023). West Africa, in particular, is increasingly identified as a climate change hotspot due to the intersection of climate hazards, high vulnerability, and exposure, which amplify both environmental and socio-economic impacts (Tarif et al., 2022). Climate change and variability (CCV) are leading to significant alterations in land use and land cover (LULC) within the region, including deforestation, land degradation, and ecosystem decline (Dimobe et al., 2015; Zoungrana et al., 2018). These trends necessitate adopting effective adaptation and mitigation strategies to safeguard West Africa's socio-ecological systems (APRI, 2024). Sustainable Development Goals (SDGs) initiatives, particularly SDG 15 on reversing land degradation, and policies such as REDD+ emphasize the importance of biomass monitoring for both carbon stock assessment and ecosystem health (Panwar et al., 2022).

Quantifying above-ground biomass (AGB) is essential for assessing carbon stocks and supporting mitigation strategies (Mishra et al., 2022). This approach is relevant in sub-Saharan Africa, where up to 90% of the population depends on fuelwood (Njengac et al., 2023). Accurate estimation of the biomass remains a challenge. Limited resources and region-specific allometric equations are scarce (Walker et al., 2016). New technological advances with recent advancements in remote sensing technologies, such as lidar and airborne laser scanning (ALS), provide reliable, noninvasive methods for large-scale biomass assessments (Campbell et al., 2024). However, the high costs of these technologies remain a barrier for many developing countries (Pereira and Lim, 2024).

Lower-cost remote sensing solutions, including Landsat and Sentinel imagery, have made biomass estimation more accessible (Chen et al., 2021; Mauya & Madundo, 2022). These tools are often combined with advanced machine learning methods such as Random Forest, Support Vector Machine (SVM), k-Nearest Neighbor (K-NN) (Singh et al., 2023; Opelele et al., 2021; Ibrahim et al., 2024), allowing for robust biomass predictions using diverse variables. By refining these methods, researchers can better estimate AGB, fostering climate resilience and sustainable forest management in West Africa while contributing to global climate goals.

Although numerous studies have examined AGB or aboveground carbon (AGC) in West Africa's forest-savanna mosaics using field data or remote sensing, they often focus on broad LULC types. This approach can introduce biases due to uneven tree distributions and imbalanced sampling. Our study focused on different woody tree cover within the Saloum Delta to address this limitation. We estimated AGB across distinct woody cover types and evaluated the relationship between estimated and machine learning-predicted AGB. This approach aims to support biomass/ carbon assessment and climate resilience in West Africa while providing valid insight for REDD+ policy implementation.

5.2. METHODOLOGY

5.2.1. Pre-Inventory

A pre-inventory was carried out with three plots for each woody cover type to estimate the number of survey plots required. The plot dimensions were set at 30 m × 30 m for Close Woodlands (CW), Open Woodlands (OW), and Plantations (PT), and 10 m × 10 m for Mangroves (MG). The total number of sampling plots was determined using Chacko's (1965) report (Heyojoo & Nandy, 2015). A total of 138 plots were established.

$$\mathbf{N} = \frac{t^2 \times CV^2}{SE^2}$$

N is the total number of sample plots, $\mathbf{t}$ is the statistical value at 95% significance level,

$\boldsymbol{CV}$ is the coefficient of variation of the DBH , and $\boldsymbol{SE}$ is the standard error percentage.

5.2.2. Field Inventory

Dendrometry tree measurement was conducted from May 9 to September 18, 2021. Plots were distributed across the study area based on the stratified sampling design. Within each plot, the diameter at breast height (DBH) was measured for all trees with a circumference of at least 5 cm (Figure 5.1) from a conventional height of 1.3 m (Alamgir & Al-Amin, 2008). Species identification was performed on-site whenever possible. Samples of unidentified woody species were collected and later identified at the laboratory using Berhaut's Flora of Senegal (1967) and other botanical reference materials. Figure 5.2 shows the spatial distribution of the plots.

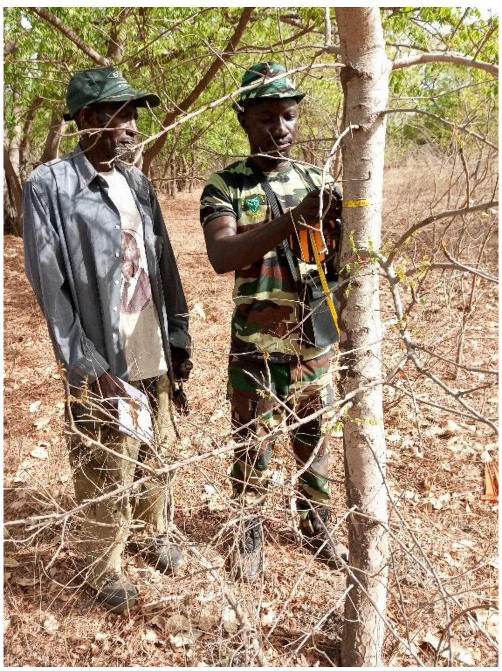


Figure 5.1: DBH Measurement of trees

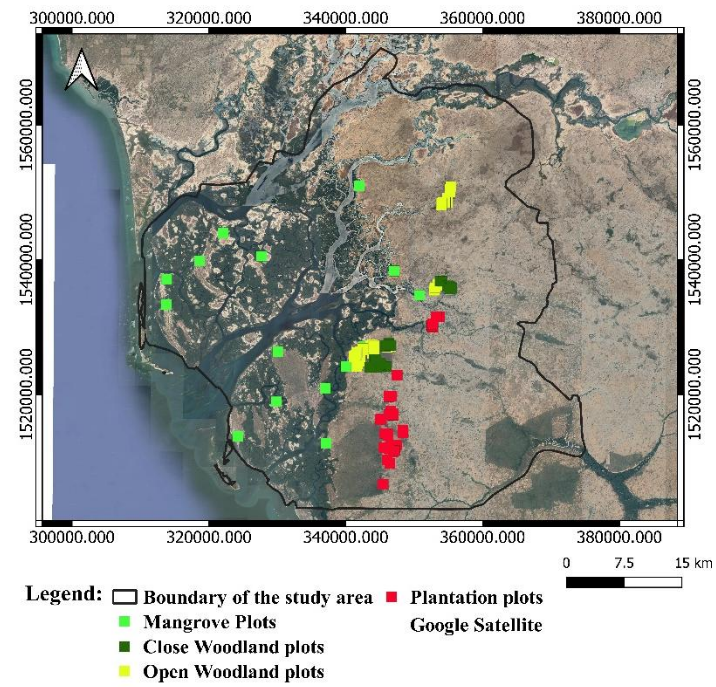


Figure 5.2: Spatial Distribution of the plots

5.2.3. Above-Ground Biomass Estimation

Given the scarcity of species-specific allometric equations, previously validated ones for Open Woodlands (OW) and Close Woodlands (CW), precisely the one of Mbow et al. (2014) were employed. In Plantations, species-specific allometric equations were used, mainly composed by mango (Mangifera spp.) and cashew (Anacardium spp.). For Mangroves areas, to avoid overestimations, the estimation relied on equations proven suitable in prior studies done in one part of the study area (Gomis et al., 2023). Table 5-1 shows the allometric equations used in this study. Wood density values for the sampled species were obtained from the Global Wood Density Database. For species lacking specific density values, a default value of 0.58 g/cm³ was applied, following recommendations for African tropical forests by Reyes et al. (1992) reported in Vroh et al. (2015). Biomass values were converted to carbon using a 0.5 conversion factor, as outlined in IPCC (2006) guidelines.

Table 5-1: Allometric equations used to estimate the AGB

Woody class	Equation	Sources
Mangroves	$AGB = \rho * \exp(-1.349 + 1.980 * \ln(\mathrm{DBH}) + 0.2072(\ln(\mathrm{DHP}))^2$	(Chave et al, 2005 ;Gomis et al, 2023)
Close Woodland	$\mathrm{AGB} = 1.929 \times \mathrm{DB} + 0.116 \times DBH^2 + 0.013 \times DBH^3$	(Cheikh Mbow et al., 2014)
Open Woodland	$\mathrm{AGB} = 1.929 \times \mathrm{DB} + 0.116 \times DBH^2 + 0.013 \times DBH^3$	(Cheikh Mbow et al., 2014)
Plantation ***Mangifera spp.*** **:AGB_1**	$AGB_1 = \exp(-2.6554) \times DBH\text{^}2.26$	(Dao et al., 2021)
Annacardiun Spp.:**AGB_2**	$AGB_2 = exp\ [-1{,}85645+0{,}01656+2{,}02288*ln\ (Dbh)]$	(Biah et al., 2018)

5.2.4. Aboveground Biomass (AGB) Modelling

Machine learning techniques were employed to model the AGB. These methods leverage advanced regression techniques to solve complex, non-linear problems by learning from diverse data sources without relying on specific distributions (Soori et al., 2023).

5.2.4.1. Preparation of Spatial Datasets

Selection of suitable vegetation indices is essential for the success of any biomass estimation model, and it is done mainly using a trial-and-error method, starting from the most common to the least standard index (Maynard et al., 2006; Wijaya et al., 2010). It has become a standard procedure to characterise vegetation using Green (B3), Red (B4), and NIR (B8) spectral bands (Lu 2005; Lu et al. 2016). Then, the spatial data for AGB modelling were prepared using multi-spectral bands and their combinations from Sentinel-2 satellite imagery. Two Sentinel-2 data corresponding to the wet (October 2022) and dry period (May 2022) were used. Sentinel-2 bands included the standard ones B3, B4, and B8 in addition to the Blue band (B2). This band was added because the study also comprises vegetation in coastal areas where water may influence the reflectance. Band combinations were generated using the equation below, facilitating the integration of spectral information for biomass estimation.

This approach enabled a robust analysis of AGB while addressing the limitations posed by the lack of localized allometric equations and ensuring compatibility with diverse data sources.

$$w_{(i,j)_n} \frac{x_{(j,n)} - x_{(i,n)}}{x_{(j,n)} + x_{(j,n)}}$$

where, for any sample plot n, $w_{(i,j)_n}$is the reflectance value from the band combination of ith and jth spectral bands; $x_{(i,n)}$and $x_{(j,n)}$ are the reflectance values of any two spectral bands of Sentinel-2 satellite imagery (j > i).

Building on their demonstrated effectiveness in AGB estimation from prior research (Pandit et al., 2018; Basin et al., 2024), we also selected the Normalized Difference Vegetation Index (NDVI), Green NDVI (GNDVI), Enhanced Vegetation Index (EVI), and Soil-Adjusted Vegetation Index (SAVI), as core indicators for this study. Four independent multi-spectral bands, six unique band combinations and four indices were created based on the method described earlier. This came up in fourteen independent variables for AGB estimation in this study.

5.2.4.2. Variable Selection and Spectral Extraction

Two main challenges in developing models are the multi-collinearity among independent variables and the risk of overfitting. Thus, to effectively reduce the risks associated with overfitting and multi-collinearity, the Boruta feature selection algorithm (Kursa & Rudnicki, 2010) was used. Boruta evaluates and ranks variables according to their importance with the dependent variable, effectively reducing the risks associated with overfitting and multi-collinearity.

Following guidelines from O'Brien (2007) to further reduce multicollinearity variables, the Variance Inflation Factor (VIF) was used. The variables exceeding 5 VIF will be excluded. Although alternative techniques such as Principal Component Analysis (PCA) also reduce multicollinearity (Singh et al., 2022), Boruta and VIF were chosen for their interpretability, minimal bias, and strong performance, as highlighted by Hayah et al. (2021).

A pixel-based approach (PBA) was used to extract reflectance values to train the models. A 3 × 3 pixel bounding box (equivalent to 30 m × 30 m on the ground) was established around the GPS coordinates of each sampling plot. The average reflectance value of all pixels within the plot size was treated as the spectral value for each sampling plot, minimizing errors associated with abrupt reflectance changes among neighboring pixels (Mutanga et al., 2012).

This process was repeated for all multi-spectral bands and their combinations, ensuring consistent and accurate variable preparation for model development.

5.2.4.3. Model training and validation

The study used four machine learning (ML) techniques to develop and compare aboveground biomass (AGB) models. The machine learning techniques included k-Nearest Neighbors (k-NN), Support Vector Machine (SVM), XG-Boost (XGB), and Random Forest (RF). These methods' comprehensive descriptions and tuning parameters are presented in Tables 5-2. All the processes were done using R software, as shown in Figure 5.3.

5.2.4.4. Biomass maping

InVEST software was used to show the observed aboveground biomass spatially. InVEST Carbon Storage model has been used to map carbon stock based on these data (Nel et al., 2022). To show the model's accuracy in spatially predicting biomass, biomass maps from the machine learning model were compared with those obtained from the InVEST model.

Table 5-2: Models used for biomass modelling

Model	Relevance	Description/Parameters	References
SVM	Effective for high-dimensional data, non-linear classification using kernels, binary classification, and applications in diverse fields.	SVM works by finding the best dividing line (hyperplane) between different classes. It uses mathematical functions called kernels (e.g., linear, RBF, polynomial) to handle data that is not linearly separable. Key settings include regularization (C), which controls how much error is allowed, and kernel scaling, which adjusts the size of the decision boundary.	(Cortes et al., 1995); (Abedi et al., 2012); (Wu et al., 2023); (Singh et al., 2017)
K-NN	Instance-based learning, effective for classification and regression, robust to noisy training data.	K-NN predicts a data point category by looking at the closest points (neighbors) in the dataset and choosing the most common category among them. The key factors are the number of neighbors (k) to consider and the method for measuring distance (e.g., straight-line distance).	(Chen et al., 2013); (Wang et al., 2024); (Tang et al., 2024)
RF	Handles high-dimensional data, robust against overfitting, effective for large datasets and categorical features.	Random Forest builds many decision trees during training and combines their predictions for a final result. It works well with diverse datasets and avoids overfitting. Key settings include the number of trees to build and the number of features considered for splitting at each step.	(Forkuor et al., 2020); (Wang et al., 2016); (Zhang et al., 2024)
XGB	Highly efficient gradient boosting method; widely used in structured data classification and regression tasks.	XGBoost improves predictions by building a series of small decision trees, each one correcting errors from the previous one. It is highly customizable with settings like learning rate (step size), number of trees, tree depth, and regularization to prevent overfitting.	(Bui et al., 2024); (Jia et al., 2024); (Roy & Debbarma, 2024)

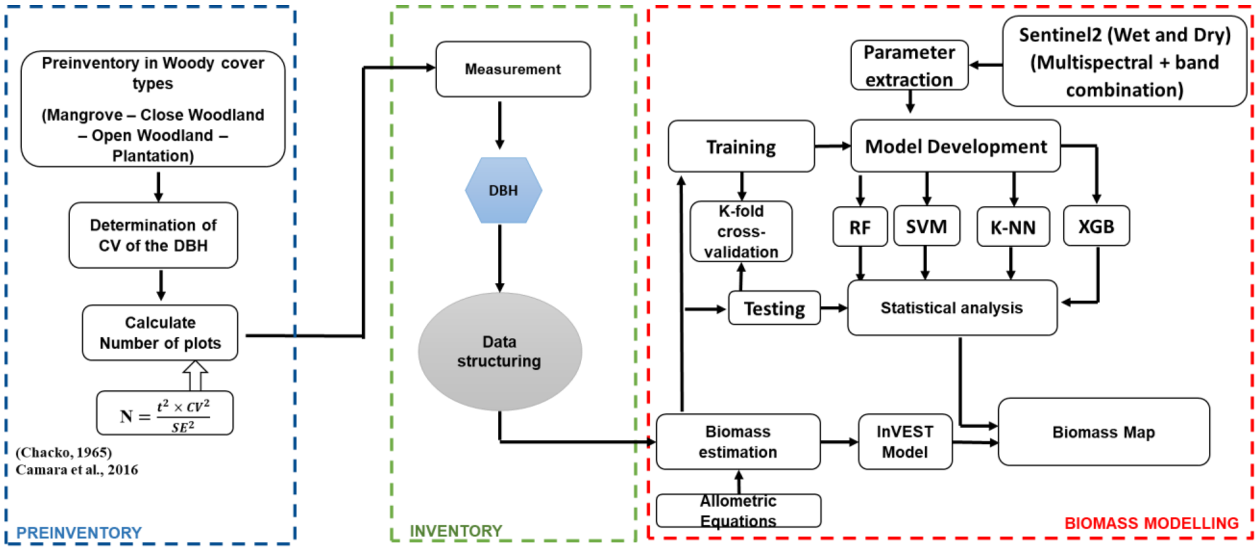


Figure 5.3: Workflow of the machine learning process

5.3. RESULTS

5.3.1. Biodiversity Richness and Structural Characteristics

The inventory identified 38 species distributed across 32 genera and 14 families. Species richness and Shannon index values (Figure 5.4) were highest in Close Woodlands (CW), with 30 species richness and a Shannon index of 3.08, respectively. Open Woodlands (OW) followed, with 24 species and a Shannon index 2.32. Mangroves (MG) and Plantations (PT) recorded the lowest species richness, with only two species each. The Shannon indices for MG and PT were 0.58 and 0.64, respectively.

The structural characteristics of woody vegetation using the DBH class are illustrated in Figure 5.5. In Mangroves, the breast height (DBH) diameter ranged from 5 to 20.5 cm, with the highest values concentrated between 5.5–10.5 cm and 10.5–15.5 cm. In Close Woodlands, the DBH ranged from 5.5 to 55.5 cm, with the highest frequency observed in the lower DBH categories. Open Woodlands exhibited a DBH range of 5 to 55.5 cm, with a similar pattern dominated by lower DBH values. In Plantations, the DBH ranged from 20.5 to 55.5 cm, with the highest frequency recorded in the upper DBH categories.

5.3.2. Biomass Estimation Using Allometric Equations

The biomass estimation results (Table 5-3) revealed that Close Woodlands had the highest biomass density, with 295.08 ± 9.54 Mg/ha. Open Woodlands followed, with 79.88 ± 83.37 Mg/ha. Mangroves recorded 42.19 ± 12.90 Mg/ha, while Plantations had 75.39 ± 13.75 Mg/ha.

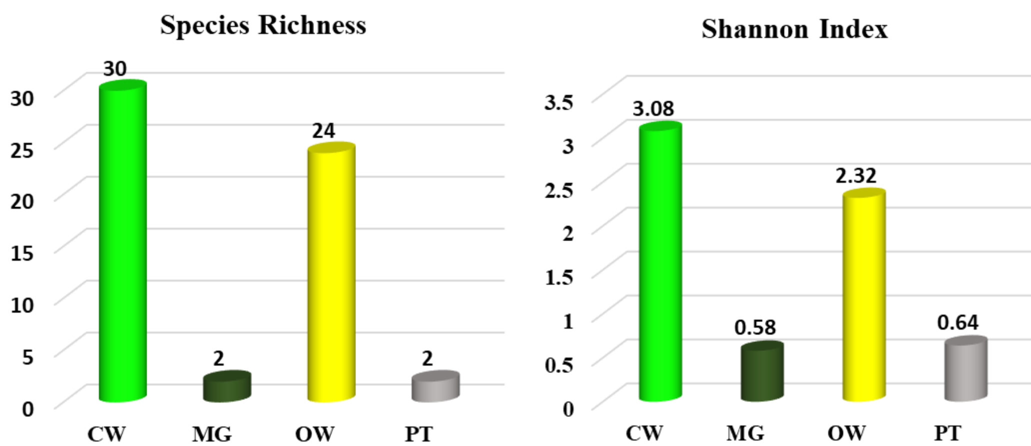


Figure 5.4: Biodiversity indices in the different woody cover

CW: Close Woodlands; MG: Mangroves; OW: Open Woodlands; PT: Plantations

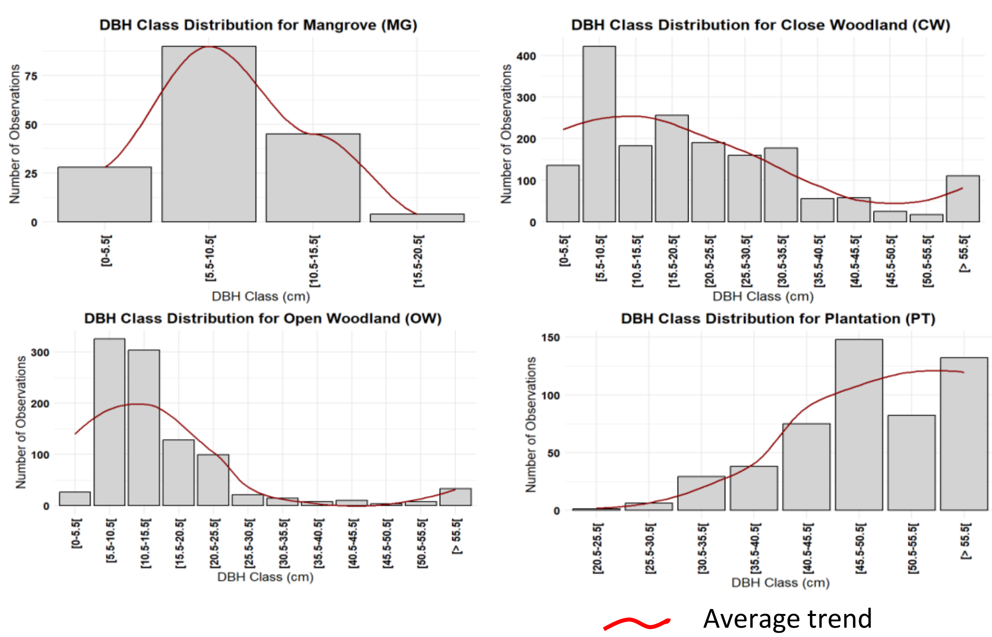


Figure 5.5: DBH Class in the different woody cover

Table 5-3: Aboveground biomass and carbon stock in the different woody tree cover

	VEGETATION TYPES			
	Mangroves	**Close-Woodland**	**Open-Woodland**	**Plantations**
Mean Density (trees/ha)	3811.76 ±51	523.98 ±259.2	240.83 ±78.93	148.61 ±31.90
Mean DBH (cm)	8.52 ±1.20	25.49 ±9.06	16.74 ±7.26	51.04 ±1.26
Mean AGB (Mg/ha)	**42.19 ± 12.90**	**295.08 ± 9.54**	**79.88 ± 83.37**	**75.39 ± 13.75**
Mean Carbon (Mg·C/ha)	**21.09 ± 6.45**	**147.54 ± 4.77**	**39.94 ± 41.69**	**37.70 6.86**

5.3.3. Machine Learning Biomass Modelling

5.3.3.1. Performance of Machine Learning Models for the Wet and Dry Season

Assessing the model performance using the Adjusted R-squared reveals that values for all models were higher during the wet season, with SVM and Random Forest achieving the highest values (0.60 and 0.58, respectively). The models perform significantly better using satellite data from the wet season than the dry season. In contrast, dry season data yields poor performance, with very low or negative adjusted R-squared values for most models (K-NN and XG-Boost), indicating a lack of fit or predictive ability (Table 5-4). This suggests that the wet season data captures more meaningful variability relevant to the modelled outcomes.

The results also revealed that the RF performed better than the other models for the wet and dry seasons (Table 5-5). The K-NN model was the least accurate in estimating AGB for dry and wet seasons.

Table 5-4: Model performance with the Adjusted R-square in dry and wet seasons

Models	**DRY**	**WET**
SVM	0.02	0.58
RF	0.14	0.60
K-NN	-0.01	0.20
XG-Boost	-0.40	0.49

Table 5-5: Machine learning model statistics

Model	RMSE		STD DEV.		Mean_Bias		R2	
	Dry	Wet	Dry	Wet	Dry	Wet	Dry	Wet
SVM	70.53	47.20	71.66	48.11	-6.07	-1.35	0.60	0.83
RF	66.63	46.21	65.30	46.83	18.41	-5.10	0.70	0.84
K-NN	73.35	65.30	74.18	64.97	-9.45	14.30	0.57	0.70
XG-Boost	64.91	52.16	64.78	53.16	-13.37	-1.60	0.67	0.79

5.3.3.2. Variable importance of the model

The Figure 5.6 illustrates the feature importance scores of the RF and XBG models. B3 emerged as the most essential feature in the RF model, followed by the combination B2_B3, highlighting its significant role in predictions. In the XGBoost model, B8 was identified as the most crucial feature, with B2_B3 also ranked highly. Both models consistently recognized B2_B3 as a key predictor, underscoring its critical contribution to the modelling process across the two machine learning approaches. This agreement emphasizes the relevance of both single band and feature combinations in enhancing model accuracy.

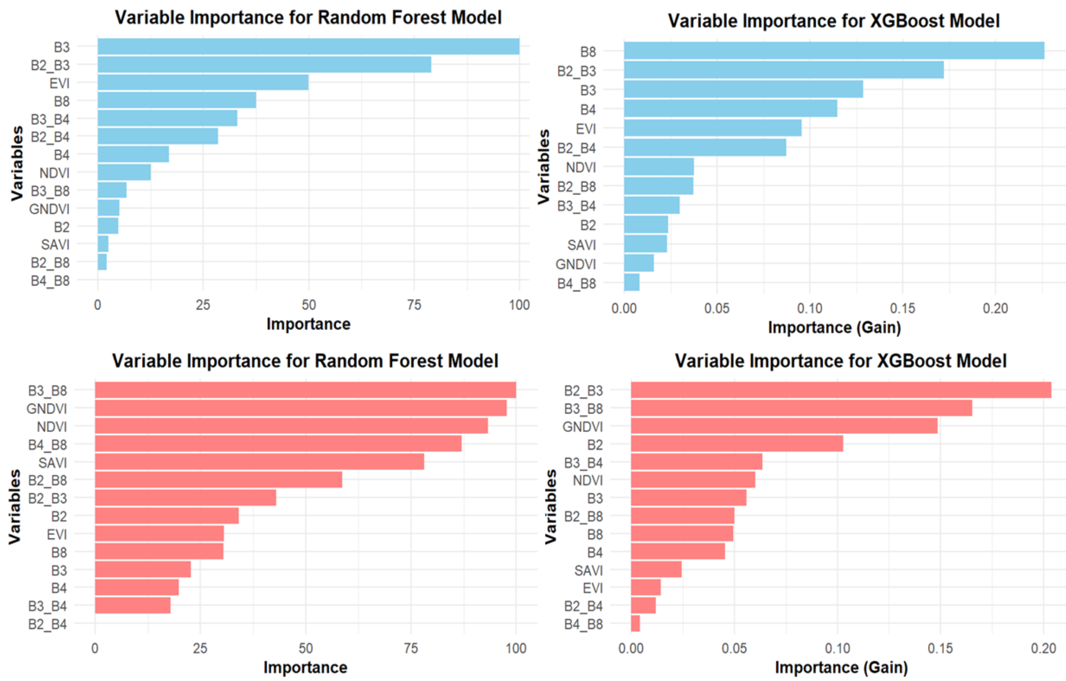


Figure 5.6: Variable importance of the model for RF and XGB

Blue: Wet season ; Red: Dry season

5.3.3.3. Accuracy Assessments

The density plot (Figure 5.7) illustrates the prediction accuracy by comparing in-situ AGB with prediction errors. The results indicate that all models overestimate at low in-situ AGB values, while underestimation predominantly occurs at the highest. Among the models, SVM and XGB demonstrate a relative balance between overestimation and underestimation, though both also exhibit overestimation for low and high in-situ AGB values.

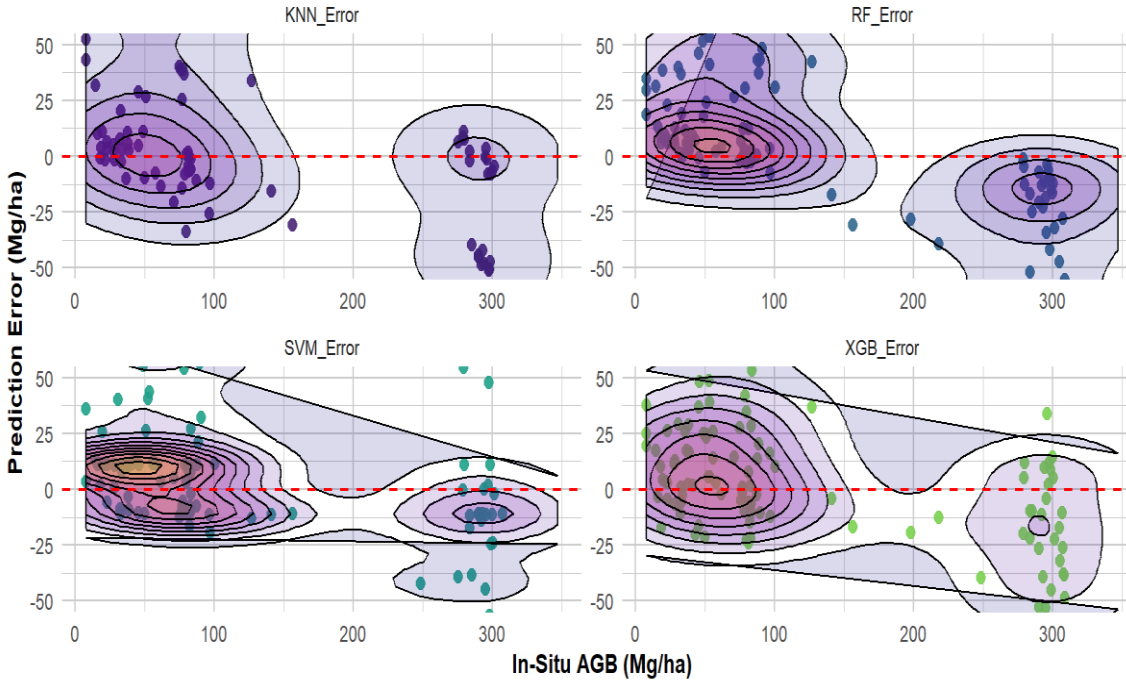


Figure 5.7: Density plot comparison of in-situ AGB and Predicted Error

5.3.3.4. Spatial Distribution of AGB

Figure 5.8 shows the RF, SVM, K-NN, and XG-Boost prediction compared to the InVEST Observed AGB map. The maps accurately reflect the spatial heterogeneity of the area, displaying areas of low and high biomass. The spatial distribution of biomass for RF was closer to the Observed AGB. The RF and XGB were similar, with a pattern showing more overestimation in the XG-Boost model. The two algorithms demonstrated higher accuracy with the validation datasets. The map from K-NN appeared to conform slightly better to those of RF and XG-Boost.

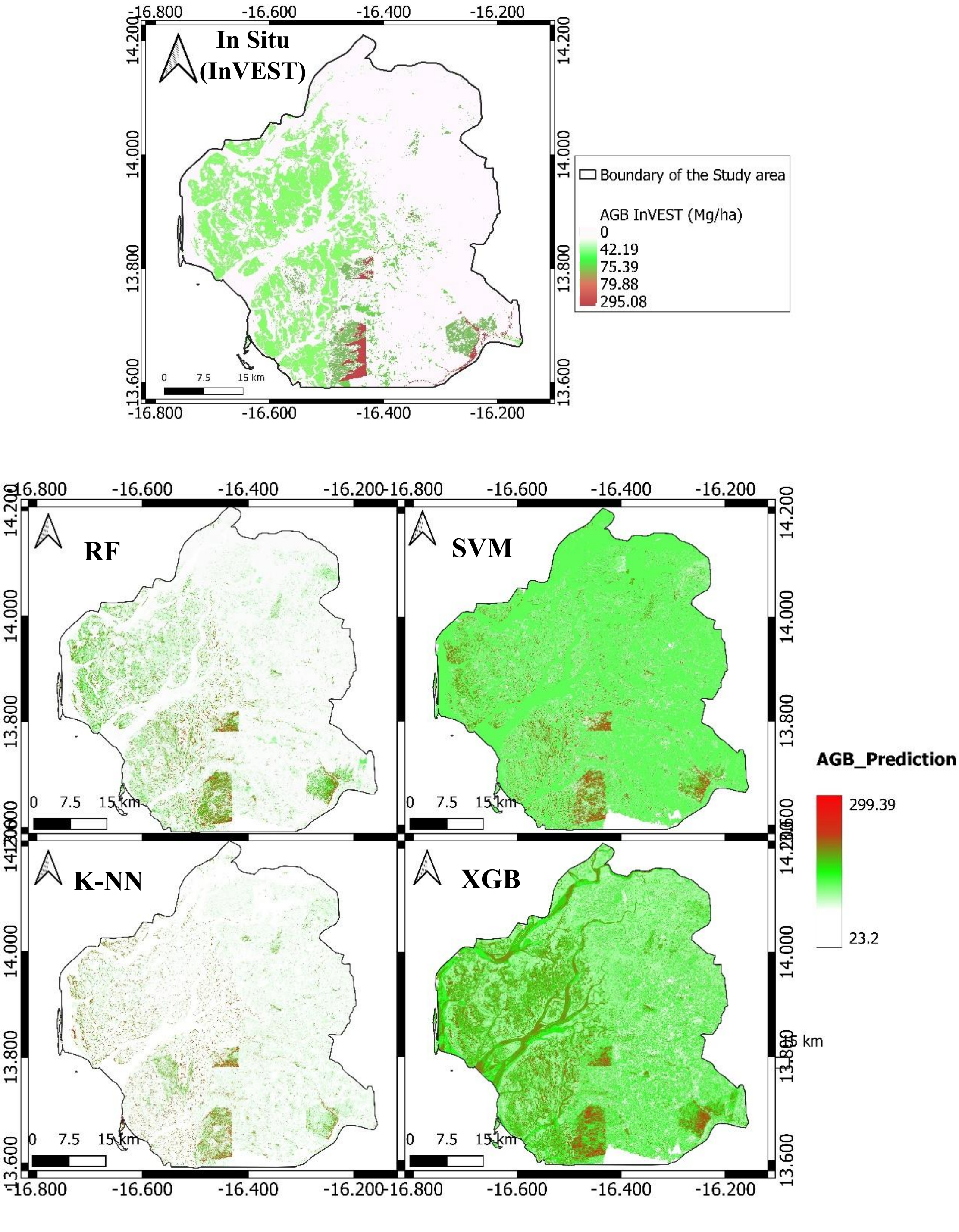


Figure 5.8: AGB Predicted map for the different models

5.4. DISCUSSION

5.4.1. Aboveground Biomass/ Carbon Stock Estimation

The biomass density estimates revealed significant variations among the land cover types studied. Close Woodlands exhibited the highest biomass density, averaging 295.08 ± 9.54 Mg/ha. Open Woodlands followed this at 79.88 ± 83.37 Mg/ha, Plantations at 75.39 ± 13.75 Mg/ha, and Mangroves at 42.19 ± 12.90 Mg/ha. Notably, the biomass density recorded for Mangroves aligns closely with findings by Gomis et al. (2023), who reported 40.3 Mg/ha. Similarly, our estimate for Close Woodlands is comparable to the 209.4 Mg/ha reported for close canopy forests by Atsri et al. (2020), and the biomass density for Open Woodlands aligns well with their findings of 79.7 Mg/ha in open forests. In addition, the carbon storage capacity of Plantations/agroforestry systems, such as those involving mango trees and cashews, was highlighted in our study. The total carbon stored in Plantations was estimated at 37.70 Mg/ha, aligning with previous studies such as Dao et al. (2021), emphasizing the significant role of agroforestry in carbon sequestration and sustainable land management. These findings underscore the substantial variability in biomass and carbon storage across different land cover types, reflecting their unique ecological functions and potential contributions to climate change mitigation. The greater value lies in leveraging advanced technologies for biomass assessment, enabling more accurate estimations across larger areas highlighting the importance of exploring machine learning models for enhanced precision and scalability.

5.4.2. Machine Learning Models

The performance of models using satellite data often depends on the season of image acquisition. For example, studies have shown that models perform significantly better with data captured during the wet season than the dry season (Singh et al., 2022). However, contrasting findings indicate that dry-season imagery can be more effective for predicting aboveground biomass (AGB) (Forkuor et al., 2020). These discrepancies can be attributed to various characteristics of the Sudanian Savanna (SS) zone that influence carbon stocks' intra- and inter-annual dynamics. Unlike the evergreen tropical rainforest, the vegetation in the Sudano-Sahelian zone is predominantly deciduous, shedding leaves during the dry season (Hall & Swaine, 1981). This seasonal leaf loss and frequent bushfires during the dry season significantly reduce available foliage. Consequently, biomass and carbon stocks measured during the dry season can differ markedly from those during the rainy season, even for the same area. These dynamics highlight the importance of considering seasonal variability when selecting satellite data for biomass and carbon stock modelling in the SS zone.

The Random Forest (RF) model demonstrated the best performance in this study. Comparable findings have been reported in previous research, where RF consistently outperformed or matched the performance of other machine learning models (Ibrahim et al., 2024; Bhattacharjee et al., 2021; Singh et al., 2023; Opelele et al., 2021). These studies further highlight the robustness and effectiveness of RF in handling complex datasets and accurately modelling environmental variables.

The band combination B2_B3 played a significant role in the Random Forest (RF) and XGBoost models, emphasizing its importance for prediction accuracy. This result aligns with previous findings that band combinations like traditional vegetation indices (VIs), raw spectral bands, and Gray Level Co-occurrence Matrix (GLCM) texture metrics derived from the near-infrared region are key variables in biomass estimation (Singh et al., 2023).

VIs demonstrated higher sensitivity for predicting AGB in deciduous forests (Wai et al., 2022). Additionally, Puliti et al. (2020) identified the three most important Sentinel-2 variables as the mean values of bands B5 (red edge), B11 (shortwave infrared), and B3 (green), further highlighting the value of specific bands and combinations in biomass modelling.

These findings underscore the importance of leveraging diverse data sources, including spectral bands and VIs variables, to optimize AGB predictions across forest types and ecosystems.

5.5. CONCLUSION

This study underscores the utility of machine learning and ensemble approaches in estimating aboveground biomass (AGB) across diverse woody landscapes in the Saloum region. The findings reveal significant variations in biomass density and carbon storage among land cover types, reflecting their ecological roles and contributions to climate change mitigation. Close Woodlands emerged as the most biomass-dense land cover, with an average AGB of 295.08 ± 9.54 Mg/ha, while Mangroves and Plantations recorded the lowest values, 42.19 ± 12.90 Mg/ha and 75.39 ±

13.75 Mg/ha, respectively. The results align with previous studies, validating the robustness of our methods and enhancing our understanding of ecosystem dynamics.

The performance of machine learning models, particularly the RF model, demonstrated strong predictive capabilities, with the wet season data producing higher accuracy than the dry season. The adjusted R-squared and RMSE values confirm RF's ability to model AGB across seasons, supported by its ability to integrate various predictor variables. Band combinations like B2_B3 variables played a pivotal role in improving model performance. These findings emphasize the importance of leveraging diverse data sources and seasonal imagery to optimize biomass estimation. The findings underscore the critical role of accurate biomass estimation in shaping effective REDD+ policies and supporting local stakeholder initiatives.

CHAPTER 6 : SUMMARY OF FINDINGS, CONCLUSIONS AND RECOMMENDATIONS

6.1. INTRODUCTION

This study involved an in-depth investigation of the woody vegetation hotspot in the Saloum Delta, aiming to support optimal landscape management for land restoration, carbon sink, and policy implementation. This chapter summarises the key findings, conclusions, and recommendations aligned with each objective.

6.2. SUMMARY OF FINDINGS

Research Objective 1: To assess the dynamic of the woody cover and related patterns of fragmentation from 2002 to 2022.

The thesis revealed that Mangroves dominate in both Protected Forests (PF) and Outside Protected Forests (OPF), with significant gain from "Water" and "No Woody Cover." Notably, Plantations in OPF showed progressive gains from "No Woody Cover" over the study period, indicating substantial land-use shifts outside protected forests. Pattern analysis in PF from landscape metrics has shown increased connectivity and reduced fragmentation in Mangroves and Close Woodlands areas. Open Woodlands shows alternating trends of fragmentation and cohesion. In OPF, Mangroves areas became more connected with reduced fragmentation, while Close and Open Woodlands showed fluctuating fragmentation patterns, and Plantations experienced a continuous increase of small patches.

These findings underscore the critical importance of the woody covers' dynamic and pattern, identifying restoration challenges and opportunities. It also balances land-use changes and conservation efforts in the Saloum Delta, thereby promoting regreening and land restoration policies and enhancing the ecological resilience of this vital region.

Research Objective 2: To predict habitat suitability and environmental drivers associated with the spatial distribution.

This study explores a novel approach by applying Species Distribution Models (SDMs) to woody cover classes, representing ecological communities, not individual species. Conducted in Senegal's Saloum Delta, a UNESCO World Heritage Site, the research predicts the spatial distribution of Mangroves, Close Woodlands, Open Woodlands, and Plantations, along with their environmental drivers. Data inputs include classified woody cover rasters, ground-truthing occurrences, and ten environmental variables encompassing climate, soil, anthropogenic, and natural features.

The Random Forest model consistently outperformed Maxent and Generalized Linear Models (GLM) in predictive accuracy, with the highest AUC values across vegetation types. Model results identified key drivers for each habitat: salinity and bulk density for Mangroves, rainfall and salinity for Close Woodlands, salinity and burn area index for Open Woodlands, and rainfall and proximity to villages for Plantations. Predicted suitability maps revealed distinct zones for each woody cover class. Mangroves thrive in high-salinity, low bulk-density areas, while Close Woodlands align with moderate rainfall and salinity regions. Open Woodlands are associated with burn-scarred zones, and Plantations show high suitability in minimal rainfall and distance to villages, revealing their adaptation aspect.

These insights support future regreening policy initiatives and sustainable land management strategies, demonstrating the potential of SDMs in guiding optimum ecological restoration and conservation of woody tree communities.

Research Objective 3: To assess and model the aboveground Biomass/carbon stock

Results show that Close Woodlands (CW) had the highest species richness and biomass density (295.08 Mg/ha), followed by Open Woodlands, Plantations, and Mangroves. Seasonal variability significantly influenced biomass predictions, with wet-season imagery yielding more accurate results. The study highlights that the key predictor for AGB modelling included spectral band combinations from Sentinel-2 data, with Random Forest (RF) achieving the highest accuracy ($R^2 = 0.83$, RMSE = 47.20).

The findings underscore the need for tailored land management strategies, enhanced by machine learning, to support reliable carbon stock assessment and climate resilience in Saloum Delta.

6.3. GENERAL CONCLUSION

The study concludes that Mangroves cover in the Saloum Delta, particularly in the northern area, has increased due to successful conservation efforts and natural regeneration. Protected Forests (PFs) demonstrated cohesive and resilient Mangrove structures with more extensive, connected patches, whereas Outside Protected Forests (OPFs) experienced more significant fragmentation.

Land use pressures such as agriculture and urbanization substantially contributed to this fragmentation. Plantations, particularly of cashews and mangoes, contributed to regreening efforts. Landscape metrics underscored reduced fragmentation and higher connectivity in PF Mangroves, emphasizing the importance of expanding protected areas and enhancing community-led management to support biodiversity and local livelihoods.

Secondly, salinity emerged as a critical environmental predictor influencing the spatial distribution of vegetation, particularly for Mangroves and woodlands. Rainfall was also a significant factor for Close Woodlands. That same factor also drives Plantations, with the distance to villages reflecting an adaptation purpose. Optimum regeneration can be predicted following the habitat suitability map. The mismatching of suitability between Close Woodlands and Open Woodlands remains obvious. Consequently, the manager would instead go for Close Woodlands, paying full attention to Open Woodlands drivers like fire burn. Using species distribution models (SDMs) demonstrated that Random Forest (RF) consistently outperformed other models in predicting vegetation types. Adaptive management strategies, including salt-tolerant species and effective fire management, are essential for mitigating environmental challenges and ensuring the sustainability of the Saloum Delta's ecosystems.

Thirdly, allometric equations and the application of machine learning approaches, especially the Random Forest (RF) model, proved effective in estimating aboveground biomass (AGB) across the region. Allometric equations showed that Close Woodlands exhibited the highest biomass density, while Mangroves and Plantations recorded lower values. The Random Forest (RF) model demonstrated exceptional predictive performance, particularly when utilizing wet season data, which yielded higher accuracy than the dry season. Strong adjusted R-squared and RMSE values further validated the model's effectiveness, highlighting its ability to incorporate diverse predictor variables. Specific band combinations, such as B2_B3, significantly enhanced model accuracy. These results underline the importance of integrating diverse data sources and leveraging seasonal imagery to optimize biomass estimation.

These findings filled the identified gap by employing advanced geospatial analyses and helped understand woody vegetation patterns, further suitable areas, and biomass potential. Supporting future land management strategies for optimizing land restoration and policy regreening.

6.4. RECOMMENDATIONS

6.4.1. RECOMMENDATION FOR POLICY

The findings of this study highlight the need for targeted policies to ensure the sustainable management and restoration of woody vegetation in the Saloum Delta. To address the insights gained from specific objective 1, policies should focus on strengthening the conservation of Mangroves and Close Woodlands in Protected Forests (PF) and Outside Protected Forests (OPF). Expanding conservation zones and enforcing regulations are critical to maintaining connectivity and reducing fragmentation. Policies should also integrate ecological restoration with sustainable land-use practices in OPF, ensuring that Plantations are developed in degraded areas without compromising natural ecosystems. Furthermore, it is essential to establish ecological corridors to connect fragmented woodlands and reduce habitat isolation, thereby promoting biodiversity and resilience.

For specific objective 2, the findings emphasize the importance of data-driven restoration policies. Suitability maps developed using Species Distribution Models (SDMs) should guide restoration and conservation activities by identifying priority areas based on environmental drivers like salinity, rainfall, and proximity to human settlements. Climate-smart restoration strategies are essential, including salinity-adaptive techniques for Mangroves and Close Woodlands, and fire management programs to address burn-scarred zones in Open Woodlands. Policies should also regulate Plantations expansion to balance ecological restoration with socio-economic benefits, especially in areas near villages where Plantations show high suitability.

Regarding specific objective 3, policies should aim to incorporate high-biomass areas such as Close Woodlands and increasing woody such Mangroves and Plantation into national carbon accounting frameworks. This includes developing carbon credit programs to incentivize local communities and stakeholders to engage in restoration and conservation efforts. Establishing guidelines for aboveground biomass monitoring using machine learning models and remote sensing will improve the consistency and accuracy of carbon stock assessments. Additionally, policies should include seasonal variability data in monitoring frameworks to enhance the precision of carbon stock estimates. Incentives for carbon sequestration, such as payments for ecosystem services, should be introduced to align restoration efforts with global climate goals and attract international funding for restoration initiatives.

These policy recommendations aim to balance conservation and restoration efforts while fostering ecological and socio-economic resilience in the Saloum Delta.

6.4.2. RECOMMENDATIONS FOR FUTURE RESEARCH

For Research Objective 1, which assessed the dynamics of woody cover and fragmentation patterns from 2002 to 2022, a study is recommended to investigate the socio-ecological drivers behind the observed patterns of fragmentation and connectivity. This study should explore the influence of human activities, climate variability, and policy interventions on woody cover dynamics in Protected Forests (PF) and Outside Protected Forests (OPF). Additionally, it should examine how different land management practices impact the temporal trends of fragmentation and connectivity across Mangroves, Close Woodlands, and Open Woodlands. Understanding these drivers will provide critical insights for adaptive land management and restoration strategies.

For Research Objective 2, which focuses on predicting habitat suitability and identifying environmental drivers, future research should consider incorporating additional predictors, such as land-use changes and socio-economic factors, to enhance model accuracy and applicability. Moreover, integrating temporal dynamics could provide valuable insights into how vegetation distributions respond to ongoing environmental changes, thereby informing adaptive management strategies. Furthermore, this research should investigate how key ecological drivers, such as salinity, rainfall, and burn areas, interact with changing climate conditions to influence the suitability of these woody cover types. Such work will help inform robust restoration and conservation plans under future climate uncertainties.

For Research Objective 3, which involved assessing and modelling aboveground biomass and carbon stock, future research should explore the long-term impacts of restoration efforts on carbon stock dynamics and their contributions to climate change mitigation. This includes conducting detailed field-based and remote sensing studies to monitor biomass recovery in restored Mangroves and Close Woodlands areas. Additionally, studies should examine the relationship between biomass density, species richness, and ecosystem services such as carbon sequestration and biodiversity enhancement over time. This research will provide valuable insights into the effectiveness of restoration activities and their role in enhancing ecological resilience and carbon storage in the Saloum Delta.

REFERENCES

Aabeyir, R., Adu-Bredu, S., Agyare, W. A., & Weir, M. J. C. (2020). Allometric models for estimating aboveground biomass in the tropical woodlands of Ghana, West Africa. Forest Ecosystems, 7(1), 1–23. https://doi.org/10.1186/S40663-020-00250-3/TABLES/10

Abanikannda, J. O., & Dantani, A. (2021). Fuel Wood Exploitation and Sustainable Forest Management. Journal of Applied Sciences and Environmental Management, 25(6), 987–993. https://doi.org/10.4314/JASEM.V25I6.16

ABARES. (2020). Australia's forests and forestry glossary (Issue June).

Abedi, M., Norouzi, G. H., & Bahroudi, A. (2012). Support vector machine for multi-classification of mineral prospectivity areas. Computers and Geosciences, 46, 272–283. https://doi.org/10.1016/J.CAGEO.2011.12.014

Abreu, R. C. R., Hoffmann, W. A., Vasconcelos, H. L., Pilon, N. A., Rossatto, D. R., & Durigan, G. (2017). The biodiversity cost of carbon sequestration in tropical savanna. Science Advances, 3(8). https://doi.org/10.1126/SCIADV.1701284

Adjorlolo, C., & Mutanga, O. (2013). Integrating remote sensing and geostatistics to estimate woody vegetation in an African savanna. Journal of Spatial Science, 58(2), 305–322. https://doi.org/10.1080/14498596.2013.815577

Ahmadi, K., Mahmoodi, S., Pal, S. C., Saha, A., Chowdhuri, I., Nguyen, T. T., Jarvie, S., Szostak, M., Socha, J., & Thai, V. N. (2023). Improving species distribution models for dominant trees in climate data-poor forests using high-resolution remote sensing. Ecological Modelling, 475(October 2022), 110190. https://doi.org/10.1016/j.ecolmodel.2022.110190

Aide, T. M., Grau, H. R., Graesser, J., Andrade-Nuñez, M. J., Aráoz, E., Barros, A. P., Campos-Cerqueira, M., Chacon-Moreno, E., Cuesta, F., Espinoza, R., Peralvo, M., Polk, M. H., Rueda, X., Sanchez, A., Young, K. R., Zarbá, L., & Zimmerer, K. S. (2019). Woody vegetation dynamics in the tropical and subtropical Andes from 2001 to 2014: Satellite image interpretation and expert validation. Global Change Biology, 25(6), 2112–2126. https://doi.org/10.1111/gcb.14618

Alamgir, M., & Al-Amin, M. (2008). Allometric models to estimate biomass organic carbon stock in forest vegetation. Journal of Forestry Research, 19(2), 101–106. https://doi.org/10.1007/S11676-008-0017-4/METRICS

Alongi, D. M. (2002). Present state and future of the world's mangrove forests. Environmental Conservation, 29(3), 331–349. https://doi.org/10.1017/S0376892902000231

Amani, M., Ghorbanian, A., Ahmadi, S. A., Kakooei, M., Moghimi, A., Mirmazloumi, S. M., Moghaddam, S. H. A., Mahdavi, S., Ghahremanloo, M., Parsian, S., Wu, Q., & Brisco, B. (2020). Google Earth Engine Cloud Computing Platform for Remote Sensing Big Data Applications: A Comprehensive Review. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 13, 5326–5350. https://doi.org/10.1109/JSTARS.2020.3021052

Amissah, L., Mohren, G. M. J., Bongers, F., Hawthorne, W. D., & Poorter, L. (2014). Rainfall and temperature affect tree species distribution in Ghana. Journal of Tropical Ecology, 30(5), 435–446. https://doi.org/10.1017/S026646741400025X

Andrew, S. M., Nyanghura, Q. M., & Mombo, F. M. (2023). Land cover change and utilization of village land forest reserves in Ludewa, Tanzania. Environmental Challenges, 10(December 2022), 100668. https://doi.org/10.1016/j.envc.2022.100668

Andrieu, J. (2018). Land cover changes on the West-African coastline from the Saloum Delta (Senegal) to Rio Geba (Guinea-Bissau) between 1979 and 2015. European Journal of Remote Sensing, 51(1), 314–325. https://doi.org/10.1080/22797254.2018.1432295

Andrieu, J. (2021). L'ÉVOLUTION DE LA MANGROVE (1979-2019) DU SALOUM AU GEBA, PAR TÉLÉDETECTION.

Andrieu, J., & Alexandre, F. (2010). Paysages forestiers et agro-forestiers en changement dans la partie septentrionale des Rivières du Sud (Afrique de l'Ouest). Des Milieux Aux Territoires Forestiers, Itinéraires Biogéographiques, December 2018, 15. https://www.researchgate.net/publication/297712327_Paysages_forestiers_et_agro-forestiers_en_changement_dans_la_partie_septentrionale_des_Rivieres_du_Sud_Afrique_de_l'Ouest

Andrieu, J., Lombard, F., Fall, A., Thior, M., Ba, B. D., & Dieme, B. E. A. (2020). Botanical field-study and remote sensing to describe mangrove resilience in the Saloum Delta (Senegal) after 30 years of degradation narrative. Forest Ecology and Management, 461(December 2019), 117963. https://doi.org/10.1016/j.foreco.2020.117963

ANDS. (2013). Situation économique et sociale. http://www.ansd.sn/ressources/ses/chapitres/1-demographie.pdf

ANSD. (2014). Rapport Definitif RGPHAE 2013 - Chapitre II: Etat et structure de la population. 54–70.

ANSD. (2021). SITUATION ECONOMIQUE ET SOCIALE REGIONALE 2019. In Service Régional de la Statistique et de la Démographie de Fatick.

Aoki, I. (2012). Ecological Communities. Entropy Principle for the Development of Complex Biotic Systems, 63–71. https://doi.org/10.1016/B978-0-12-391493-4.00006-8

APRI. (2024). Local Solutions, Global Impact: Climate Adaptation in West Africa. https://doi.org/https://doi.org/10.59184/ca024.01 Designed

Arévalo, P., Baccini, A., Woodcock, C. E., Olofsson, P., & Walker, W. S. (2023). Continuous mapping of aboveground biomass using Landsat time series. Remote Sensing of Environment, 288. https://doi.org/10.1016/j.rse.2023.113483

Arshad, A., Azhar Ali, A., & Anjali, K. S. (2022). Impact of forest fire on forest ecosystem. Journal of Agriculture and Technology, 9(1&2), 18–29.

Atsri, H. K., Kokou, K., Abotsi, K. E., Kokutse, A. D., & Cuni-Sanchez, A. (2020). Above-ground biomass and vegetation attributes in the forest-savannah mosaic of Togo, West Africa. African Journal of Ecology, 58(4), 733–745. https://doi.org/10.1111/aje.12758

Avitabile, V., Baccini, A., Friedl, M. A., & Schmullius, C. (2012). Capabilities and limitations of Landsat and land cover data for aboveground woody biomass estimation of Uganda. Remote Sensing of Environment, 117, 366–380. https://doi.org/10.1016/j.rse.2011.10.012

Badji, M., Sanogo, D., & Akpo, L. E. (2014). Dynamique de la végétation ligneuse des espaces sylvo-pastoraux villageois mis en défens dans le Sud du Bassin arachidier au Sénégal. Bois & Forets Des Tropiques, 319(319), 43. https://doi.org/10.19182/bft2014.319.a20551

Barik, J., Mukhopadhyay, A., Ghosh, T., Mukhopadhyay, S. K., Chowdhury, S. M., & Hazra, S. (2018). Mangrove species distribution and water salinity: an indicator species approach to Sundarban. Journal of Coastal Conservation, 22(2), 361–368. https://doi.org/10.1007/S11852-017-0584-7

Barker, J. R., & MacIsaac, H. J. (2022). Species distribution models: Administrative boundary centroid occurrences require careful interpretation. Ecological Modelling, 472, 110107. https://doi.org/10.1016/J.ECOLMODEL.2022.110107

Barrio, I. C., & Rapini, A. (2023). Plants under pressure: the impact of environmental change on plant ecology and evolution. BMC Ecology and Evolution, 23(1), 1–3. https://doi.org/10.1186/S12862-023-02115-Z/METRICS

Basin, B. N., Kerebeh, H., & Forkel, M. (2024). Above Ground Forest Biomass Estimation Using Sentinel-2 Data in the Upper. 1–18.

Bernardie, S., Vandromme, R., Thiery, Y., Houet, T., Grémont, M., Masson, F., Grandjean, G., & Bouroullec, I. (2021). Modelling landslide hazards under global changes: The case of a Pyrenean valley. Natural Hazards and Earth System Sciences, 21(1), 147–169. https://doi.org/10.5194/nhess-21-147-2021

Bhattacharjee, S., Islam, M. T., Kabir, M. E., & Kabir, M. M. (2021). Land-Use and Land-Cover Change Detection in a North-Eastern Wetland Ecosystem of Bangladesh Using Remote Sensing and GIS Techniques. Earth Systems and Environment, 5(2), 319–340. https://doi.org/10.1007/s41748-021-00228-3

Biah, I., Guendehou, S., Goussanou, C., Kaire, M., & Sinsin, B. A. (2018). Allometric models for estimating biomass stocks in cashew (Anacardium occidentale L.) plantation in Benin. 229, 16–27.

Boateng, K. O., Asubam, B. W., & Laar, D. S. (2012). Improving the Effectiveness of the Median Filter. International Journal of Electronics and Communication Engineering, 5(1), 85–97. http://www.irphouse.com

Bonthoux, S., Baselga, A., & Balent, G. (2013). Assessing Community-Level and Single-Species Models Predictions of Species Distributions and Assemblage Composition after 25 Years of Land Cover Change. PLOS ONE, 8(1), e54179. https://doi.org/10.1371/JOURNAL.PONE.0054179

Borsah, A. A., Nazeer, M., & Wong, M. S. (2023). LIDAR-Based Forest Biomass Remote Sensing: A Review of Metrics, Methods, and Assessment Criteria for the Selection of Allometric Equations. Forests 2023, Vol. 14, Page 2095, 14(10), 2095. https://doi.org/10.3390/F14102095

Boyd, R. J., Harvey, M., Roy, D. B., Barber, T., Haysom, K. A., Macadam, C. R., Morris, R. K. A., Palmer, C., Palmer, S., Preston, C. D., Taylor, P., Ward, R., Ball, S. G., & Pescott, O. L. (2023). Causal inference and large-scale expert validation shed light on the drivers of SDM accuracy and variance. Diversity and Distributions, 29(6), 774–784. https://doi.org/10.1111/ddi.13698

Bracken, J. T., Davis, A. Y., O'Donnell, K. M., Barichivich, W. J., Walls, S. C., & Jezkova, T. (2022). Maximizing species distribution model performance when using historical occurrences and variables of varying persistency. Ecosphere, 13(3), e3951. https://doi.org/10.1002/ECS2.3951

Brandt, M., Grau, T., Mbow, C., & Samimi, C. (2014). Modeling soil and woody vegetation in the Senegalese Sahel in the context of environmental change. Land, 3(3), 770–792. https://doi.org/10.3390/LAND3030770

Brandt, M., Rasmussen, K., Hiernaux, P., Herrmann, S., Tucker, C. J., Tong, X., Tian, F., Mertz, O., Kergoat, L., Mbow, C., David, J. L., Melocik, K. A., Dendoncker, M., Vincke, C., & Fensholt, R. (2018). Reduction of tree cover in West African woodlands and promotion in semi-arid farmlands. Nature Geoscience, 11(5), 328–333. https://doi.org/10.1038/s41561-018-0092-x

Brandt, M., Tappan, G., Diouf, A. A., Beye, G., Mbow, C., & Fensholt, R. (2017). Woody vegetation die off and regeneration in response to rainfall variability in the west african sahel. Remote Sensing, 9(1). https://doi.org/10.3390/rs9010039

Brown, S., Saxena, D., Wall, P. J., Roche, C., Hussain, F., & Lewis, D. (2022). Data Collection in the Global South and Other Resource-Constrained Environments: Practical, Methodological and Ethical Challenges. IFIP Advances in Information and Communication Technology, 657 IFIP, 608–618. https://doi.org/10.1007/978-3-031-19429-0_37

Bui, Q. T., Pham, Q. T., Pham, V. M., Tran, V. T., Nguyen, D. H., Nguyen, Q. H., Nguyen, H. D., Do, N. T., & Vu, V. M. (2024). Hybrid machine learning models for aboveground biomass estimations. Ecological Informatics, 79, 102421. https://doi.org/10.1016/J.ECOINF.2023.102421

Campbell, M. J., Eastburn, J. F., Dennison, P. E., Vogeler, J. C., & Stovall, A. E. L. (2024). Evaluating the performance of airborne and spaceborne lidar for mapping biomass in the United States' largest dry woodland ecosystem. Remote Sensing of Environment, 308(March), 114196. https://doi.org/10.1016/j.rse.2024.114196

Carré, M., Quichaud, L., Camara, A., Azzoug, M., Cheddadi, R., Ochoa, D., Cardich, J., Pérez, A., Salas-Gismondi, R., Thébault, J., & Thomas, Y. (2022). Climate change, migrations, and the peopling of sine-Saloum mangroves (Senegal) in the past 6000 years. Quaternary Science Reviews, 293. https://doi.org/10.1016/j.quascirev.2022.107688

Case, M. F., & Staver, A. C. (2017). Fire prevents woody encroachment only at higher-than-historical frequencies in a South African savanna. Journal of Applied Ecology, 54(3), 955–962. https://doi.org/10.1111/1365-2664.12805

Cavender-Bares, J., Schweiger, A. K., Pinto-Ledezma, J. N., & Meireles, J. E. (2020). Applying remote sensing to biodiversity science. Remote Sensing of Plant Biodiversity, 13–42.

https://doi.org/10.1007/978-3-030-33157-3_2/FIGURES/8

Chatrabhuj, Meshram, K., Mishra, U., & Omar, P. J. (2024). Integration of remote sensing data and GIS technologies in river management system. Discover Geoscience 2024 2:1, 2(1), 1–22. https://doi.org/10.1007/S44288-024-00080-8

Chauvier, Y., Thuiller, W., Brun, P., Lavergne, S. E., Descombes, P., Karger, D. N., Renaud, J., Zimmermann, N. E., Chauvier, C. :, Thuiller, W., Brun, P., Lavergne, S., Descombes, P., Karger, D. N., Renaud, J., & Zimmermann, N. E. (2021). Influence of climate, soil, and land cover on plant species distribution in the European Alps. Ecological Monographs, 91(2), e01433. https://doi.org/10.1002/ECM.1433

Chave, J., Réjou-Méchain, M., Búrquez, A., Chidumayo, E., Colgan, M. S., Delitti, W. B. C., Duque, A., Eid, T., Fearnside, P. M., Goodman, R. C., Henry, M., Martínez-Yrízar, A., Mugasha, W. A., Muller-Landau, H. C., Mencuccini, M., Nelson, B. W., Ngomanda, A., Nogueira, E. M., Ortiz-Malavassi, E., … Vieilledent, G. (2014). Improved allometric models to estimate the aboveground biomass of tropical trees. Global Change Biology, 20(10), 3177–3190. https://doi.org/10.1111/GCB.12629

Chen, H. L., Huang, C. C., Yu, X. G., Xu, X., Sun, X., Wang, G., & Wang, S. J. (2013). An efficient diagnosis system for detection of Parkinson's disease using fuzzy k-nearest neighbor approach. Expert Systems with Applications, 40(1), 263–271. https://doi.org/10.1016/J.ESWA.2012.07.014

Chen, S., Woodcock, C. E., Bullock, E. L., Arévalo, P., Torchinava, P., Peng, S., & Olofsson, P. (2021). Monitoring temperate forest degradation on Google Earth Engine using Landsat time series analysis. Remote Sensing of Environment, 265, 1–5. https://doi.org/10.1016/j.rse.2021.112648

Chen, Y., Guerschman, J., Shendryk, Y., Henry, D., & Harrison, M. T. (2021). Estimating pasture biomass using sentinel-2 imagery and machine learning. Remote Sensing, 13(4), 1–20. https://doi.org/10.3390/rs13040603

Cheng, C., & Li, F. (2024). Ecosystem restoration and management based on nature-based solutions in China: Research progress and representative practices. Nature-Based Solutions, 6, 100176. https://doi.org/10.1016/J.NBSJ.2024.100176

Cheng, Z., Aakala, T., & Larjavaara, M. (2023). Elevation, aspect, and slope influence woody vegetation structure and composition but not species richness in a human-influenced landscape in northwestern Yunnan, China. Frontiers in Forests and Global Change, 6(June), 1–12. https://doi.org/10.3389/ffgc.2023.1187724

Chiou, K. L., & Blair, M. E. (2021). Modeling niches and mapping distributions: progress and promise of ecological niche models for primate research. In Spatial Analysis in Field Primatology: Applying GIS at Varying Scales. https://www.cambridge.org/core/books/spatial-analysis-in-field-primatology/modeling-niches-and-mapping-distributions/FFC1944D60BFED7B3BE573ADE25B7DCC

Chirwa, P. W., Kozanayi, W., Uisso, A. J., Tshidzumba, R. P., Babalola, F. D., Amusa, T. O., Chirwa, P. W., Kozanayi, W., Uisso, A. J., Tshidzumba, R. P., Babalola, F. D., & Amusa, T. O. (2024). Socio-economic Factors, Policy and Governance Systems Influencing

Multifunctional Landscapes. Trees in a Sub-Saharan Multi-Functional Landscape, 305–327. https://doi.org/10.1007/978-3-031-69812-5_13

Chollet Ramampiandra, E., Scheidegger, A., Wydler, J., & Schuwirth, N. (2023). A comparison of machine learning and statistical species distribution models: Quantifying overfitting supports model interpretation. Ecological Modelling, 481, 110353. https://doi.org/10.1016/J.ECOLMODEL.2023.110353

Coleman, K., Müller, J., & Kuenzer, C. (2024). Remote Sensing of Forests in Bavaria: A Review. Remote Sensing, 16(10). https://doi.org/10.3390/rs16101805

Coly, M. L. (2016). Etude des caractéristiques morphologiques et de la germination des noix de Anacardium occidentale L . de la région de Ziguinchor. UNIVERSITE DE THIES.

Cortes, C., Vapnik, V., & Saitta, L. (1995). Support-vector networks. Machine Learning 1995 20:3, 20(3), 273–297. https://doi.org/10.1007/BF00994018

Dada, A. D., Matthew, O. J., & Odiwe, A. I. (2024). Nexus between carbon stock, biomass, and CO2 emission of woody species composition: evidence from Ise-Ekiti Forest Reserve, Southwestern Nigeria. Carbon Research, 3(1), 1–16. https://doi.org/10.1007/S44246-024-00115-2/FIGURES/6

Dahan, K. S., Kasei, R. A., & Husseini, R. (2023). Contribution of remote sensing to wildfire trend and dynamic analysis in two of Ghana's ecological zones: Guinea-savanna and Forest-savanna mosaic. Fire Ecology, 19(1). https://doi.org/10.1186/s42408-023-00198-z

Dao, A., Bationo, B. A., Traoré, S., Bognounou, F., & Thiombiano, A. (2021). Using allometric models to estimate aboveground biomass and predict carbon stocks of mango (Mangifera indica L.) parklands in the Sudanian zone of Burkina Faso. Environmental Challenges, 3(February), 100051. https://doi.org/10.1016/j.envc.2021.100051

Daou, I., Diancoumba, O., Touré, A., Konaré, S., & Bokar, H. (2023). Accurate evaluation of Land Use Land Cover (LULC) Dynamics in the Southern part of Mali, West Africa. International Journal of Innovation and Scientific Research, 65(1), 109–117. http://www.ijisr.issr-journals.org/

de Almeida, D. R. A., Vedovato, L. B., Fuza, M., Molin, P., Cassol, H., Resende, A. F., Krainovic, P. M., de Almeida, C. T., Amaral, C., Haneda, L., Albuquerque, R. W., Gorgens, E., Romanelli, J., Ferreira, M., Salk, C., Espinoza, N., Silva, C., Broadbent, E., & Brancalion, P. H. S. (2025). Remote sensing approaches to monitor tropical forest restoration: Current methods and future possibilities. Journal of Applied Ecology, 62(2), 188–206. https://doi.org/10.1111/1365-2664.14830

Dendoncker, M., Brandt, M., Rasmussen, K., Taugourdeau, S., Fensholt, R., Tucker, C. J., & Vincke, C. (2020). 50 years of woody vegetation changes in the Ferlo (Senegal) assessed by high-resolution imagery and field surveys. Regional Environmental Change, 20(4). https://doi.org/10.1007/s10113-020-01724-4

Descombes, P., Chauvier, Y., Brun, P., Righetti, D., Wüest, R. O., Karger, D. N., Zurell, D., & Zimmermann, N. E. (2022). Strategies for sampling pseudo-absences for species distribution models in complex mountainous terrain. https://doi.org/10.1101/2022.03.24.485693

Descroix, L., San, Y., Thior, M., Manga, S., Ba, B. D., Mingou, J., Mendy, V., Coly, S., Di, A., Badiane, A., Senghor, M., Diedhiou, A., Sow, D., Bouaita, Y., Soumar, S., Diop, A., Faty, B., & Sow, B. A. (2020). Inverse Estuaries in West Africa : Evidence of the.

Dia, M. I. (2012). Vulnerability Assessment of Central Coast Senegal (Saloum) and The Gambia Marine Coast and Estuary to Climate Change Induced Effects. Coastal Resources Center and WWF-WAMPO, April, 1–40.

Díaz-Pacheco, J., Van Delden, H., & Hewitt, R. (2018). The Importance of Scale in Land Use Models: Experiments in Data Conversion, Data Resampling, Resolution and Neighborhood Extent. Lecture Notes in Geoinformation and Cartography, 163–186. https://doi.org/10.1007/978-3-319-60801-3_9

Díaz, S., Settele, J., Brondízio, E. S., Ngo, H. T., Agard, J., Arneth, A., Balvanera, P., Brauman, K. A., Butchart, S. H. M., Chan, K. M. A., Lucas, A. G., Ichii, K., Liu, J., Subramanian, S. M., Midgley, G. F., Miloslavich, P., Molnár, Z., Obura, D., Pfaff, A., … Zayas, C. N. (2019). Pervasive human-driven decline of life on Earth points to the need for transformative change. Science, 366(6471). https://doi.org/10.1126/science.aax3100

Diederich, P. B. (2014). The Meaning of "The Meaning of Meaning." The English Journal, 30(1), 31. https://doi.org/10.2307/805411

Dieye, E. H. B., Diaw, A. T., Sané, T., & Ndour, N. (2013). Dynamique de la mangrove de l'estuaire du Saloum (Sénégal) entre 1972 et 2010. CyberGeo, 2013(January). https://doi.org/10.4000/cybergeo.25671

Dimobe, K., Ouédraogo, A., Soma, S., Goetze, D., Porembski, S., & Thiombiano, A. (2015). Identification of driving factors of land degradation and deforestation in the Wildlife Reserve of Bontioli (Burkina Faso, West Africa). Global Ecology and Conservation, 4(July), 559–571. https://doi.org/10.1016/j.gecco.2015.10.006

Diop, A., Samb, C., Ndour, A., Barry, M., Cissé, O., Ahouandjinou, S., Kouagou, S., Mate, M.-P., Diansambu, M., & Bogaert, J. (2024). Caractérisation de la Mangrove du Saloum, Sénégal Characterization of the Saloum Mangrove, Senegal. REB-PASRES, July.

Diop, M., Sambou, B., Goudiaby, A., Guiro, I., & Niang-diop, F. (2011). Ressources végétales et préférences sociales en milieu rural sénégalais PREFERENCES IN RURAL ENVIRONMENT. 310(4), 57–68.

Dittmann, S., Mosley, L., Stangoulis, J., Nguyen, V. L., Beaumont, K., Dang, T., Guan, H., Gutierrez-Jurado, K., Lam-Gordillo, O., & McGrath, A. (2022). Effects of Extreme Salinity Stress on a Temperate Mangrove Ecosystem. Frontiers in Forests and Global Change, 5(May), 1–18. https://doi.org/10.3389/ffgc.2022.859283

Doherty, T. S., Geary, W. L., Jolly, C. J., Macdonald, K. J., Miritis, V., Watchorn, D. J., Cherry, M. J., Conner, L. M., González, T. M., Legge, S. M., Ritchie, E. G., Stawski, C., & Dickman, C. R. (2022). Fire as a driver and mediator of predator–prey interactions. Biological Reviews, 97(4), 1539–1558. https://doi.org/10.1111/brv.12853

Dubos, N., Préau, C., Lenormand, M., Papuga, G., Monsarrat, S., Denelle, P., Louarn, M. Le, Heremans, S., May, R., Roche, P., & Luque, S. (2022). Assessing the effect of sample bias correction in species distribution models. Ecological Indicators, 145, 109487. https://doi.org/10.1016/J.ECOLIND.2022.109487

Durbecq, A., Jaunatre, R., Buisson, E., Cluchier, A., & Bischoff, A. (2020). Identifying reference communities in ecological restoration: the use of environmental conditions driving vegetation composition. Restoration Ecology, 28(6), 1445–1453. https://doi.org/10.1111/rec.13232

E. S. Diop. (1998). Contribution à l'élaboration du plan de gestion intégrée de la Réserve de la Biosphère du Delta de Saloum - Recherche Google [UCAD-UNESCO-MAB]. https://www.google.com/search?q=Diop+E.+S.%2C+1998.+Contribution+à+l'élaboration+du+plan+de+gestion+intégrée+de+la+Réserve+de+la+Biosphère+du+Delta+de+Saloum&rlz=1C1EJFC_enCV886CV886&sxsrf=AOaemvJWihD57WeIPvQB1n9hHLm6ONnf6Q%3A1630375122442&ei=0owtYYiwGqq5gwfTzoEw&oq=Diop+E.+S.%2C+1998.+Contribution+à+l'élaboration+du+plan+de+gestion+intégrée+de+la+Réserve+de+la+Biosphère+du+Delta+de+Saloum&gs_lcp=Cgdnd3Mtd2l6EANKBAhBGABQ0vAJWNLwCWC58wloAHAAeACAAQCIAQCSAQCYAQCgAQHAAQE&sclient=gws-wiz&ved=0ahUKEwiI4ZfQlNryAhWq3OAKHVNnAAYQ4dUDCA8&uact=5

Emmanuel, O., & Williams, A. (2017). Effects of Deforestation on Land Degradation in Gbonyin LGA of EKITI. July, 30–32. https://www.researchgate.net/publication/318921682_Effects_of_Deforestation_on_Land_Degradation

Ermida, S. L., Soares, P., Mantas, V., Göttsche, F. M., & Trigo, I. F. (2020). Google earth engine open-source code for land surface temperature estimation from the landsat series. Remote Sensing, 12(9), 1–21. https://doi.org/10.3390/RS12091471

Faisal, A. Al, Kafy, A. A., Al Rakib, A., Akter, K. S., Jahir, D. M. A., Sikdar, M. S., Ashrafi, T. J., Mallik, S., & Rahman, M. M. (2021). Assessing and predicting land use/land cover, land surface temperature and urban thermal field variance index using Landsat imagery for Dhaka Metropolitan area. Environmental Challenges, 4, 100192. https://doi.org/10.1016/J.ENVC.2021.100192

Fanday, H., & Tchobsala. (2024). Impact of Human Activities on Woody Vegetation in Gallery Forests in the Mandara Mountains (Far North, Cameroon). The Scientific World Journal, 2024(1), 9198533. https://doi.org/10.1155/2024/9198533

FARM RADIO.FM. (2022). The cashew tree: A defense against bush fires - Farm Radio Scripts. https://scripts.farmradio.fm/radio-script/cashew-tree-defense-bush-fires/?utm_source=chatgpt.com

Fassnacht, F. E., White, J. C., Wulder, M. A., & Næsset, E. (2024). Remote sensing in forestry: current challenges, considerations and directions. Forestry, 97(1), 11–37. https://doi.org/10.1093/FORESTRY/CPAD024

Faye, E., Dieng, H., Bogaert, J., & Lejoly, J. (2014). Dynamique de la flore et de la végétation des Niayes et du Bassin arachidier au Sénégal. Journal of Agriculture and Environment for International Development-JAEID, 2014(2), 191–206. https://doi.org/10.12895/jaeid.20142.240

Faye, M., Tine, D., Diouf, F., Cissay, A., & Faye, C. S. (2022). Climate Change and Land Use

Dynamics in Djirnda Commune (Fatick Region - Senegal): Remote Sensing Approach. European Journal of Biology and Biotechnology, 3(4), 1–7. https://doi.org/10.24018/EJBIO.2022.3.4.375

Fazan, L., Song, Y. G., & Kozlowski, G. (2020). The woody planet: From past triumph to manmade decline. Plants, 9(11), 1–14. https://doi.org/10.3390/plants9111593

Forkuor, G., Benewinde Zoungrana, J. B., Dimobe, K., Ouattara, B., Vadrevu, K. P., & Tondoh, J. E. (2020). Above-ground biomass mapping in West African dryland forest using Sentinel-1 and 2 datasets - A case study. Remote Sensing of Environment, 236(October 2019), 111496. https://doi.org/10.1016/j.rse.2019.111496

Fournier, A., Barbet-Massin, M., Rome, Q., & Courchamp, F. (2017). Predicting species distribution combining multi-scale drivers. Global Ecology and Conservation, 12, 215–226. https://doi.org/10.1016/j.gecco.2017.11.002

Franklin, J. (2023). Species distribution modelling supports the study of past, present and future biogeographies. Journal of Biogeography, 50(9), 1533–1545. https://doi.org/10.1111/jbi.14617

Friedlingstein, P., O'sullivan, M., Jones, M. W., Andrew, R. M., Gregor, L., Hauck, J., Le Quéré, C., Luijkx, I. T., Olsen, A., Peters, G. P., Peters, W., Pongratz, J., Schwingshackl, C., Sitch, S., Canadell, J. G., Ciais, P., Jackson, R. B., Alin, S. R., Alkama, R., … Zheng, B. (2022). Global Carbon Budget 2022. Earth System Science Data, 14(11), 4811–4900. https://doi.org/10.5194/essd-14-4811-2022

Fundisi, E., Tesfamichael, S. G., & Ahmed, F. (2022). Remote sensing of savanna woody species diversity: A systematic review of data types and assessment methods. PLoS ONE, 17(12 December), 1–29. https://doi.org/10.1371/journal.pone.0278529

G20 Global Land Initiative. (2023). G20 GLOBAL LAND INITIATIVE.

Galidaki, G., Zianis, D., Gitas, I., Radoglou, K., Karathanassi, V., Tsakiri–Strati, M., Woodhouse, I., & Mallinis, G. (2017). Vegetation biomass estimation with remote sensing: focus on forest and other wooded land over the Mediterranean ecosystem. International Journal of Remote Sensing, 38(7), 1940–1966. https://doi.org/10.1080/01431161.2016.1266113

Gallé, R., Korányi, D., Tölgyesi, C., Lakatos, T., Marcolin, F., Török, E., Révész, K., Szabó, Á. R., Torma, A., Gallé-Szpisjak, N., Marja, R., Szitár, K., Deák, B., & Batáry, P. (2022). Landscape-scale connectivity and fragment size determine species composition of grassland fragments. Basic and Applied Ecology, 65, 39–49. https://doi.org/10.1016/J.BAAE.2022.10.001

Gallup, L., Sonnenfeld, D. A., & Dahdouh-guebas, F. (2019). Mangrove use and management within the Sine-Saloum Delta , Senegal. Ocean and Coastal Management, November 2018, 105001. https://doi.org/10.1016/j.ocecoaman.2019.105001

Gallup, L., Sonnenfeld, D. A., & Dahdouh-guebas, F. (2020). Mangrove use and management within the Sine-Saloum Delta , Senegal. Ocean and Coastal Management, 185(November 2018), 105001. https://doi.org/10.1016/j.ocecoaman.2019.105001

Ganamé, M., Bayen, P., Ouédraogo, I., Balima, L. H., & Thiombiano, A. (2021). Allometric models for improving aboveground biomass estimates in West African savanna ecosystems. Trees, Forests and People, 4, 100077. https://doi.org/10.1016/J.TFP.2021.100077

Ganjirad, M., & Bagheri, H. (2024). Google Earth Engine-based mapping of land use and land cover for weather forecast models using Landsat 8 imagery. Ecological Informatics, 80, 102498. https://doi.org/10.1016/J.ECOINF.2024.102498

Gilbert, K. M., & Shi, Y. (2023). Land Use/Land Cover Changes Detection in Lagos City of Nigeria Using Remote Sensing and GIS. Advances in Remote Sensing, 12(04), 145–165. https://doi.org/10.4236/ars.2023.124008

Goicolea, T., Adde, A., Broennimann, O., García-Viñas, J. I., Gastón, A., José Aroca-Fernández, M., Guisan, A., & G. Mateo, R. (2024). Spatially-nested hierarchical species distribution models to overcome niche truncation in national-scale studies. Ecography, e07328. https://doi.org/10.1111/ECOG.07328

Gomez, J. J., & Cassini, M. H. (2015). Environmental predictors of habitat suitability and biogeographical range of Franciscana dolphins (Pontoporia blainvillei). Global Ecology and Conservation, 3, 90–99. https://doi.org/10.1016/J.GECCO.2014.11.007

Gomis, D., Mbengue, N. P., Badiane, S. D., Thiaw-Benga, A. D., Guisse, A., & Ndiaye, A. (2023). Potentialities and economic benefits of the mangrove in the fight against global warming: case of the Djilor District (Fatick, Senegal). International Journal of Biological and Chemical Sciences, 17(1), 154–172. https://doi.org/10.4314/ijbcs.v17i1.12

Gonzalez, P., Tucker, C. J., & Sy, H. (2012). Tree density and species decline in the African Sahel attributable to climate. Journal of Arid Environments, 78, 55–64. https://doi.org/10.1016/j.jaridenv.2011.11.001

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sensing of Environment, 202, 18–27. https://doi.org/10.1016/J.RSE.2017.06.031

Gould, W. A., González, G., Hudak, A. T., Hollingsworth, T. N., & Hollingsworth, J. (2008). Forest structure and downed woody debris in boreal, temperate, and tropical forest fragments. Ambio, 37(7–8), 577–587. https://doi.org/10.1579/0044-7447-37.7.577

Grace, J., José, J. S., Meir, P., Miranda, H. S., & Montes, R. A. (2006). Productivity and carbon fluxes of tropical savannas. Journal of Biogeography, 33(3), 387–400. https://doi.org/10.1111/J.1365-2699.2005.01448.X

Graw, V., Oldenburg, C., & Dubovyk, O. (2016). ZEF-Discussion Papers on Development Policy No. 218 Bush Encroachment Mapping for Africa: Multi-scale analysis with remote sensing and GIS. http://ssrn.com/abstract=2807811Electroniccopyavailableat:https://ssrn.com/abstract=2807811

Grieco, E., Vangi, E., Chiti, T., & Collalti, A. (2024). Impacts of deforestation and land use/land cover change on carbon stock dynamics in Jomoro District, Ghana. Journal of Environmental Management, 367, 121993. https://doi.org/10.1016/J.JENVMAN.2024.121993

Guan, K., Medvigy, D., Wood, E. F., Caylor, K. K., Li, S., & Jeong, S. J. (2014). Deriving vegetation phenological time and trajectory information over africa using seviri daily LAI. IEEE Transactions on Geoscience and Remote Sensing, 52(2), 1113–1130. https://doi.org/10.1109/TGRS.2013.2247611

Hackman, K. O., Li, X., Asenso-Gyambibi, D., Asamoah, E. A., & Nelson, I. D. (2020). Analysis of geo-spatiotemporal data using machine learning algorithms and reliability enhancement for urbanization decision support. International Journal of Digital Earth, 13(12), 1717–1732. https://doi.org/10.1080/17538947.2020.1805036

Hailu, F., & Hailu, F. (2023). Climate change as a trigger for desertification and possible alternatives to reduce biodiversity loss. Journal of the Selva Andina Biosphere, 11(1), 94–111. https://doi.org/10.36610/J.JSAB.2023.110100091

Hall, J. B., & Swaine, M. D. (1981). Distribution and ecology of vascular plants in a tropical rain forest. Distribution and Ecology of Vascular Plants in a Tropical Rain Forest. https://doi.org/10.1007/978-94-009-8650-3

Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S. V., Goetz, S. J., Loveland, T. R., Kommareddy, A., Egorov, A., Chini, L., Justice, C. O., & Townshend, J. R. G. (2013). High-resolution global maps of 21st-century forest cover change. Science, 342(6160), 850–853. https://doi.org/10.1126/SCIENCE.1244693

Hao, L., Qingdong, S., Imin, B., & Kasim, N. (2020). Methodology for optimizing quadrat size in sparse vegetation surveys: A desert case study from the Tarim Basin. PLoS ONE, 15(8). https://doi.org/10.1371/JOURNAL.PONE.0235469

Hariyono, M. I., Rokhmatuloh, & Dewi, R. S. (2023). Land Use and Land Cover (LULC) Classification with Machine Learning Approach Using Orthophoto Data. Majalah Ilmiah Globe, 25(1), 87–96.

Hashim, M., Pour, A. B., & Onn, C. H. (2014). Optimizing cloud removal from satellite remotely sensed data for monitoring vegetation dynamics in humid tropical climate. IOP Conference Series: Earth and Environmental Science, 18(1). https://doi.org/10.1088/1755-1315/18/1/012010

Hayah, I., Ababou, M., Botti, S., & Badaoui, B. (2021). Comparison of three statistical approaches for feature selection for fine-scale genetic population assignment in four pig breeds. Tropical Animal Health and Production, 53(3). https://doi.org/10.1007/S11250-021-02824-X

Hermosilla, T., Wulder, M. A., White, J. C., Coops, N. C., Hobart, G. W., Hermosilla, T., Wulder, M. A., White, J. C., & Coops, N. C. (2018). Disturbance-Informed Annual Land Cover Classification Maps of Canada ' s Forested Ecosystems for a 29-Year Landsat Time Series Disturbance-Informed Annual Land Cover Classification Maps of Canada ' s. Canadian Journal of Remote Sensing, 44(1), 67–87. https://doi.org/10.1080/07038992.2018.1437719

Herrmann, S. M., & Tappan, G. G. (2013). Vegetation impoverishment despite greening: A case study from central Senegal. Journal of Arid Environments, 90, 55–66. https://doi.org/10.1016/j.jaridenv.2012.10.020

Herrmann, Stefanie M., Brandt, M., Rasmussen, K., & Fensholt, R. (2020). Accelerating land cover change in West Africa over four decades as population pressure increased. Communications Earth & Environment 2020 1:1, 1(1), 1–10. https://doi.org/10.1038/s43247-020-00053-y

Herrmann, Stefanie M., Sall, I., & Sy, O. (2014). People and pixels in the Sahel: A study linking coarse-resolution remote sensing observations to land users' perceptions of their changing environment in Senegal. Ecology and Society, 19(3). https://doi.org/10.5751/ES-06710-190329

Herrmann, Stefanie M., Wickhorst, A. J., & Marsh, S. E. (2013). Estimation of tree cover in an agricultural parkland of senegal using rule-based regression tree modeling. Remote Sensing, 5(10), 4900–4918. https://doi.org/10.3390/rs5104900

Heyojoo, B. P., & Nandy, S. (2015). Estimation of above-ground phytomass and carbon in tree resources outside the forest (TROF): A geo-spatial approach. Banko Janakari, 24(1), 34–40. https://doi.org/10.3126/banko.v24i1.13488

Hickler, T., Eklundh, L., Seaquist, J. W., Smith, B., Ardö, J., Olsson, L., Sykes, M. T., & Sjöström, M. (2005). Precipitation controls Sahel greening trend. Geophysical Research Letters, 32(21), 1–4. https://doi.org/10.1029/2005GL024370

Hiernaux, P., Diarra, L., Trichon, V., Mougin, E., Soumaguel, N., & Baup, F. (2009). Woody plant population dynamics in response to climate changes from 1984 to 2006 in Sahel (Gourma, Mali). Journal of Hydrology, 375(1–2), 103–113. https://doi.org/10.1016/j.jhydrol.2009.01.043

Hlásny, T., Augustynczik, A. L. D., & Dobor, L. (2021). Time matters: Resilience of a post-disturbance forest landscape. Science of The Total Environment, 799, 149377. https://doi.org/10.1016/J.SCITOTENV.2021.149377

Hossain, M., Siddique, M. R. H., Abdullah, S. M. R., Saha, C., Islam, S. M. Z., Iqbal, M. Z., Akhter, M., Hossain, M., Siddique, M. R. H., Abdullah, S. M. R., Saha, C., Islam, S. M. Z., Iqbal, M. Z., & Akhter, M. (2019). Development and Evaluation of Species-Specific Biomass Models for Most Common Timber and Fuelwood Species of Bangladesh. Open Journal of Forestry, 10(1), 172–185. https://doi.org/10.4236/OJF.2020.101012

Houghton, R. A., & Nassikas, A. A. (2017). Global and regional fluxes of carbon from land use and land cover change 1850–2015. Global Biogeochemical Cycles, 31(3), 456–472. https://doi.org/10.1002/2016GB005546

Houndjo Kpoviwanou, M. R. J., Sourou, B. N. K., & Ouinsavi, C. A. I. N. (2024). Challenges in adoption and wide use of agroforestry technologies in Africa and pathways for improvement: A systematic review. Trees, Forests and People, 17, 100642. https://doi.org/10.1016/J.TFP.2024.100642

Hu, Y. (2019). Land Cover Changes and Their Driving Mechanisms in Central Asia from 2001 to 2017 Supported by Google Earth Engine. 2000. https://doi.org/10.3390/rs11050554

Huntley, B. J. (2023). The Ecological Role of Fire. Ecology of Angola, 149–165. https://doi.org/10.1007/978-3-031-18923-4_7

Ibrahim, S., Balzter, H., & Tansey, K. (2024a). Machine learning feature importance selection for predicting aboveground biomass in African savannah with landsat 8 and ALOS PALSAR data. Machine Learning with Applications, 16(January), 100561. https://doi.org/10.1016/j.mlwa.2024.100561

Ibrahim, S., Balzter, H., & Tansey, K. (2024b). Machine learning feature importance selection for predicting aboveground biomass in African savannah with landsat 8 and ALOS PALSAR data. Machine Learning with Applications, 16(May), 100561. https://doi.org/10.1016/j.mlwa.2024.100561

IPCC. (2006). 2006 IPCC - Guidelines for National Greenhouse Gas Inventories. Directrices Para Los Inventarios Nacionales GEI, 12. http://www.ipcc-nggip.iges.or.jp/public/2006gl/index.html

IRD. (2015). Semi-arid zones: the Sahel is sensitive to variations in rainfall. 115–128.

Jia, Z., Zhang, Z., Cheng, Y., Buhebaoyin, Borjigin, S., Quan, Z., Jia, Z., Zhang, Z., Cheng, Y., Buhebaoyin, Borjigin, S., & Quan, Z. (2024). Grassland biomass spatiotemporal patterns and response to climate change in eastern Inner Mongolia based on XGBoost model estimates. EcInd, 158, 111554. https://doi.org/10.1016/J.ECOLIND.2024.111554

Jiang, F., Sun, H., Ma, K., Fu, L., & Tang, J. (2022). Improving aboveground biomass estimation of natural forests on the Tibetan Plateau using spaceborne LiDAR and machine learning algorithms. Ecological Indicators, 143, 109365. https://doi.org/10.1016/J.ECOLIND.2022.109365

Johnson, E. A., & Miyanishi, K. (2008). Testing the assumptions of chronosequences in succession. Ecology Letters, 11(5), 419–431. https://doi.org/10.1111/j.1461-0248.2008.01173.x

Kafy, A. Al, Saha, M., Fattah, M. A., Rahman, M. T., Duti, B. M., Rahaman, Z. A., Bakshi, A., Kalaivani, S., Nafiz Rahaman, S., & Sattar, G. S. (2023). Integrating forest cover change and carbon storage dynamics: Leveraging Google Earth Engine and InVEST model to inform conservation in hilly regions. Ecological Indicators, 152(May), 110374. https://doi.org/10.1016/j.ecolind.2023.110374

Kalimantan, I. (2017). AN ABSTRACT OF THE DISSERTATION OF Title: Carbon Dynamics in Response to Land Cover Change in Tropical Peatlands.

Kaly, E., Sarr, O., Diatta, S., Diouf, A. A., Diouck, D., & Ngom, D. (2021). Characterization and Risk Assessment of the Collapse of the Woody Stand of Ecosystems of the Fathala Forest (Saloum Delta Biosphere Reserve-Senegal). American Journal of Plant Sciences, 12(07), 975–993. https://doi.org/10.4236/ajps.2021.127066

Kapuka, A., Dobor, L., & Hlásny, T. (2022). Climate change threatens the distribution of major woody species and ecosystem services provision in southern Africa. Science of The Total Environment, 850, 158006. https://doi.org/10.1016/J.SCITOTENV.2022.158006

Karlson, M., & Ostwald, M. (2016). Remote sensing of vegetation in the Sudano-Sahelian zone: A literature review from 1975 to 2014. Journal of Arid Environments, 124(124), 257–269. https://doi.org/10.1016/j.jaridenv.2015.08.022

Kauffman, J. B., & Bhomia, K. R. (2017). Ecosystem carbon stocks of mangroves across broad environmental gradients in West-Central Africa: Global and regional comparisons. PLoS ONE, 12(11), 1–17. https://doi.org/10.1371/journal.pone.0187749

Kebebew, Z., & Ozanne, C. (2024). Woody plants diversity and the associated provisioning ecosystem services across three contrasting forest management regimes in Southwest Ethiopia. Frontiers in Conservation Science, 5, 1382843. https://doi.org/10.3389/FCOSC.2024.1382843/BIBTEX

Kibet, S., Nyangito, M., MacOpiyo, L., & Kenfack, D. (2021). Savanna woody plants responses to mammalian herbivory and implications for management of livestock–wildlife landscape. Ecological Solutions and Evidence, 2(3), 1–13. https://doi.org/10.1002/2688-8319.12083

Kirschbaum, M. U. F., Cowie, A. L., Peñuelas, J., Smith, P., Conant, R. T., Sage, R. F., Brandão, M., Cotrufo, M. F., Luo, Y., Way, D. A., & Robinson, S. A. (2024). Is tree planting an effective strategy for climate change mitigation? Science of The Total Environment, 909, 168479. https://doi.org/10.1016/J.SCITOTENV.2023.168479

Knapp, N., Fischer, R., & Huth, A. (2018). Linking lidar and forest modeling to assess biomass estimation across scales and disturbance states. Remote Sensing of Environment, 205, 199–209. https://doi.org/10.1016/J.RSE.2017.11.018

KOMBATE, B., Atakpama, W., Egbelou, H., Yandja, M., Dourma, M., Batawila, K., Akpagana, K., Dourma, M., Batawila, K., & Akpagana, K. (2023). Structure and Modeling of the Forest Carbone of the Classified Forest of Missahohoé in Togo. African Journal on Land Policy and Geospatial Sciences, 6(1), 2657–2664. https://doi.org/10.48346/IMIST.PRSM/ajlp-gs.v6i1.35320

Kumar, M., Denis, D. M., Singh, S. K., Szabó, S., & Suryavanshi, S. (2018). Landscape metrics for assessment of land cover change and fragmentation of a heterogeneous watershed. In Remote Sensing Applications: Society and Environment (Vol. 10). Elsevier B.V. https://doi.org/10.1016/j.rsase.2018.04.002

Kursa, M. B., & Rudnicki, W. R. (2010). Feature selection with the boruta package. Journal of Statistical Software, 36(11), 1–13. https://doi.org/10.18637/jss.v036.i11

Lambin, E. F., & Meyfroidt, P. (2011). Global land use change, economic globalization, and the looming land scarcity. Proceedings of the National Academy of Sciences of the United States of America, 108(9), 3465–3472. https://doi.org/10.1073/PNAS.1100480108

Le, T. D. H., Pham, L. H., Dinh, Q. T., Hang, N. T. T., & Tran, T. A. T. (2022). Rapid method for yearly LULC classification using Random Forest and incorporating time-series NDVI and topography: a case study of Thanh Hoa province, Vietnam. Geocarto International, 37(27), 17200–17215. https://doi.org/10.1080/10106049.2022.2123959

Lebel, S., Ulrich, A., Bobb-semple, A., Matsumoto, I., Sinnassamy, J., Secretariat, G. E. F., Metternicht, G., & Duron, G. (2024). Land Degradation Neutrality Knowledge Management and Learning Initiative Learning from the GEF portfolio of projects.

Li, H., Hiroshima, T., Li, X., Hayashi, M., & Kato, T. (2024). High-resolution mapping of forest structure and carbon stock using multi-source remote sensing data in Japan. Remote Sensing of Environment, 312, 114322. https://doi.org/10.1016/J.RSE.2024.114322

Li, J., Lewis, J., Rowland, J., Tappan, G., & Tieszen, L. L. (2004). Evaluation of land performance in Senegal using multi-temporal NDVI and rainfall series. Journal of Arid Environments, 59(3), 463–480. https://doi.org/10.1016/J.JARIDENV.2004.03.019

Liu, J., Zhang, Y., Feng, Q., Yin, G., Zhang, D., Li, Y., Gong, J., Li, Y., & Li, J. (2024). Understanding urban expansion and shrinkage via green plastic cover mapping based on GEE cloud platform: A case study of Shandong, China. International Journal of Applied Earth Observation and Geoinformation, 128, 103749. https://doi.org/10.1016/J.JAG.2024.103749

Löhr, K., Eshetu, S. B., Moluh Njoya, H., Hagan, J. A., Gebremedhin, A. T., Hounkpati, K., Raharinaivo, H., Rakoto Ratsimba, H., Bekele, T., Adjonou, K., Kokou, K., & Sieber, S. (2024). Toward a social-ecological forest landscape restoration assessment framework: a review. Discover Sustainability, 5(1), 1–18. https://doi.org/10.1007/S43621-024-00342-Y/FIGURES/7

Lu, D. (2005). Aboveground biomass estimation using Landsat TM data in the Brazilian Amazon. International Journal of Remote Sensing, 26(12), 2509–2525. https://doi.org/10.1080/01431160500142145

Lu, Dengsheng, Chen, Q., Wang, G., Liu, L., Li, G., & Moran, E. (2016). A survey of remote sensing-based aboveground biomass estimation methods in forest ecosystems. International Journal of Digital Earth, 9(1), 63–105. https://doi.org/10.1080/17538947.2014.990526

Lund, H. G. (2015). Definitions of ‘ Tree ’ and ‘ Shrub .’ 1–17.

Lykke, A. M. (2000). Local perceptions of vegetation change and priorities for conservation of woody-savanna vegetation in Senegal. Journal of Environmental Management, 59(2), 107–120. https://doi.org/10.1006/jema.2000.0336

Ma, Y., Zhao, Y., Im, J., Zhao, Y., & Zhen, Z. (2024). A deep-learning-based tree species classification for natural secondary forests using unmanned aerial vehicle hyperspectral images and LiDAR. Ecological Indicators, 159, 111608. https://doi.org/10.1016/J.ECOLIND.2024.111608

Maguire, K. C., Nieto-Lugilde, D., Blois, J. L., Fitzpatrick, M. C., Williams, J. W., Ferrier, S., & Lorenz, D. J. (2016). Controlled comparison of species- and community-level models across novel climates and communities. Proceedings of the Royal Society B: Biological Sciences, 283(1826). https://doi.org/10.1098/RSPB.2015.2817

Mahmud, A. A., Raj, A., & Jhariya, M. K. (2021). Agroforestry systems in the tropics: A critical review. Agricultural and Biological Research, 37(1), 83–87. https://doi.org/10.35248/0970-1907.21.37.83-87

Makunga, J. E., Misana, S. B., Makunga, J. E., & Misana, S. B. (2017). The Extent and Drivers of Deforestation and Forest Degradation in Masito-Ugalla Ecosystem, Kigoma Region, Tanzania. Open Journal of Forestry, 7(2), 285–305. https://doi.org/10.4236/OJF.2017.72018

MANGA, B. A. B., NDOUR, N., DIATTA, A. A., & DASYLVA, M. (2022). Assessment of carbon sequestration by mangrove plantations in Casamance (Oussouye, Ziguinchor, Senegal). Journal of Ecology and The Natural Environment, 14(4), 109–120. https://doi.org/10.5897/jene2022.0936

Mathewos, M., Lencha, S. M., & Tsegaye, M. (2022). Land Use and Land Cover Change Assessment and Future Predictions in the Matenchose Watershed, Rift Valley Basin, Using CA-Markov Simulation. Land, 11(10). https://doi.org/10.3390/land11101632

Matyukira, C., & Mhangara, P. (2023). Land Cover and Landscape Structural Changes Using Extreme Gradient Boosting Random Forest and Fragmentation Analysis. Remote Sensing 2023, Vol. 15, Page 5520, 15(23), 5520. https://doi.org/10.3390/RS15235520

Matyukira, C., & Mhangara, P. (2024). Advances in vegetation mapping through remote sensing and machine learning techniques: a scientometric review. European Journal of Remote Sensing, 57(1). https://doi.org/10.1080/22797254.2024.2422330

Mauya, E. W., & Madundo, S. (2022). Modelling Above Ground Biomass Using Sentinel 2 and Planet Scope Data in Dense Tropical Montane Forests of Tanzania. Tanzania Journal of Forestry and Nature Conservation, 91(1), 132–153.

Maynard, C. L., Lawrence, R. L., Nielsen, G. A., & Decker, G. (2006). Modeling Vegetation Amount Using Bandwise Regression and Ecological Site Descriptions as an Alternative to Vegetation Indices. 4, 1–14.

Mazlan, S. M., Jaafar, W. S. W. M., Kamarulzaman, A. M. M., Saad, S. N. M., Ghazali, N. M., Adrah, E., Maulud, K. N. A., Omar, H., Teh, Y. A., Dzulkifli, D., & Mahmud, M. R. (2023). A Review on the Use of LiDAR Remote Sensing for Forest Landscape Restoration. Concepts and Applications of Remote Sensing in Forestry, 49–74. https://doi.org/10.1007/978-981-19-4200-6_3

Mbawine, J. S., & Dzekoto, G. E. (2023). Community-Based Woodland Restoration for Livelihoods and Sustainable Wood Fuel Utilisation in the Mole Ecological Landscape, Ghana. 13–33. https://doi.org/10.1007/978-981-99-1292-6_2

Mbow, C., Nielsen, T. T., & Rasmussen, K. (2000). Savanna Fires in East-Central Senegal : Distribution Patterns , Resource Management and Perceptions Author (s): C . Mbow , T . T . Nielsen and K . Rasmussen Published by : Springer Stable URL : http://www.jstor.org/stable/4603372 Savanna Fires in East-C. 28(4), 561–583.

Mbow, Cheikh, Verstraete, M. M., Sambou, B., Diaw, A. T., & Neufeldt, H. (2014). Allometric models for aboveground biomass in dry savanna trees of the Sudan and Sudan-Guinean ecosystems of Southern Senegal. Journal of Forest Research, 19(3), 340–347. https://doi.org/10.1007/s10310-013-0414-1

McNicol, I. M., Keane, A., Burgess, N. D., Bowers, S. J., Mitchard, E. T. A., & Ryan, C. M. (2023). Protected areas reduce deforestation and degradation and enhance woody growth across African woodlands. Communications Earth & Environment 2023 4:1, 4(1), 1–14. https://doi.org/10.1038/s43247-023-01053-4

MEDD. (2015). Stratégie nationale & plan natioal d’actions pour la Biodiversité. chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://www.cbd.int/doc/world/sn/sn-nbsap-v2-fr.pdf

Mercker, D., & Yang, S.-I. (2022). A Simple Guide to Common Forest Measurements. UT Extension, W1117, 1–7. www.uhcl.edu

Mildrexler, D. J., Berner, L. T., Law, B. E., Birdsey, R. A., & Moomaw, W. R. (2023). Protect large trees for climate mitigation, biodiversity, and forest resilience. Conservation Science and Practice, 5(7), 1–10. https://doi.org/10.1111/csp2.12944

Mishra, S. N., Kulkarni, N., Mishra, Y., Pandey, K., & Kumar, R. (2022). Quantification of Above Ground Biomass (AGB) and Carbon Stock, Help to Mitigate Climate Change in the Western Plateau Forest Division of Jharkhand. Advance in Sustainability, 2(1), 1–10. https://doi.org/10.26855/as.2022.04.001

Mitchard, E. T. A. (2018). The tropical forest carbon cycle and climate change. Nature, 559(7715), 527–534. https://doi.org/10.1038/S41586-018-0300-2

Mograbi, P. J., Erasmus, B. F. N., Witkowski, E. T. F., Asner, G. P., Wessels, K. J., Mathieu, R., Knapp, D. E., Martin, R. E., & Main, R. (2015). Biomass Increases Go under Cover: Woody Vegetation Dynamics in South African Rangelands. PloS One, 10(5). https://doi.org/10.1371/JOURNAL.PONE.0127093

Mohamed Mahamoud, C., Lô, M., Bassène, E., & Akpo, L, E. (2008). Caractéristiques de la flore et de la végétation ligneuses des forêts communautaires de la zone soudano-sahélienne au Sénégal. Journal Des Sciences et Technologies, 6(August), 72–85.

Mohammed, A. M., Robinson, J. S., Midmore, D., & Verhoef, A. (2016). Carbon storage in Ghanaian cocoa ecosystems. Carbon Balance and Management, 11(1), 1–8. https://doi.org/10.1186/S13021-016-0045-X/FIGURES/3

Moore, S., Adu-Bredu, S., Duah-Gyamfi, A., Addo-Danso, S. D., Ibrahim, F., Mbou, A. T., de Grandcourt, A., Valentini, R., Nicolini, G., Djagbletey, G., Owusu-Afriyie, K., Gvozdevaite, A., Oliveras, I., Ruiz-Jaen, M. C., & Malhi, Y. (2018). Forest biomass, productivity and carbon cycling along a rainfall gradient in West Africa. Global Change Biology, 24(2), e496–e510. https://doi.org/10.1111/GCB.13907

Moreno-Martínez, Á., Camps-Valls, G., Kattge, J., Robinson, N., Reichstein, M., van Bodegom, P., Kramer, K., Cornelissen, J. H. C., Reich, P., Bahn, M., Niinemets, Ü., Peñuelas, J., Craine, J. M., Cerabolini, B. E. L., Minden, V., Laughlin, D. C., Sack, L., Allred, B., Baraloto, C., … Running, S. W. (2018). A methodology to derive global maps of leaf traits using remote sensing and climate data. Remote Sensing of Environment, 218, 69–88. https://doi.org/10.1016/J.RSE.2018.09.006

Moyo, H., Slotow, R., Rouget, M., Mugwedi, L., Douwes, E., Tsvuura, Z., & Tshabalala, T. (2021). Adaptive management in restoration initiatives: Lessons learned from some of South Africa's projects. South African Journal of Botany, 139, 352–361. https://doi.org/10.1016/J.SAJB.2021.03.016

Mulatu, A., Negash, M., & Asrat, Z. (2024). Species-specific allometric models for reducing uncertainty in estimating above ground biomass at Moist Evergreen Afromontane Forest of Ethiopia. Scientific Reports 2024 14:1, 14(1), 1–11. https://doi.org/10.1038/s41598-023-51002-6

Mussa, M., Ebro, A., & Nigatu, L. (2016). Impact of woody plants species on soil physico-chemical properties along grazing gradients in rangelands of eastern Ethiopia. Tropical and Subtropical Agroecosystems, 19(3), 343–355. https://doi.org/10.56369/TSAES.2254

Mutanga, O., Adam, E., & Cho, M. A. (2012). High density biomass estimation for wetland vegetation using WorldView-2 imagery and random forest regression algorithm. International Journal of Applied Earth Observation and Geoinformation, 18(1), 399–406. https://doi.org/10.1016/J.JAG.2012.03.012

Nalivata, P., Kibunja, C., Mutegi, J., Tetteh, F., Tarfa, B., Dicko, M. K., Ouattara, K., Cyamweshi, R. A., Nouri, M. K., Bayu, W., & Wortmann, C. S. (2017). Integrated soil fertility management in sub-Saharan Africa. Fertilizer Use Optimization in Sub-Saharan Africa, 25–39. https://doi.org/10.1079/9781786392046.0025

Nam, V. T., Van Kuijk, M., & Anten, N. P. R. (2016). Allometric equations for aboveground and belowground biomass estimations in an evergreen forest in Vietnam. PLoS ONE, 11(6). https://doi.org/10.1371/JOURNAL.PONE.0156827

Nasr, M., & Orwin, J. F. (2024). A geospatial approach to identifying and mapping areas of relative environmental pressure on ecosystem integrity. Journal of Environmental Management, 370, 122445. https://doi.org/10.1016/J.JENVMAN.2024.122445

Nawaz, M., Sun, J., Shabbir, S., Khattak, W. A., Ren, G., Nie, X., Bo, Y., Javed, Q., Du, D., & Sonne, C. (2023). A review of plants strategies to resist biotic and abiotic environmental stressors. Science of The Total Environment, 900, 165832. https://doi.org/10.1016/J.SCITOTENV.2023.165832

Ndao, B., Leroux, L., Hema, A., Diouf, A. A., Bégué, A., & Sambou, B. (2022). Tree species diversity analysis using species distribution models: A Faidherbia albida parkland case study in Senegal. Ecological Indicators, 144(September). https://doi.org/10.1016/j.ecolind.2022.109443

Nel, L., Boeni, A. F., Prohászka, V. J., Szilágyi, A., Tormáné Kovács, E., Pásztor, L., & Centeri, C. (2022). InVEST Soil Carbon Stock Modelling of Agricultural Landscapes as an Ecosystem Service Indicator. Sustainability (Switzerland), 14(16). https://doi.org/10.3390/SU14169808

Nero, B. F., Kuusaana, E. D., Ahmed, A., & Campion, B. B. (2024). Carbon storage and tree species diversity of urban parks in Kumasi, Ghana. City and Environment Interactions, 24, 100156. https://doi.org/10.1016/J.CACINT.2024.100156

Nguyen, T. T., Grote, U., Neubacher, F., Rahut, D. B., Do, M. H., & Paudel, G. P. (2023). Security risks from climate change and environmental degradation: implications for sustainable land use transformation in the Global South. Current Opinion in Environmental Sustainability, 63, 101322. https://doi.org/10.1016/J.COSUST.2023.101322

Niklas, K. J. . (1994). Plant allometry : the scaling of form and process. 395.

Nizamani, M. M., Zhang, Q., Muhae-Ud-Din, G., Awais, M., Qayyum, M., Farhan, M., Jabran, M., & Wang, Y. (2023). Application of GIS and Remote-Sensing Technology in Ecosystem Services and Biodiversity Conservation. Deep Learning for Multimedia Processing Applications, 284–321. https://doi.org/10.1201/9781032646268-12

Njenga, M., Sears, R. R., & Mendum, R. (2023). Sustainable woodfuel systems: a theory of change for sub-Saharan Africa. Environmental Research Communications, 5(5). https://doi.org/10.1088/2515-7620/acd0f3

Noi Phan, T., Kuch, V., & Lehnert, L. W. (2020). Land cover classification using google earth engine and random forest classifier-the role of image composition. Remote Sensing, 12(15). https://doi.org/10.3390/RS12152411

Nyamekye, C., Thiel, M., Schönbrodt-Stitt, S., Zoungrana, B. J. B., & Amekudzi, L. K. (2018). Soil and water conservation in Burkina Faso, West Africa. Sustainability (Switzerland), 10(9). https://doi.org/10.3390/su10093182

O'Brien, R. M. (2007). A caution regarding rules of thumb for variance inflation factors. Quality and Quantity, 41(5), 673–690. https://doi.org/10.1007/S11135-006-9018-6

Oduro Appiah, J., Agyemang-Duah, W., Sobeng, A. K., & Kpienbaareh, D. (2021). Analysing patterns of forest cover change and related land uses in the Tano-Offin forest reserve in Ghana: Implications for forest policy and land management. Trees, Forests and People, 5, 100105. https://doi.org/10.1016/J.TFP.2021.100105

Oehmcke, S., Li, L., Revenga, J. C., Nord-Larsen, T., Trepekli, K., Gieseke, F., & Igel, C. (2021). Deep Learning Based 3D Point Cloud Regression for Estimating Forest Biomass. GIS: Proceedings of the ACM International Symposium on Advances in Geographic Information Systems. https://doi.org/10.1145/3557915.3561471

Olagoke, A. (2016). Towards a Better Characterization of Morphological Plasticity and Biomass Partitioning of Trees in Structural Dynamics of Mangrove Forests. https://hal.ird.fr/tel-02077742%0Ahttps://hal.ird.fr/tel-02077742/document

Olatujoye, F., Oluwajuwon, T. V., Olasuyi, K. E., Bukoye, J. A., Bodunde, T. O., & Oke, D. O. (2025). Farmers' perceptions of the practices, benefits and challenges of on-farm tree planting in Akure, Nigeria. Agroforestry Systems, 99(1), 1–20. https://doi.org/10.1007/S10457-024-01109-0/TABLES/5

Opelele, O. M., Yu, Y., Fan, W., Chen, C., & Kachaka, S. K. (2021). Biomass estimation based on multilinear regression and machine learning algorithms in the mayombe tropical forest, in the democratic republic of congo. Applied Ecology and Environmental Research, 19(1), 359–377. https://doi.org/10.15666/aeer/1901_359377

Oumar, C., Mamoudou Abdoul, T., Elhadji, F., Halimatou Sadyane, B., Adja Madjiguene, D., Souleye, B., & Diaminatou, S. (2018). Caractéristiques sociodémographique, structurale et agronomique des plantations d'anacardier (Anacardium occidentale L.) du Bassin arachidier et de la Casamance / Sénégal. Journal of Animal & Plant Sciences, 38(January), 6307–6325.

Pal, S. C., Chatterjee, U., Chakrabortty, R., Roy, P., Chowdhuri, I., Saha, A., Towfiqul Islam, A. R. M., Alam, E., & Islam, M. K. (2023). Anthropogenic drivers induced desertification under changing climate: Issues, policy interventions, and the way forward. Progress in Disaster Science, 20, 100303. https://doi.org/10.1016/J.PDISAS.2023.100303

Pandit, S., Tsuyuki, S., & Dube, T. (2018). Estimating above-ground biomass in sub-tropical buffer zone community forests, Nepal, using Sentinel 2 data. Remote Sensing, 10(4). https://doi.org/10.3390/rs10040601

Panwar, P., Shukla, G., Bhat, J. A., & Chakravarty, S. (2022). Land Degradation Neutrality: Achieving SDG 15 by Forest Management. Land Degradation Neutrality: Achieving SDG 15 by Forest Management, January 2023, 1–452. https://doi.org/10.1007/978-981-19-5478-8

Pereira Mendes, C., & Lim, N. T. L. (2024). EcoLiDAR: An economical LiDAR scanner for ecological research. PloS One, 19(6), e0298712. https://doi.org/10.1371/journal.pone.0298712

Picard, N., Boyemba Bosela, F., & Rossi, V. (2015). Reducing the error in biomass estimates strongly depends on model selection. Annals of Forest Science, 72(6), 811–823. https://doi.org/10.1007/S13595-014-0434-9/FIGURES/2

Poorter, L., van der Sande, M. T., Amissah, L., Bongers, F., Hordijk, I., Kok, J., Laurance, S. G. W., Martínez-Ramos, M., Matsuo, T., Meave, J. A., Muñoz, R., Peña-Claros, M., van Breugel, M., Herault, B., Jakovac, C. C., Lebrija-Trejos, E., Norden, N., & Lohbeck, M. (2024). A comprehensive framework for vegetation succession. Ecosphere, 15(4), 1–25. https://doi.org/10.1002/ecs2.4794

Porfirio, L. L., Harris, R. M. B., Lefroy, E. C., Hugh, S., Gould, S. F., Lee, G., Bindoff, N. L., & Mackey, B. (2014). Improving the Use of Species Distribution Models in Conservation Planning and Management under Climate Change. PLOS ONE, 9(11), e113749. https://doi.org/10.1371/JOURNAL.PONE.0113749

Potter, E. F., Monney, I., & Rutten, M. (2023). Bridging the data gap: using remote sensing and open-access data for assessing sustainable groundwater use in Kumasi, Ghana. Journal of Water and Climate Change, 14(9), 3237–3256. https://doi.org/10.2166/WCC.2023.261

Prance, G. T. (2006). Tropical savannas and seasonally dry forests: An introduction. Journal of Biogeography, 33(3), 385–386. https://doi.org/10.1111/J.1365-2699.2005.01471.X

Prudente, V. H. R., Martins, V. S., Vieira, D. C., Silva, N. R. de F. e., Adami, M., & Sanches, I. D. A. (2020). Limitations of cloud cover for optical remote sensing of agricultural areas across South America. Remote Sensing Applications: Society and Environment, 20. https://doi.org/10.1016/J.RSASE.2020.100414

Puliti, S., Hauglin, M., Breidenbach, J., Montesano, P., Neigh, C. S. R., Rahlf, J., Solberg, S., Klingenberg, T. F., & Astrup, R. (2020). Modelling above-ground biomass stock over Norway using national forest inventory data with ArcticDEM and Sentinel-2 data. Remote Sensing of Environment, 236(January), 111501. https://doi.org/10.1016/j.rse.2019.111501

Rahman, A. ur, Khan, S. M., Ahmad, Z., Alamri, S., Hashem, M., Ilyas, M., Aksoy, A., Dülgeroğlu, C., & Shahab Ali, G. K. (2021). -Impact of multiple environmental factors on species abundance in various forest layers using an integrative modeling approach. Global Ecology and Conservation, 29, e01712. https://doi.org/10.1016/J.GECCO.2021.E01712

Raihan, A. (2023). Artificial intelligence and machine learning applications in forest management and biodiversity conservation. Natural Resources Conservation and Research, 6(2), 3825. https://doi.org/10.24294/NRCR.V6I2.3825

Ranius, T., Hämäläinen, A., Egnell, G., Olsson, B., Eklöf, K., Stendahl, J., Rudolphi, J., Sténs, A., & Felton, A. (2018). The effects of logging residue extraction for energy on ecosystem services and biodiversity: a synthesis. https://doi.org/10.17011/CONFERENCE/ECCB2018/107245

Reinke, K., & Jones, S. (2006). Integrating vegetation field surveys with remotely sensed data. Ecological Management and Restoration, 7(SUPPL. 1). https://doi.org/10.1111/J.1442-8903.2006.00287.X

Reutebuch, S. E., Andersen, H. E., & McGaughey, R. J. (2005). Light detection and ranging (LIDAR): An emerging tool for multiple resource inventory. Journal of Forestry, 103(6), 286–292. https://doi.org/10.1093/JOF/103.6.286

Reyes, G., Brown, S., Chapman, J., & Lugo, A. E. (1992). Wood Densities of Tropical Tree Species. Gen. Tech. Rep. SO-88. New Orleans, LA: U.S. Dept of Agriculture, Forest Service, Southern Forest Experiment Station. 15 P., 88. https://doi.org/10.2737/SO-GTR-88

Richards, D. R., & Belcher, R. N. (2019). Global Changes in Urban Vegetation Cover.

Richards, S. J., Warneke, J. E., Marsh, A. W., & Aljibury, F. K. (2024). Physical properties of soil mixes. Soil Science, 98(2), 129–132. https://doi.org/10.1097/00010694-196408000-00009

Rivas, C. A., Guerrero-Casado, J., & Navarro-Cerrillo, R. M. (2022). A New Combined Index to Assess the Fragmentation Status of a Forest Patch Based on Its Size, Shape Complexity, and Isolation. Diversity, 14(11). https://doi.org/10.3390/d14110896

Robinson, L. W., Eba, B., Flintan, F., Frija, A., Nganga, I. N., Ontiri, E. M., Sghaier, M., Abdu, N. H., & Moiko, S. S. (2021). The Challenges of Community-Based Natural Resource Management in Pastoral Rangelands. Society and Natural Resources, 34(9), 1213–1231. https://doi.org/10.1080/08941920.2021.1946629

Rodrigues de Almeida, C., Garcia, N., Campos, J. C., Alírio, J., Arenas-Castro, S., Gonçalves, A., Sillero, N., & Teodoro, A. C. (2023). Time-series analyses of land surface temperature changes with Google Earth Engine in a mountainous region. Heliyon, 9(8), e18846. https://doi.org/10.1016/J.HELIYON.2023.E18846

Rodríguez-Medina, K., Yañez-Arenas, C., Peterson, A. T., Ávila, J. E., & Herrera-Silveira, J. (2020). Evaluating the capacity of species distribution modeling to predict the geographic distribution of the mangrove community in Mexico. PLoS ONE, 15(8), e0237701. https://doi.org/10.1371/JOURNAL.PONE.0237701

Rosa, I. M. D., Gabriel, C., & Carreiras, J. M. B. (2017). Spatial and temporal dimensions of landscape fragmentation across the Brazilian Amazon. Regional Environmental Change, 17(6), 1687–1699. https://doi.org/10.1007/s10113-017-1120-x

Roy, A. D., & Debbarma, S. (2024). Comparing the allometric model to machine learning algorithms for aboveground biomass estimation in tropical forests. https://doi.org/10.1016/j.ecofro.2024.05.010

Rueda-M, N., Salgado-Roa, F. C., Gantiva-Q, C. H., Pardo-Díaz, C., & Salazar, C. (2021). Environmental Drivers of Diversification and Hybridization in Neotropical Butterflies. Frontiers in Ecology and Evolution, 9. https://doi.org/10.3389/FEVO.2021.750703

Ruhana, F., Suwartiningsih, S., Mulyandari, E., Handoyo, S., & Afrilia, U. A. (2024). Innovative Strategies for Achieving Sustainable Development Goals Amidst Escalating Global Environmental and Social Challenges. International Journal of Science and Society, 6(1), 662–677. https://doi.org/10.54783/IJSOC.V6I1.1054

Salimi, H., Fadaei Nezhad Bahramjerdi, S., & Tootoonchi, R. (2024). The Role of Geographic Information Systems (GIS) in Participatory Conservation of Heritage Areas. European Journal of Geography, 16(1), 1–11. https://doi.org/10.48088/EJG.SI.SPAT.HUM.H.SAL.1.11

Sallmannshofer, M., Chakraborty, D., Vacik, H., Illés, G., Löw, M., Rechenmacher, A., Lapin, K., Ette, S., Stojanović, D., Kobler, A., & Schueler, S. (2021). Continent-wide tree species distribution models may mislead regional management decisions: A case study in the transboundary biosphere reserve mura-drava-danube. Forests, 12(3), 1–25. https://doi.org/10.3390/f12030330

Salvini, G., Ligtenberg, A., van Paassen, A., Bregt, A. K., Avitabile, V., & Herold, M. (2016). REDD+ and climate smart agriculture in landscapes: A case study in Vietnam using companion modelling. Journal of Environmental Management, 172, 58–70. https://doi.org/10.1016/j.jenvman.2015.11.060

Sambou, A., Sambou, B., & Ræbild, A. (2017). Farmers' contributions to the conservation of tree diversity in the Groundnut Basin, Senegal. Journal of Forestry Research, 28(5), 1083–1096. https://doi.org/10.1007/S11676-017-0374-Y/METRICS

Sambou, A., Theilade, I., Fensholt, R., & Ræbild, A. (2016). Decline of woody vegetation in a saline landscape in the Groundnut Basin, Senegal. Regional Environmental Change, 16(6), 1765–1777. https://doi.org/10.1007/s10113-016-0929-z

Sambou, B., Bâ, A., Mbow, C., & Goudiaby, A. (2008). Studies of the Woody Vegetation of the Welor Forest Reserve (Senegal) for Sustainable Use. West African Journal of Applied Ecology, 13(1). https://doi.org/10.4314/wajae.v13i1.40577

Sambou, S. (2015). Land Use-Land Cover Change and Drivers of Deforestation in the Patako Protected Area (Center-West of Senegal). American Journal of Environmental Protection, 4(6), 306. https://doi.org/10.11648/j.ajep.20150406.17

Sanguet, A., Wyler, N., Petitpierre, B., Honeck, E., Poussin, C., Martin, P., & Lehmann, A. (2022). Beyond topo-climatic predictors: Does habitats distribution and remote sensing information improve predictions of species distribution models? Global Ecology and Conservation, 39, e02286. https://doi.org/10.1016/J.GECCO.2022.E02286

Sankaran, M. (2019). Droughts and the ecological future of tropical savanna vegetation. Journal of Ecology, 107(4), 1531–1549. https://doi.org/10.1111/1365-2745.13195

Sarr, O., Ngom, D., Bakhoum, A., & Akpo, L. E. (2013). Dynamique du peuplement ligneux dans un parcours agrosylvopastoral du Sénégal. VertigO, Volume 13 Numéro 2. https://doi.org/10.4000/vertigo.14067

SDG. (2015). Sustainable Development Goals . https://www.google.com/search?q=sustainable+development+goals+pdf&sca_esv=1f4a6e3d386086c2&sxsrf=ADLYWILZZWiv587b8faiOm7TWSqkcfw8kQ%3A1737211948967&ei=LMCLZ_zgOqaAhbIPoZGQiQ8&ved=0ahUKEwj8pvjowv-KAxUmQEEAHaEIJPEQ4dUDCBA&uact=5&oq=sustainable+development+goals+pdf&gs_lp=Egxnd3Mtd2l6LXNlcnAiIXN1c3RhaW5hYmxlIGRldmVsb3BtZW50IGdvYWxzIHBkZjIIEAAYgAQYywEyCBAAGIAEGMsBMggQABiABBjLATIIEAAYgAQYywEyCBA

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Seghieri, J., Vescovo, A., Padel, K., Soubie, R., Arjounin, M., Boulain, N., de Rosnay, P., Galle, S., Gosset, M., Mouctar, A. H., Peugeot, C., & Timouk, F. (2009). Relationships between climate, soil moisture and phenology of the woody cover in two sites located along the West African latitudinal gradient. Journal of Hydrology, 375(1–2), 78–89. https://doi.org/10.1016/J.JHYDROL.2009.01.023

Sene, J. H. B., Faye, E., & Tine, A. K. (2024). Curbing the Salinization of Arable Land and Agronomically Restoring Salt-affected Soils, a food security challenge: assessment and prospects, the case of Senegal, West Africa. Moscow University Soil Science Bulletin 2023 78:5, 78(5), 461–466. https://doi.org/10.3103/S014768742305006X

Sertel, E., Topaloğlu, R. H., Şallı, B., Algan, I. Y., & Aksu, G. A. (2018). Comparison of landscape metrics for three different level land cover/land use maps. ISPRS International Journal of Geo-Information, 7(10). https://doi.org/10.3390/ijgi7100408

Seware, B. (2015). Rangeland degradation and restoration: A global perspective. Point Journal of Agriculture and Biotechnology Research, Citation:(August), 18.

Shaffer, J. G., Doumbia, S. O., Ndiaye, D., Diarra, A., Gomis, J. F., Nwakanma, D., Abubakar, I., Ahmad, A., Affara, M., Lukowski, M., Valim, C., Welty, J. C., Mather, F. J., Keating, J., & Krogstad, D. J. (2018). Development of a data collection and management system in West Africa: Challenges and sustainability. Infectious Diseases of Poverty, 7(1), 1–14. https://doi.org/10.1186/S40249-018-0494-4/TABLES/6

Sharma, R. C. (2022). Countrywide Mapping of Plant Ecological Communities with 101 Legends including Land Cover Types for the First Time at 10 m Resolution through Convolutional Learning of Satellite Images. Applied Sciences (Switzerland), 12(14). https://doi.org/10.3390/app12147125

Shih, S.-S., Ding, T.-S., Chen, C.-P., Huang, S.-C., & Hsieh, H.-L. (2019). Landscape structured by physical settings and benthic polychaete and avifauna habitat uses in a mangrove-vegetated estuary. BioRxiv. https://doi.org/10.1101/2019.12.12.874008

Silva, J., Bacao, F., & Caetano, M. (2017). Specific land cover class mapping by semi-supervised weighted support vector machines. Remote Sensing, 9(2), 1–16. https://doi.org/10.3390/rs9020181

Sinare, H., & Gordon, L. J. (2015a). Ecosystem services from woody vegetation on agricultural lands in Sudano-Sahelian West Africa. Agriculture, Ecosystems and Environment, 200, 186–199. https://doi.org/10.1016/j.agee.2014.11.009

Sinare, H., & Gordon, L. J. (2015b). Ecosystem services from woody vegetation on agricultural lands in Sudano-Sahelian West Africa. Agriculture, Ecosystems and Environment, 200, 186–199. https://doi.org/10.1016/J.AGEE.2014.11.009

Singh, B., Verma, A. K., Tiwari, K., & Joshi, R. (2023). Above ground tree biomass modeling using machine learning algorithms in western Terai Sal Forest of Nepal. Heliyon, 9(11), e21485. https://doi.org/10.1016/j.heliyon.2023.e21485

Singh, C., Karan, S. K., Sardar, P., & Samadder, S. R. (2022). Remote sensing-based biomass estimation of dry deciduous tropical forest using machine learning and ensemble analysis. Journal of Environmental Management, 308(January), 114639. https://doi.org/10.1016/j.jenvman.2022.114639

Singh, R., Behera, M. D., Das, P., Rizvi, J., Dhyani, S. K., & Biradar, C. M. (2022). Agroforestry Suitability for Planning Site-Specific Interventions Using Machine Learning Approaches. Sustainability (Switzerland), 14(9). https://doi.org/10.3390/su14095189

Singh, S. K., Srivastava, P. K., Szabó, S., Petropoulos, G. P., Gupta, M., & Islam, T. (2017). Landscape transform and spatial metrics for mapping spatiotemporal land cover dynamics using Earth Observation data-sets. Geocarto International, 32(2), 113–127. https://doi.org/10.1080/10106049.2015.1130084

Solly, B., Andrieu, J., Dieye, E. H. B., & Jarju, A. M. (2022). Dynamiques contrastées de reverdissement et dégradation de la couverture végétale au Sénégal révélées par analyse de série temporelle du NDVI MODIS. VertigO, Volume 22 Numéro 1. https://doi.org/10.4000/vertigo.35589

Solly, B., Dieye, E. H. B., Sy, O., Sane, T., Diedhiou, I., Ba, B. D., & Thior, M. (2020). Dynamique de la déforestation en zone frontalière au nord de la Haute-Casamance (Sénégal). Norois, 257, 21–35. https://doi.org/10.4000/norois.10480

Song, D. X., Huang, C., He, T., Sexton, J. O., Li, A., Li, S., Wu, H., & Townshend, J. R. (2021). Improved modeling and analysis of the patch size–frequency distribution of forest disturbances in China based on a Landsat forest cover change product. International Journal of Digital Earth, 14(2), 181–201. https://doi.org/10.1080/17538947.2020.1810337

Soori, M., Arezoo, B., & Dastres, R. (2023). Artificial intelligence, machine learning and deep learning in advanced robotics, a review. Cognitive Robotics, 3(April), 54–70. https://doi.org/10.1016/j.cogr.2023.04.001

Souverijns, N., Buchhorn, M., Horion, S., Fensholt, R., Verbeeck, H., Verbesselt, J., Herold, M., Tsendbazar, N. E., Bernardino, P. N., Somers, B., & Van De Kerchove, R. (2021). THIRTY YEARS OF LAND COVER AND FRACTION COVER CHANGES OVER THE SUDANO-SAHEL USING LANDSAT TIME SERIES. International Geoscience and Remote Sensing Symposium (IGARSS), 6170–6173. https://doi.org/10.1109/IGARSS47720.2021.9554349

Spicer, R., & Groover, A. (2010). Evolution of development of vascular cambia and secondary growth. New Phytologist, 186(3), 577–592. https://doi.org/10.1111/J.1469-8137.2010.03236.X

Spracklen, D. V., Baker, J. C. A., Garcia-Carreras, L., & Marsham, J. H. (2018). The effects of tropical vegetation on rainfall. Annual Review of Environment and Resources, 43(December), 193–218. https://doi.org/10.1146/annurev-environ-102017-030136

Srivastava, V., Lafond, V., & Griess, V. C. (2019). Species distribution models (SDM):

Applications, benefits and challenges in invasive species management. CAB Reviews: Perspectives in Agriculture, Veterinary Science, Nutrition and Natural Resources, 14(December). https://doi.org/10.1079/PAVSNNR201914020

Stahl, A. T., Andrus, R., Hicke, J. A., Hudak, A. T., Bright, B. C., & Meddens, A. J. H. (2023). Automated attribution of forest disturbance types from remote sensing data: A synthesis. Remote Sensing of Environment, 285, 113416. https://doi.org/10.1016/J.RSE.2022.113416

Stephenson, N. L., Das, A. J., Condit, R., Russo, S. E., Baker, P. J., Beckman, N. G., Coomes, D. A., Lines, E. R., Morris, W. K., Rüger, N., Álvarez, E., Blundo, C., Bunyavejchewin, S., Chuyong, G., Davies, S. J., Duque, Á., Ewango, C. N., Flores, O., Franklin, J. F., … Zavala, M. A. (2014). Rate of tree carbon accumulation increases continuously with tree size. Nature, 507(7490), 90–93. https://doi.org/10.1038/NATURE12914

Strnad, D., Horvat, Š., Mongus, D., Ivajnšič, D., & Kohek, Š. (2023). Detection and Monitoring of Woody Vegetation Landscape Features Using Periodic Aerial Photography. Remote Sensing, 15(11), 1–18. https://doi.org/10.3390/rs15112766

Stroh, E. D., Struckhoff, M. A., Stambaugh, M. C., & Guyette, R. P. (2018). Fire and Climate Suitability for Woody Vegetation Communities in the South Central United States. Fire Ecology, 14(1), 106–124. https://doi.org/10.4996/FIREECOLOGY.140110612/FIGURES/5

Swaine, M. D. (1992). Characteristics of dry forest in West Africa and the influence of fire. Journal of Vegetation Science, 3(3), 365–374. https://doi.org/10.2307/3235762

Symeonakis, E., Petroulaki, K., & Higginbottom, T. (2016). Landsat-based woody vegetation cover monitoring in Southern African savannahs. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives, 41(July), 563–567. https://doi.org/10.5194/isprsarchives-XLI-B7-563-2016

Taelman, S. E., De Luca Peña, L. V., Préat, N., Bachmann, T. M., Van der Biest, K., Maes, J., & Dewulf, J. (2024). Integrating ecosystem services and life cycle assessment: a framework accounting for local and global (socio-)environmental impacts. International Journal of Life Cycle Assessment, 29(1), 99–115. https://doi.org/10.1007/S11367-023-02216-3/TABLES/3

Tamiminia, H., Salehi, B., Mahdianpari, M., Quackenbush, L., Adeli, S., & Brisco, B. (2020). Google Earth Engine for geo-big data applications: A meta-analysis and systematic review. ISPRS Journal of Photogrammetry and Remote Sensing, 164, 152–170. https://doi.org/10.1016/J.ISPRSJPRS.2020.04.001

Tang, X., Yu, D., Lv, H., Ou, Q., Xie, M., Fan, P., & Huang, Q. (2024). Construction of Remote Sensing Quantitative Model for Biomass of Deciduous Broad-Leaved Forest in Mazongling Nature Reserve Based on Machine Learning. Journal of the Indian Society of Remote Sensing, 52(9), 1953–1968. https://doi.org/10.1007/S12524-024-01901-6/FIGURES/6

Tarif, K., Mobjörk, M., & Krampe, F. (2022). CLIMATE CHANGE AND VIOLENT CONFLICT IN WEST AFRICA : ASSESSING THE. 20.

Thiam, S., Villamor, G. B., Faye, L. C., Sène, J. H. B., Diwediga, B., & Kyei-Baffour, N. (2021). Monitoring land use and soil salinity changes in coastal landscape: a case study from Senegal. Environmental Monitoring and Assessment, 193(5). https://doi.org/10.1007/s10661-021-

08958-7

Thimonier, A., Kull, P., Keller, W., Moser, B., Wohlgemuth, T., & Kull, P. (2011). Ground vegetation monitoring in Swiss forests: comparison of survey methods and implications for trend assessments. Environ Monit Assess, 174, 47–63. https://doi.org/10.1007/s10661-010-1759-y

Tian, W., & Zhao, Y. (2015). An Introduction to Cloud Computing. Optimized Cloud Resource Management and Scheduling, 1–15. https://doi.org/10.1016/B978-0-12-801476-9.00001-X

Tiawoun, M. A. P., Malan, P. W., & Comole, A. A. (2022). Effects of Soil Properties on the Distribution of Woody Plants in Communally Managed Rangelands in Ngaka Modiri Molema District, North-West Province, South Africa. Ecologies 2022, Vol. 3, Pages 361-375, 3(3), 361–375. https://doi.org/10.3390/ECOLOGIES3030027

Tine, D., Faye, M., Diouf, E. M., Fall, A., & Faye, B. (2020). Détection de changement d'occupation du solet analyse de la dynamique des terres salées dans le Département de Foundiougne (Sénégal). IOSR Journal of Engineering (IOSRJEN) Www.Iosrjen.Org ISSN, 10(April), 2278–8719. www.iosrjen.org

Tine, D., Faye, M., Diouf, E. M., & Faye, B. (2020). Détection de changement d ' occupation du sol et analyse de la dynamique des terres salées dans le Département de Foundiougne (Sénégal). 10(4), 18–31.

Tolentino, F. M., & de Lourdes Bueno Trindade Galo, M. (2021). Selecting features for LULC simultaneous classification of ambiguous classes by artificial neural network. Remote Sensing Applications: Society and Environment, 24, 100616. https://doi.org/10.1016/J.RSASE.2021.100616

Tong, R., Davies, A. J., Yesson, C., Yu, J., Luo, Y., Zhang, L., & Burgos, J. M. (2023). Environmental drivers and the distribution of cold-water corals in the global ocean. Frontiers in Marine Science, 10(October). https://doi.org/10.3389/fmars.2023.1217851

Touré, K., Sall, M., Diallo, M., Sabaly, I. K., Thiam, A., Sagna, O. B., Thiam, M., Sall, B., Dioum, M., & Diagne, M. (2019). Économie de la dégradation de la forêt classée de Pata au Sénégal.

Tsamardinos, I., Greasidou, E., & Borboudakis, G. (2018). Bootstrapping the out-of-sample predictions for efficient and accurate cross-validation. Machine Learning, 107(12), 1895–1922. https://doi.org/10.1007/S10994-018-5714-4/FIGURES/7

Tuanmu, M. N., Viña, A., Bearer, S., Xu, W., Ouyang, Z., Zhang, H., & Liu, J. (2010). Mapping understory vegetation using phenological characteristics derived from remotely sensed data. Remote Sensing of Environment, 114(8), 1833–1844. https://doi.org/10.1016/J.RSE.2010.03.008

Tülay, T., & Başkan, O. (2022). Assessment of Land Degradation Factors. Intech, i(tourism), 13. http://dx.doi.org/10.1039/C7RA00172J%0Ahttps://www.intechopen.com/books/advanced-biometric-technologies/liveness-detection-in-biometrics%0Ahttp://dx.doi.org/10.1016/j.colsurfa.2011.12.014

UNFCCC. (2011). Reducing emission from deforestation in developing countries. February, 1–4. https://unfccc.int/files/press/backgrounders/application/pdf/fact_sheet_reducing_emissions_ from_deforestation.pdf

van Straaten, O., Doamba, S. W. M. F., Corre, M. D., & Veldkamp, E. (2019). Impacts of burning on soil trace gas fluxes in two wooded savanna sites in Burkina Faso. Journal of Arid Environments, 165(July 2018), 132–140. https://doi.org/10.1016/j.jaridenv.2019.02.013

Van Wilgen, B. W. (2009). The evolution of fire management practices in savanna protected areas in South Africa. South African Journal of Science, 105(9–10), 343–349. https://doi.org/10.4102/sajs.v105i9/10.107

Vasconcelos, R. N., Cantillo-Pérez, T., Franca Rocha, W. J. S., Aguiar, W. M., Mendes, D. T., de Jesus, T. B., de Santana, C. O., de Santana, M. M. M., & Oliveira, R. P. (2024). Advances and Challenges in Species Ecological Niche Modeling: A Mixed Review. Earth (Switzerland), 5(4), 963–989. https://doi.org/10.3390/EARTH5040050/S1

Veenendaal, E. M., Torello-Raventos, M., Miranda, H. S., Sato, N. M., Oliveras, I., van Langevelde, F., Asner, G. P., & Lloyd, J. (2018). On the relationship between fire regime and vegetation structure in the tropics. New Phytologist, 218(1), 153–166. https://doi.org/10.1111/nph.14940

Vogel, S. M., Vasudev, D., Ogutu, J. O., Taek, P., Berti, E., Goswami, V. R., Kaelo, M., Buitenwerf, R., Munk, M., Li, W., Wall, J., Chala, D., Amoke, I., Odingo, A., & Svenning, J. C. (2023). Identifying sustainable coexistence potential by integrating willingness-to-coexist with habitat suitability assessments. Biological Conservation, 279, 109935. https://doi.org/10.1016/J.BIOCON.2023.109935

Vorster, A. G., Evangelista, P. H., Stovall, A. E. L., & Ex, S. (2020). Variability and uncertainty in forest biomass estimates from the tree to landscape scale: The role of allometric equations. Carbon Balance and Management, 15(1), 1–20. https://doi.org/10.1186/S13021-020-00143-6/FIGURES/9

Vroh, T., Yao, A., Yves, C., Djaha, K., Kouassi, K., Bi, G., Bertin, Z. S. extinction and climate change are two important components of global change. T. two components degrade the quality of both environment and human well, & Edouard, N. G. K. (2015). Trees species diversity and above ground biomass in three tropical forest types in Azaguié area , Côte d ’ Ivoire. Global Advanced Research Journal of Plant Science, 1(2), 030–038.

Wahome, T. (2024). Senegal mango season kick-starts amid lowering volumes - Selina Wamucii | Food & Agriculture News. https://www.selinawamucii.com/news/2024/05/29/senegal-mango-season-kick-starts-amid-lowering-volumes/?utm_source=chatgpt.com

Wai, P., Su, H., & Li, M. (2022). Estimating Aboveground Biomass of Two Different Forest Types in Myanmar from Sentinel-2 Data with Machine Learning and Geostatistical Algorithms. Remote Sensing, 14(9). https://doi.org/10.3390/rs14092146

Walker, S. M., Murray, L., & Tepe, T. (2016). Allometric Equation Evaluation Guidance Document. Winrock International, June, 75. https://www.winrock.org/wp-content/uploads/2018/08/Winrock-AllometricEquationGuidance-2016.pdf

Wallis, C. I. B., Tiede, Y. C., Beck, E., Böhning-Gaese, K., Brandl, R., Donoso, D. A., Espinosa, C. I., Fries, A., Homeier, J., Inclan, D., Leuschner, C., Maraun, M., Mikolajewski, K., Neuschulz, E. L., Scheu, S., Schleuning, M., Suárez, J. P., Tinoco, B. A., Farwig, N., & Bendix, J. (2021). Biodiversity and ecosystem functions depend on environmental conditions and resources rather than the geodiversity of a tropical biodiversity hotspot. Scientific Reports, 11(1), 1–15. https://doi.org/10.1038/s41598-021-03488-1

Wang, C., Zhang, W., Ji, Y., Marino, A., Li, C., Wang, L., Zhao, H., & Wang, M. (2024). Estimation of Aboveground Biomass for Different Forest Types Using Data from Sentinel-1, Sentinel-2, ALOS PALSAR-2, and GEDI. Forests 2024, Vol. 15, Page 215, 15(1), 215. https://doi.org/10.3390/F15010215

Wang, L., Zhou, X., Zhu, X., Dong, Z., & Guo, W. (2016). Estimation of biomass in wheat using random forest regression algorithm and remote sensing data. Crop Journal, 4(3), 212–219. https://doi.org/10.1016/J.CJ.2016.01.008

Wei, F., Wang, S., Fu, B., Zhang, L., Fu, C., & Kanga, E. M. (2018). Balancing community livelihoods and biodiversity conservation of protected areas in East Africa. Current Opinion in Environmental Sustainability, 33, 26–33. https://doi.org/10.1016/J.COSUST.2018.03.013

Wei, X., Liu, Y., Qi, L., Chen, J., Wang, G., Zhang, L., & Liu, R. (2023). Monitoring forest dynamics in Africa during 2000–2020 using a remotely sensed fractional tree cover dataset. International Journal of Digital Earth, 16(1), 2212–2232. https://doi.org/10.1080/17538947.2023.2220613

Wijaya, A., Kusnadi, S., Gloaguen, R., & Heilmeier, H. (2010). Improved strategy for estimating stem volume and forest biomass using moderate resolution remote sensing data and GIS. Journal of Forestry Research, 21(1), 1–12. https://doi.org/10.1007/S11676-010-0001-7/METRICS

Woomer, P. L., Tieszen, L. L., Tappan, G., Touré, A., & Sall, M. (2004). Land use change and terrestrial carbon stocks in Senegal. Journal of Arid Environments, 59(3), 625–642. https://doi.org/10.1016/J.JARIDENV.2004.03.025

Wu, N., Crusiol, L. G. T., Liu, G., Wuyun, D., & Han, G. (2023). Comparing the performance of machine learning algorithms for estimating aboveground biomass in typical steppe of northern China using Sentinel imageries. Ecological Indicators, 154, 110723. https://doi.org/10.1016/J.ECOLIND.2023.110723

Xue, Y., Zhang, B., He, C., & Shao, R. (2019). Detecting vegetation variations and main drivers over the agropastoral ecotone of northern China through the ensemble empirical mode decomposition method. Remote Sensing, 11(16). https://doi.org/10.3390/rs11161860

Yang, X., Qiu, S., Zhu, Z., Rittenhouse, C., Riordan, D., & Cullerton, M. (2023). Mapping understory plant communities in deciduous forests from Sentinel-2 time series. Remote Sensing of Environment, 293, 113601. https://doi.org/10.1016/J.RSE.2023.113601

Yao, N. A. (2010). Mapping Bushfire Distribution and Burn Severity in West Africa Using Remote Sensing Observations. 137.

Yu, H., Cooper, A. R., & Infante, D. M. (2020). Improving species distribution model predictive accuracy using species abundance: Application with boosted regression trees. Ecological Modelling, 432(March), 109202. https://doi.org/10.1016/j.ecolmodel.2020.109202

Zeng, Y., Jia, L., Menenti, M., Jiang, M., Zheng, C., Bennour, A., & Lv, Y. (2024). Regional divergent evolution of vegetation greenness and climatic drivers in the Sahel-Sudan-Guinea region: nonlinearity and explainable machine learning. Frontiers in Forests and Global Change, 7, 1416373. https://doi.org/10.3389/FFGC.2024.1416373/BIBTEX

Zhang, J., & Li, S. (2017). A Review of Machine Learning Based Species' Distribution Modelling. Proceedings - 2017 International Conference on Industrial Informatics - Computing Technology, Intelligent Technology, Industrial Information Integration, ICIICII 2017, 2017-December, 199–206. https://doi.org/10.1109/ICIICII.2017.76

Zhang, W., Brandt, M., Wang, Q., Prishchepov, A. V., Tucker, C. J., Li, Y., Lyu, H., & Fensholt, R. (2019). From woody cover to woody canopies: How Sentinel-1 and Sentinel-2 data advance the mapping of woody plants in savannas. Remote Sensing of Environment, 234(May), 111465. https://doi.org/10.1016/j.rse.2019.111465

Zhang, X., Shen, H., Huang, T., Wu, Y., Guo, B., Liu, Z., Luo, H., Tang, J., Zhou, H., Wang, L., Xu, W., & Ou, G. (2024). Improved random forest algorithms for increasing the accuracy of forest aboveground biomass estimation using Sentinel-2 imagery. Ecological Indicators, 159, 111752. https://doi.org/10.1016/J.ECOLIND.2024.111752

Zhao, Z., Xiao, N., Shen, M., & Li, J. (2022). Comparison between optimized MaxEnt and random forest modeling in predicting potential distribution: A case study with Quasipaa boulengeri in China. Science of The Total Environment, 842, 156867. https://doi.org/10.1016/J.SCITOTENV.2022.156867

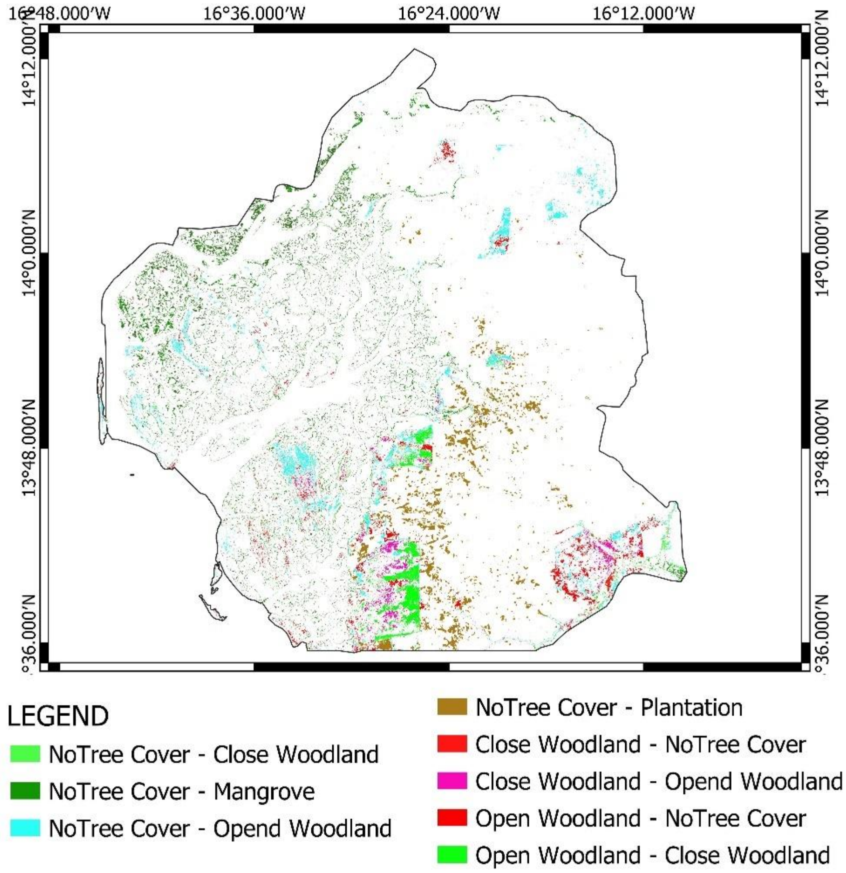
Zhu, Z., & Woodcock, C. E. (2014). Continuous change detection and classification of land cover using all available Landsat data. Remote Sensing of Environment, 144, 152–171. https://doi.org/10.1016/j.rse.2014.01.011

Zoungrana, B. J. B., Conrad, C., Thiel, M., Amekudzi, L. K., & Da, E. D. (2018). MODIS NDVI trends and fractional land cover change for improved assessments of vegetation degradation in Burkina Faso, West Africa. Journal of Arid Environments, 153(September 2017), 66–75. https://doi.org/10.1016/j.jaridenv.2018.01.005

Zurell, D. (2020). Introduction to species distribution modelling (SDM) in R. Journal of Biogeography, 47(1), 101–113. https://doi.org/10.1111/JBI.13608

APPENDICES

Appendix 1: Change detection Map from 2002 to 2022



Appendix 2: Area and Rate of change woody tree cover from 2002 to 2022

	2002-2007		2007-2017		2017-2022	
LULC CLASS	Area of change (Km^2)	Rate of Change (Km^2 /year)	Area of change (Km^2)	Rate of Change (Km^2 /year)	Area of change (Km^2)	Rate of Change (Km^2 /year
Mangrove	6.36	1.27	71.17	7.12	2.61	0.52
Close Woodlands	2.00	0.40	11.02	1.10	4.75	0.95
Open Woodlands	17.60	3.52	38.19	3.82	-57.98	-11.60
Plantation	11.81	2.36	29.53	2.95	5.03	1.01
No tree cover	-2.02	-0.40	-157.17	-15.72	62.19	12.44
Water	-35.75	-7.15	7.26	0.73	-16.60	-3.32

Appendix 3: Transition matrix from 2002 to 2007 in the study landscape

LULC change from the initial year 2002 (Km^2)

Change to final year 2007 (Km^2)

	No tree cover	Close Woodlands	Mangrove	Open Woodlands	Plantation	Water	Total	Loss
No tree cover	1693	2	21	35	2	26	1779	86
Close Woodlands	5	22	2	8	1	0	38	16
Mangrove	6	1	519	0	0	29	555	36
Open Woodlands	49	11	0	105	1	0	166	61
Plantation	16	0	0	1	11	0	28	17
Water	15	0	7	0		380	402	22
Grand Total	1784	36	549	149	15	435	2968	
Gain	91	14	30	44	4	55		

Appendix 4: Transition matrix from 2007 to 2017 in the study landscape

LULC change from the initial year 2007 (Km^2)

Change to initial year 2017 (Km^2)

	No tree cover	Close Woodlands	Mangrove	Open Woodlands	Plantation	Water	Total	Loss
No tree cover	1577	2	2	31	5	6	1623	46
Close Woodlands	3	27	0	18	1	0	49	22
Mangrove	53	2	547	0	0	24	626	79
Open Woodlands	83	7	0	114	1	0	205	91
Plantation	32	1	0	3	23	0	59	36
Water	32	0	5	0	0	369	406	37
Total	1780	39	554	166	30	399	2968	
Gain	203	12	7	52	7	30		

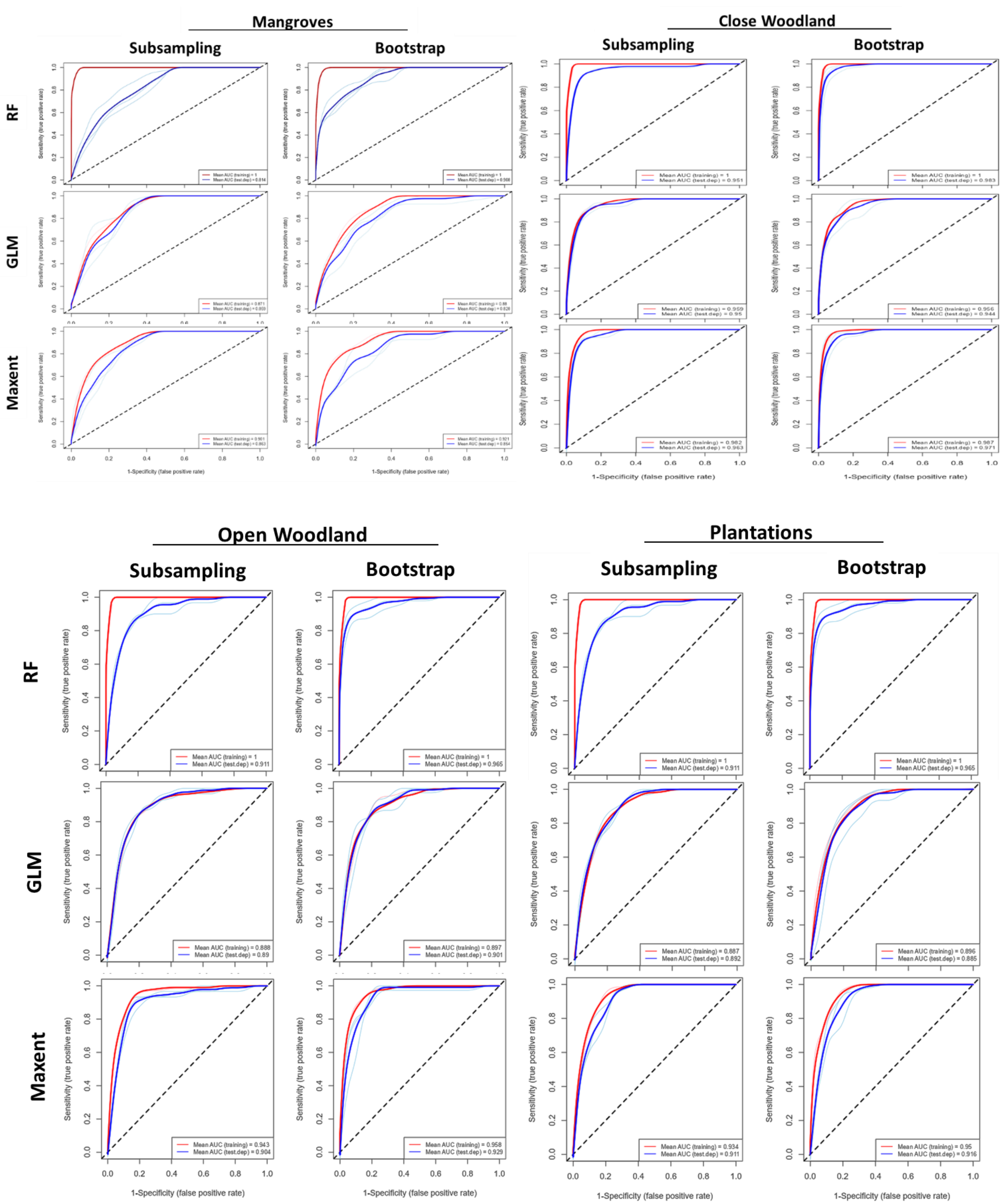
Appendix 5: Transition matrix from 2017 to 2022 in the study landscape

		LULC change from the initial year 2017 (Km^2)							
Change to final year 2022 (Km^2)		No tree cover	Close Woodlands	Mangrove	Open Woodlands	Plantation	Water	Total	Loss
	No tree cover	1571	4	15	73	10	13	1686	115
	Close Woodlands	2	31	2	18	1	0	54	23
	Mangrove	7	1	604	1	0	16	629	25
	Open Woodlands	20	14	0	112	1	0	147	35
	Plantation	15	0	0	1	46	0	62	16
	Water	7	0	4	0	0	379	390	11
	Total	1622	50	625	205	58	408	2968	
	Gain	51	19	21	93	12	29		

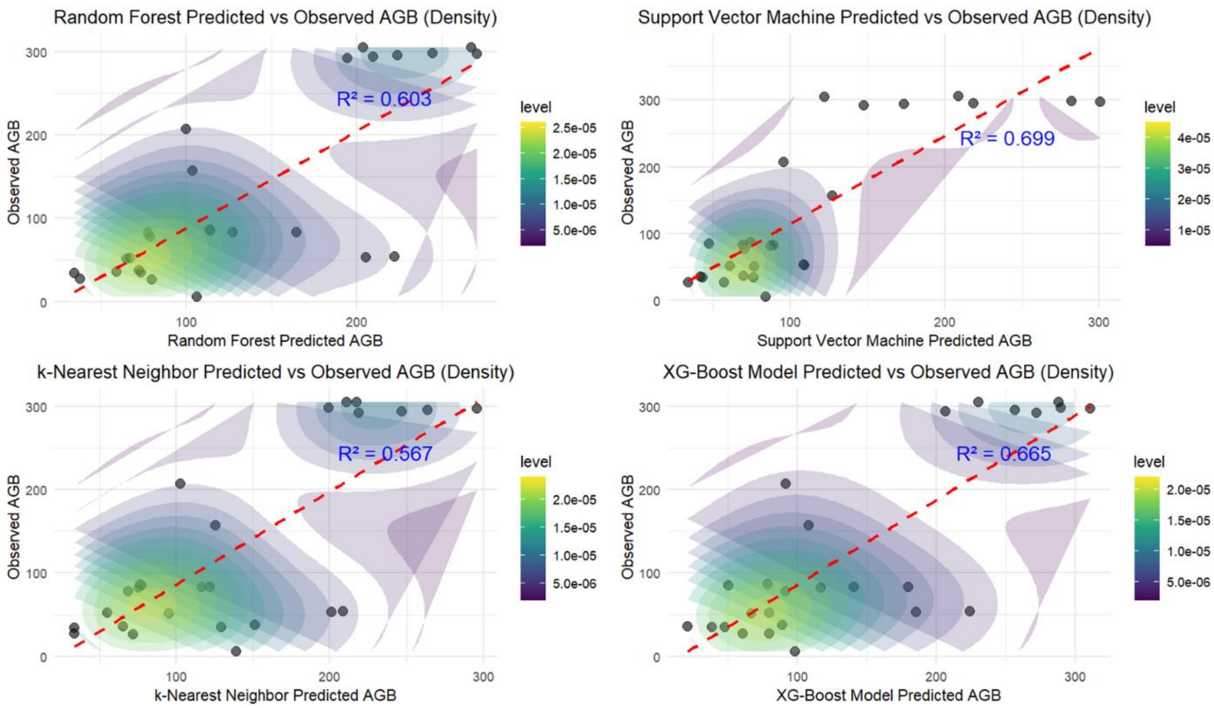
Appendix 6: Transition matrix from 2002 to 2022 in the study area

		change from the initial year 2002 (Km^2)							
		No tree cover	Close Woodlands	Mangrove	Open Woodlands	Plantation	Water	Total	Loss
Change to Final year 2022 (Km^2)	No tree cover	1634	3	5	29	2	11	1684	50
	Close Woodlands	7	20	3	23	1	0	54	34
	Mangrove	31	1	537	0	0	59	628	91
	Open Woodlands	40	12	0	94	1	0	147	53
	Plantation	49	1	0	2	12	0	64	52
	Water	22	0	3	0	0	366	391	25
	Total	1783	37	548	148	16	436	2968	
	Gain	149	17	11	54	4	70		

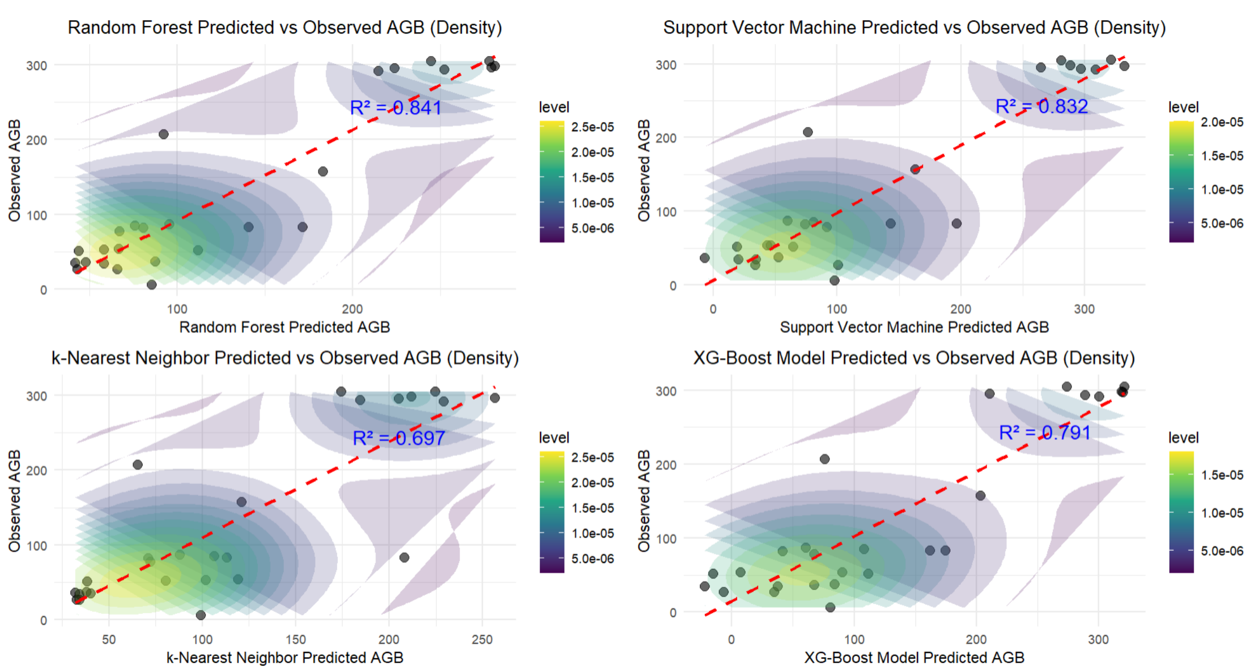
Appendix 7: Mean AUC of Sub-sampling and Bootstrap for different model in each woody communities. (red=training) ; (blue=testing)



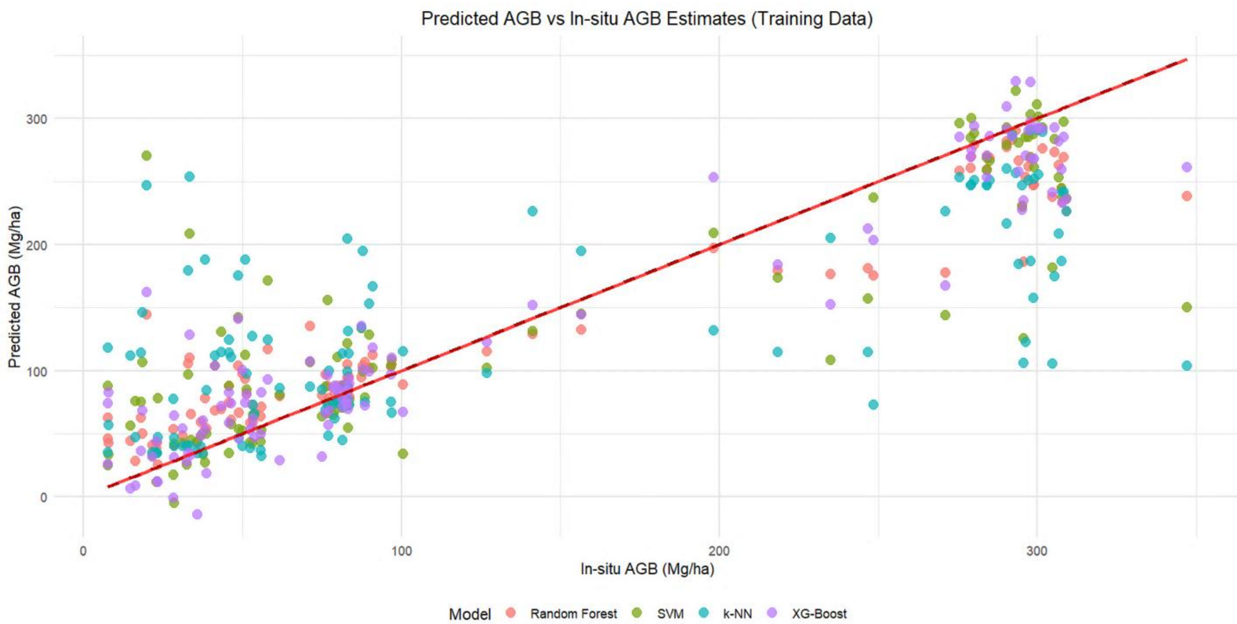
Appendix 8: Predicted AGB vs Observed AGB and related Rsquare for the dry season



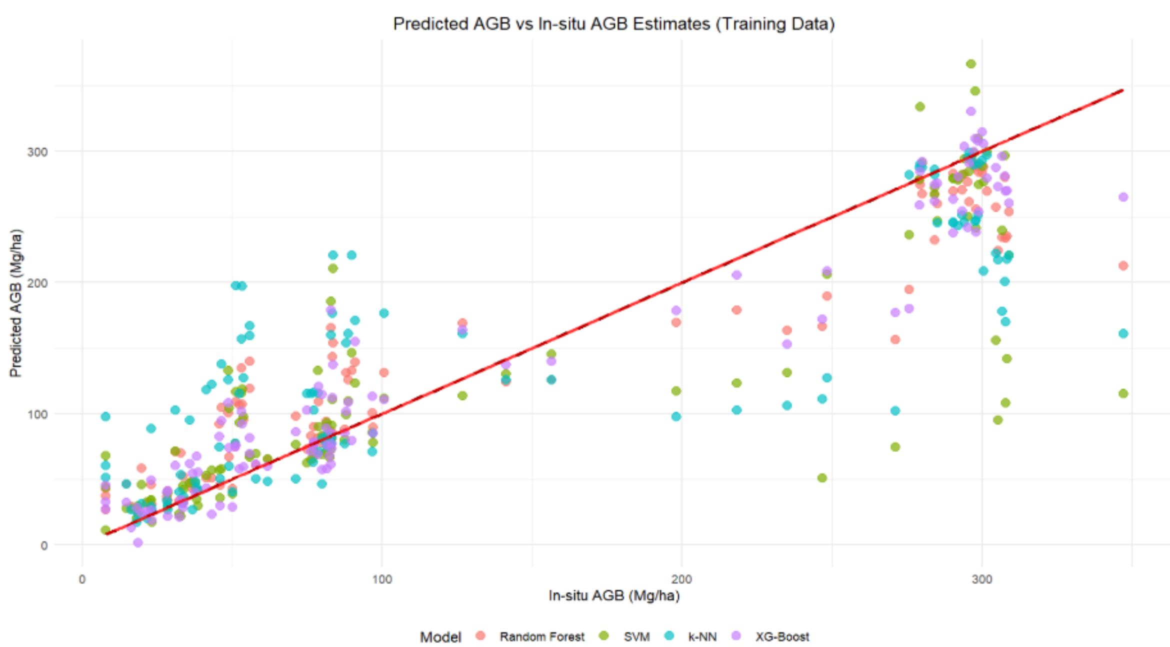
Appendix 9: Predicted AGB vs Observed AGB and related Rsquare for the wet season



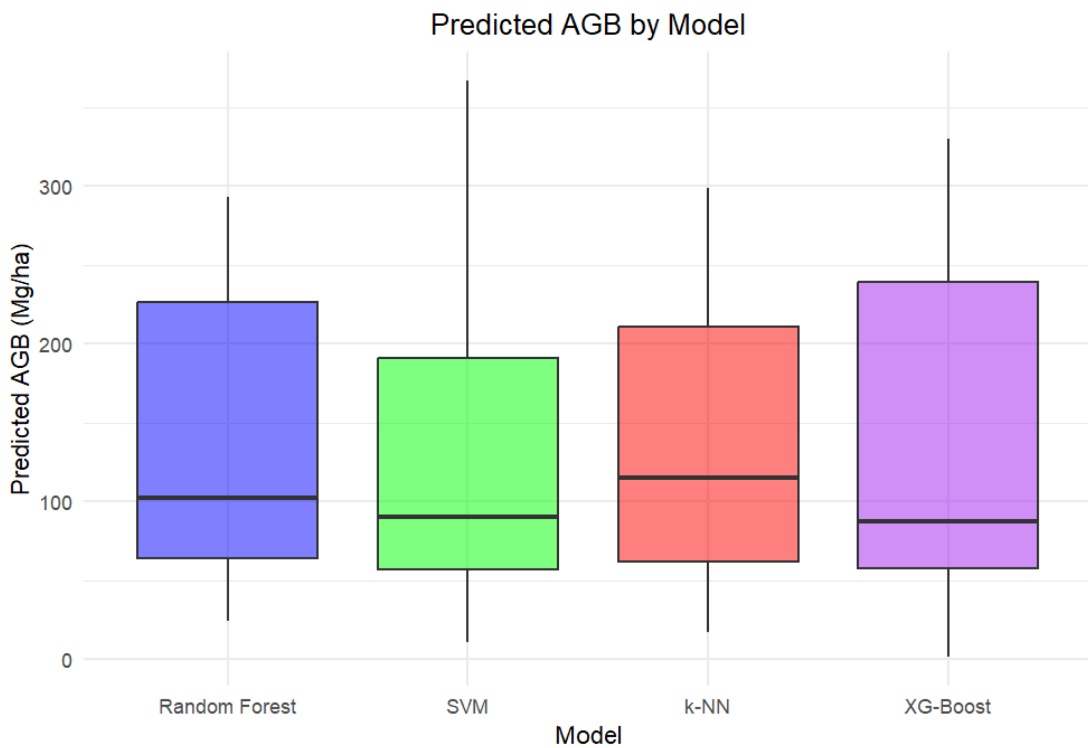
Appendix 10: Predicted vs Observed AGB for all models in dry season



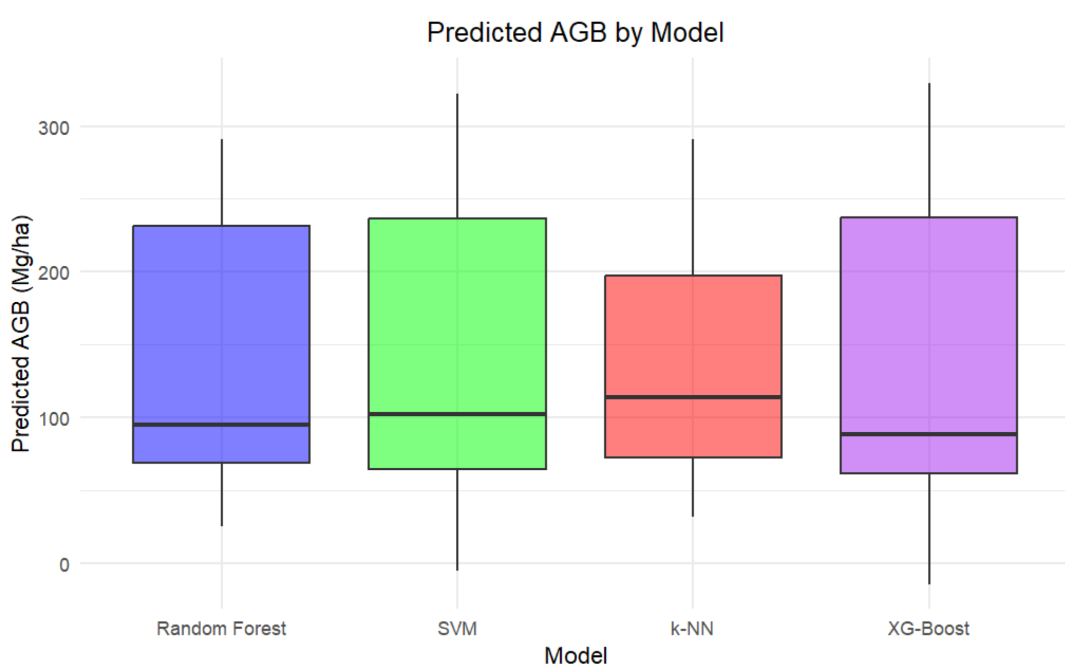
Appendix 11: Predicted vs Observed AGB for all models in wet season



Appendix 12: Boxplot of the predicted AGB for different models (Dry season)



Appendix 13: Boxplot of the predicted AGB for different models (Wet season)



Appendix 14:Environmental predictors data