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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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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 degradation of vegetation 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 in the management of 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. Random Forest algorithm (RF) was used for image classification in 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. The third objective estimated the aboveground biomass (AGB) of the different woody tree covers using allometric equations and machine learning. AGB estimation integrated ground inventory data from 138 plots with Sentinel-2 imagery from dry and wet season. 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 an increase of small patches in Plantations. The assessment of woody tree spatial drivers reveals key environmental drivers, 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 pattern highlithing their suitability for optimising their coverage. Mangroves accounted smallest gab between the actual coverage and suitable coverage with a gap of 3.47%. Strong gab still existed for the other woody tree with 5.49, 6.03 and 6.41% for Close Woodlands, Open Woodland and Plantations respectively. Lastly AGB estimation of the woody cover revealed 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 and 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$_2$eq 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 Nation Convention to Combat Desertification
UNFCCC - United Nation 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, to my wife for her unwavering support, and to my daughter, whose presence fills my life with joy and inspiration.

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CHAPTER 1 : GENERAL INTRODUCTION

1.1. BACKGROUND

Woody vegetation, particularly trees, plays a critical role 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 not only for ecological balance but also for addressing broader agro-environmental challenges (Mbawine & Dzekoto, 2023). These ecosystems present unique challenges in areas where the need to balance conservation efforts with sustainable resource use is crucial (Wei et al., 2018).

However, woody vegetation ecosystems are increasingly under pressure from both 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 of which threaten vegetation health and growth (Hailu & 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). Matyssek et al. (2017) emphasized that 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 (SDGs, 2015).

Early intervention is critical to limit further vegetation decline and to support the recovery of degraded ecosystems (Cheng & Li, 2024). This requires the integration of innovative approaches that combine scientific insights with practical solutions (Ruhana et al., 2024). Optimizing restoration efforts involves not only addressing current vegetation challenges but also 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 tree vegetation is a basis of ecosystem sustainability, particularly in regions undergoing rapid environmental and socio-economic changes. In the Sahel, the interplay of climate change impacts such as erratic rainfall, and prolonged droughts, and unsustainable human activities, including deforestation and overexploitation, has led to significant degradation of vegetation, soils, and water resources (IRD, 2015; Karlson & Ostwald, 2016). Despite these challenges, the Sahel has shown signs of a greening trend since the severe droughts of the 1970s and 1980s, offering opportunities for ecological restoration (Herrmann et al., 2014; Hickler et al., 2005; J. Li et al., 2004).

In West Africa, land-use changes, such as agricultural expansion and forest degradation, have profoundly altered vegetation patterns (Herrmann et al., 2020; Souverijns et al., 2021). Senegal, like many Sahelian countries, has experienced significant declines in forest formations, characterized by reduced woody cover, lower species density, and changes in ecosystem structure and function (Diop et al., 2011). These trends are paralleled by evidence of land degradation, though some regions show promising signs of regreening (Herrmann & Tappan, 2013; Herrmann et al., 2014).

The Saloum Delta Biosphere Reserve and Ramsar Site exemplify these dynamics. This ecologically diverse area hosts a wide range of woody species and ecosystems, but it faces challenges such as degradation from late fires and overgrazing, particularly in areas like the Fathala Protected Forest (Kaly et al., 2021). Conversely, evidence of localized revegetation suggests opportunities for restoration (Andrieu et al., 2020; Fent et al., 2019). A spatially detailed assessment is essential to reconcile these contrasting trends and inform sustainable management strategies.

Geospatial assessments in the Saloum Delta have typically focused on broad vegetation categories using standard land-use and land-cover (LULC) classifications (Faye et al., 2022; Tine et al., 2020). However, such approaches often overlook the structural and spatial diversity within woody vegetation, limiting their utility for restoration planning. Furthermore, the contribution of woody vegetation to carbon budgeting remains underexplored, as does the identification of priority areas for intervention. These gaps hinder the development of effective strategies for balancing conservation with sustainable resource use in the Saloum Delta.

This study seeks to address these challenges through advanced geospatial analyses of woody vegetation patterns and dynamics. By providing a comprehensive understanding of spatial and structural changes, the research will support evidence-based decision-making for conservation, carbon management, and land restoration in the Saloum Delta. The findings will contribute to optimizing restoration efforts in a landscape where balancing conservation and sustainable resource use is always challenging.

1.3. AIM, OBJECTIVES AND RESEARCH QUESTIONS

1.3.1. Aim

This study aims to provide a deep investigation of the Saloum Delta woody tree vegetation hotspot to promote the best landscape management 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 drivers 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 (extent, fragmentation, and connectivity) of woody tree covers changed between 2002 and 2022?
- What are the key environmental factors 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?

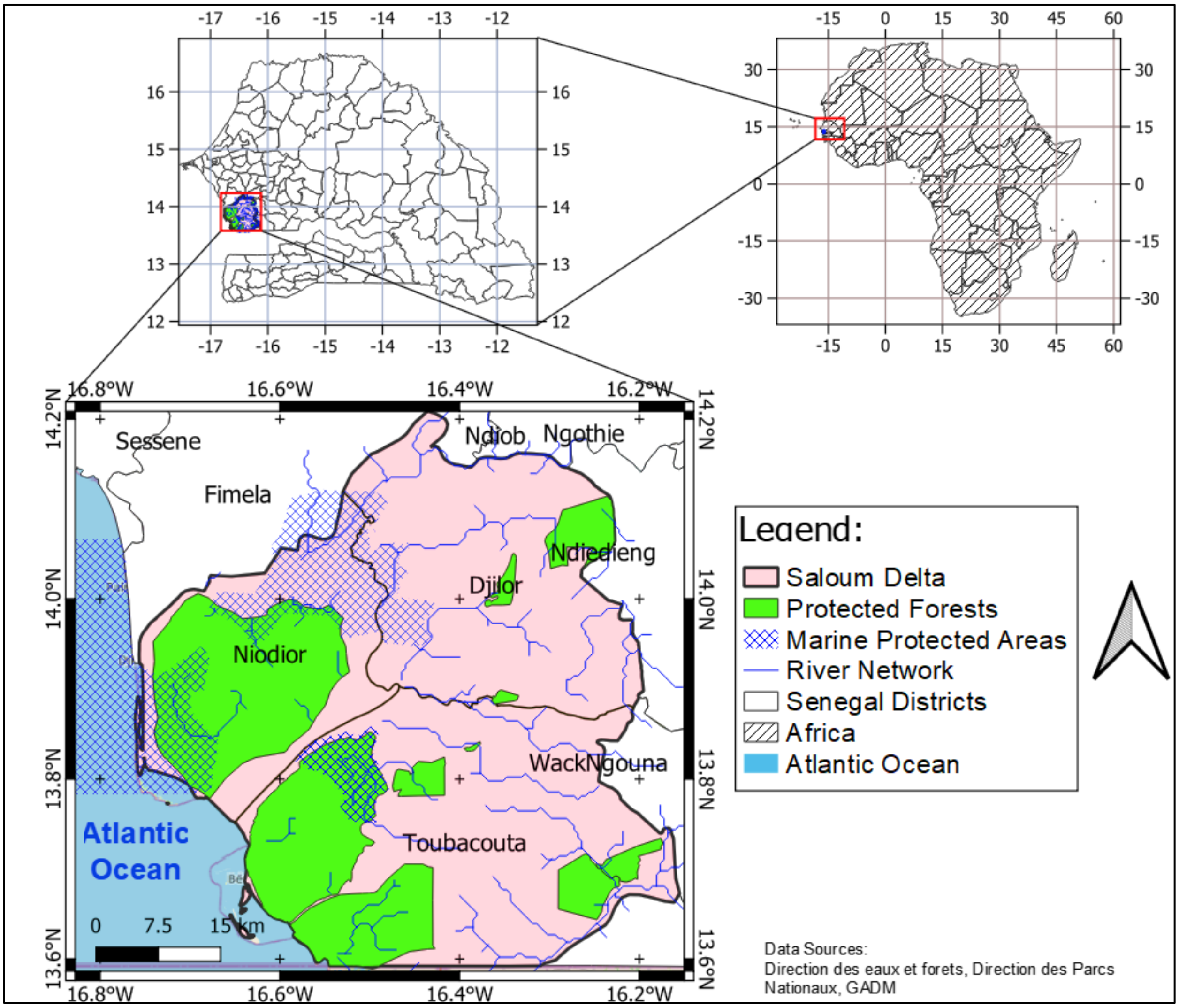
1.4. PRESENTATION OF THE STUDY AREA

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 that 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 especially from the 1970s onward.(Tine, Faye, Diouf, & Faye, 2020).

The area is crossed by the Saloum River and its tributaries, 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, Faye, Diouf, & Faye, 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. The estuary, once abundant in freshwater, now has ecosystems severely affected by increasing salinity, threatening the survival of local species (Nalivata et al., 2017).



Data Sources:
Direction des eaux et forets, Direction des Parcs Nationaux, GADM

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 is largely composed of shrubs under 5 meters, making up 80% of the total abundance. (Mohamed Mahamoud et al., 2008). The mangroves is low in species diversity, dominated by *Rhizophora racemosa* (52.11%), *R. mangle* (30.20%), and *Avicennia africana* (18.20%) (Diop et al., 2024).

1.4.3. Soil

The region has three types of soils: sandy, clay and sandy-clay. The sandy soils, which make up 30 to 80% of the area, are suitable for cultivation, particularly of 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 Fatick 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 gives the region a Sudanian-Sahelian type climate, 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 trade winds and the continental trade winds (also known as the Harmattan), easterly winds that blow from February to May. The monsoon winds from the southwest signal the onset of the rainy season 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 the distribution of rainfall, 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 Fatick 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 economy of the Fatick region 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 largely 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 both marine and river-lagoon zones with a 70 km front, rich in fish, crustaceans, and mollusks. The region’s fishing potential is enhanced by an extensive hydrographic network, a vast mangrove forest, and diverse aquatic and terrestrial ecosystems. Technical support from government and NGOs, along with development partnerships focusing on sustainable fishing, especially in the Saloum Delta, are key to strengthening this sector (ANSD, 2021).

Tourism holds significant potential and plays an important role in the region's economy. The region 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 historical sites and monument (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 assess the spatiotemporal change of woody tree vegetation and pattern analysis.
- Chapter 4: This Chapter predicts spatial distribution of the woody tree cover and associated environmental drivers.
- Chapter 5: This Chapter assess ground and remote sensing-based estimation of the Saloum Delta woody aboveground biomass using allometric equations and machine learning.
- Chapter 6: This Chapter presents the summary of 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 structure of vegetation, 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 consist of a combination of 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. 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 harvesting for fuelwood has implications for both biomass and ecosystem structure (Sankaran, 2019). Additionally, techniques such as LiDAR allow scientists to assess biomass and carbon storage across different canopy layers, contributing to a better understanding of subcanopy dynamics and fuelwood sustainability.

Woody tree vegetation plays a central role in the carbon cycle, as it is one of the primary reservoirs for carbon storage. 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, which 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 providing a balance between carbon sequestration and biodiversity. 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. 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 disturbances both natural and anthropogenic impact biomass and carbon storage.

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. Study of Grieco et al. (2024) (Figure 2.1) witness the large amount of carbon pools in different LULC 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).

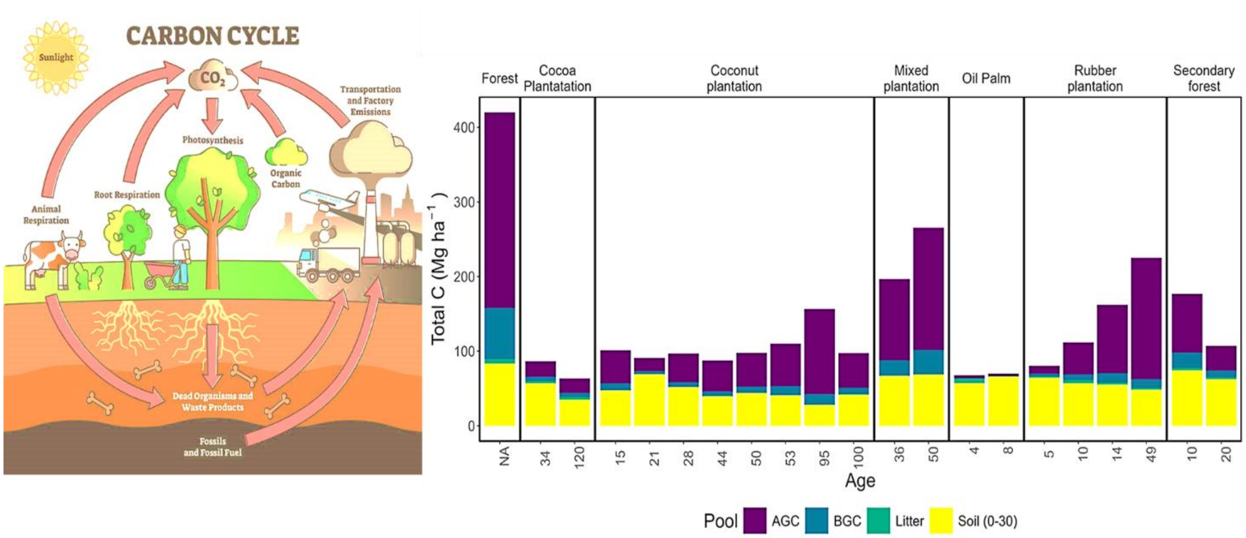


Figure 2.1: Carbon stock potential of different LULC

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

The distribution of biomass across different types of woody vegetation in Senegal and West Africa varies widely, largely due to environmental gradients and human pressures, including land conversion, overgrazing, and fuelwood collection. 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; van Straaten et al., 2019). Studies have shown that biomass levels tend to be higher in protected areas, where human activities are restricted (McNicol 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 an adaptive ability to recover post-disturbance, as shown by their species composition and biomass changes over time. 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. For instance, in fire-prone savannas, trees often develop thick bark, which protects their vital tissues, enabling them to survive periodic burns. Additionally, some species resprout from roots or basal buds, allowing them to recover rapidly after disturbances (Van 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, particularly for fuelwood, poses a significant threat in many developing regions where it serves as a primary energy source. Research shows that 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 degradation of communal rangelands, prompting calls for sustainable management practices that balance human needs with ecological health (Seware, 2015).

Effective management of woody vegetation should consider adaptive strategies that incorporate community involvement, sustainable harvesting practices, and restoration efforts. 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).

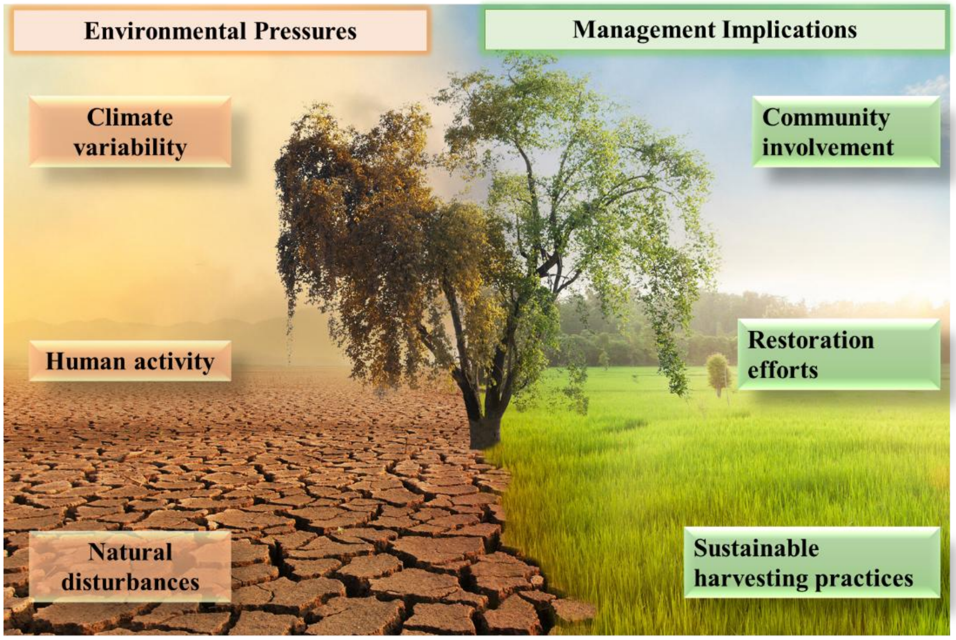


Figure 2.2: Main existing interaction between trees, environmental stress and management

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, mollusks, 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).

In terms of 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 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 provided by mangroves 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 as a means of balancing local needs with conservation efforts. Local governance reforms, such as the 1998 Forest Code, aim to empower communities in managing 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.

Research indicates that farmers play a crucial role in conserving tree diversity within agroforestry landscapes. By protecting and managing trees on their farms, they contribute to the preservation of various species, which is vital for maintaining ecosystem services and resilience against environmental stresses. 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. Studies have assessed various technologies and practices aimed at curbing soil salinization and restoring productivity. Agroforestry systems, through the strategic planting of salt-tolerant tree species, have been identified as a viable approach to rehabilitate salt-affected soils, thereby 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, along with others like Casamance and Niayes, is integral to the country's mango supply chain (Wahome, 2024).

Furthermore, agroforestry practices in the Saloum region often incorporate cashew trees as a strategy 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).

Overall, the cultivation of 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). The annual deforestation rate, though relatively low (0.09% in some cases), contributes to cumulative emissions over time. Sustainable land-use practices are essential to curb these trends (Sambou, 2015).

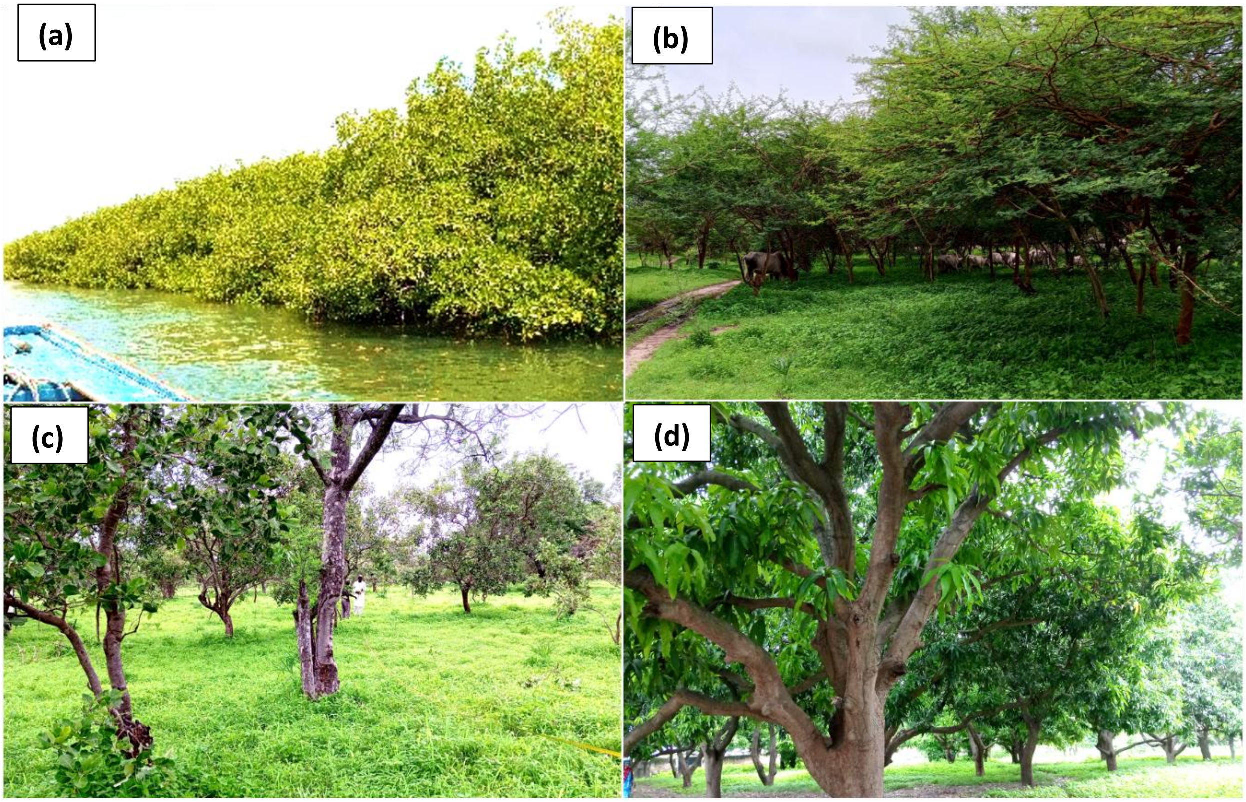


Figure 2.3: Different communities of woody cover types in the study area

(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. High-resolution satellite imagery and LiDAR (Light Detection and Ranging) are among the most widely used technologies. 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 models of vegetation, enabling researchers to estimate biomass with high accuracy, 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 is particularly useful in assessing woody vegetation health in response to climate stressors like drought, which is a growing concern in dry regions of Africa (X. Wei et al., 2023). The 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).
- Assessment of forest disturbances, including wildfires, logging, and pest or pathogen outbreaks, 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).
- Investigation of leaf traits which 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 the assessment of vegetation condition (Moreno-Martínez et al., 2018).
- Biodiversity and habitat studies leverage remote sensing data of forests as covariates for modeling 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 (Oduro Appiah et al., 2021).

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

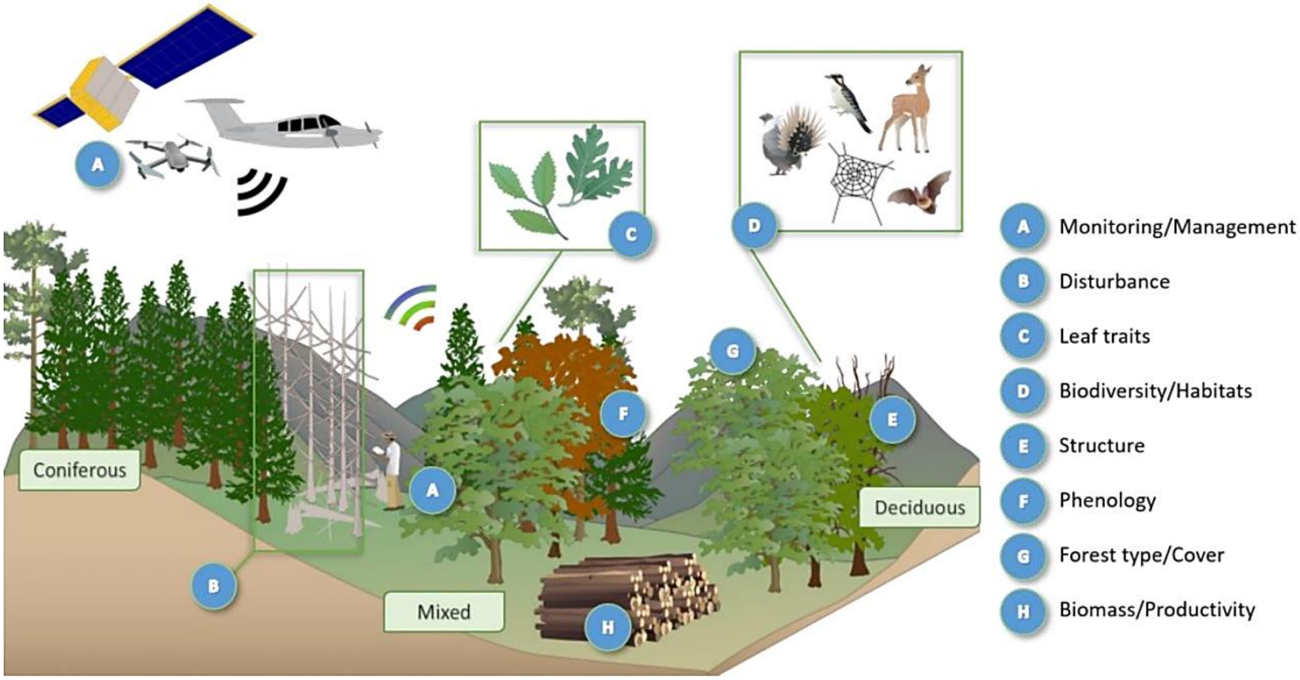


Figure 2.4: Common research areas for remote sensing of forests

Adapted graphic elements from (Coleman et al. 2024)

2.7.2. Limitations of Remote Sensing Techniques

While remote sensing has transformed large-scale vegetation assessment, it is not without limitations. One major challenge is the spatial and spectral resolution of satellite imagery, 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 underestimates of 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 the analysis of remote sensing data, these models depend on high-quality, labeled training data, which is 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 that integrate 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 challenges such as data limitations, model transferability, and validation. To overcome these issues, researchers increasingly use high-resolution satellite imagery and proxy indicators, while also employing rigorous validation frameworks that include expert assessments (Boyd et al., 2023). Recent trends include the integration of correlative and mechanistic models to account for dynamic species-environment interactions and the use of 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 European 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 rigor and interdisciplinary approaches. As SDMs continue to evolve, they offer valuable insights for both theoretical and applied ecology, fostering more effective conservation and management strategies in the face of global environmental change.

Inadequate data on species occurrences and environmental variables remains a significant hurdle. The use of proxy indicators and high-resolution satellite imagery has 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. Conceptuel Framework

SDMs are rooted in ecological niche theory, which posits that species distributions are determined by their interactions with the environment. 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. 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-Medina et al., 2020).

2.7.4.2. Scientific Support Justification

SDMs utilize georeferenced biodiversity observations alongside environmental data (e.g., climate, land cover). By integrating data on multiple species and their respective environmental tolerances, it is 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. 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. This supports their utility in predicting established vegetation types, especially when the focus is 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 their 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 modeling 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 as a class 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

Field-based assessments, while highly accurate and essential for obtaining ground-truth data, face several limitations. One significant limitation is their resource-intensive nature; collecting data in the field requires substantial time, labor, 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). Seasonal weather patterns, like heavy rains, often restrict data collection to certain periods and limit overall spatial coverage. For instance, in Sierra Leone, data collection has been affected by major floods, which have impacted 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 the choice of 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 those found in 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. 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.

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. This integrative approach facilitated the detection of woody vegetation across the continent, illustrating the effectiveness of combining field data with remote sensing techniques (Graw et al., 2016).

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 and AI Applications

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. For instance, deep learning algorithms can process complex image data to classify vegetation types, identify individual trees, and predict biomass with greater accuracy than traditional models. 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. 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).

Moreover, AI-driven models can integrate diverse environmental variables, such as rainfall, temperature, and soil properties, to predict vegetation dynamics under different climate scenarios. This predictive capability supports conservation planning by forecasting how woody vegetation might respond to changing conditions, particularly in vulnerable regions like the Sahel. Studies have explored the role of vegetation dynamics in influencing low-frequency variability of Sahel rainfall, highlighting the importance of integrating vegetation models in climate predictions (Wang and Eltahir 2000).

These advancements demonstrate the potential of ML and AI in improving the accuracy and efficiency of woody vegetation assessments, thereby supporting effective ecosystem management and conservation efforts.

2.7.5.5. Challenges and Future Directions

Despite significant advancements, woody vegetation assessment continues to face several challenges, particularly in regions with limited access to high-quality remote sensing data or field resources. The refinement of 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). Major 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). In Africa, climate change threatens major woody species, impacting woody vegetation patterns (Kapuka et al. 2022). Apart from the conservation and biodiversity aspect, protecting trees is crucial for mitigation purposes due to their high carbon storage capacity (Mildrexler et al., 2023). Tree planting is also considered as 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 since 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 all together 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 density of the woody species (B. 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), mangroves revegetation has also been observed in the Saloum estuary (Andrieu, 2018; Andrieu et al., 2020; Carré et al., 2022).

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 both human labour and materials, as well as 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 scale (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 and 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, with the aim of promoting optimal landscape management for carbon sequestration and supporting effective policy implementation.

3.2. METHODOLOGY

The most effective approach for spatially assessing extensive woody vegetation cover is through the use of Earth Observation (EO) technologies (Symeonakis, Petroulaki, and Higginbottom 2016). Numerous research endeavors have used Landsat data to monitor woody cover or access its dynamic (Arévalo et al., 2023; Avitabile et al., 2012; S. 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 cover 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).

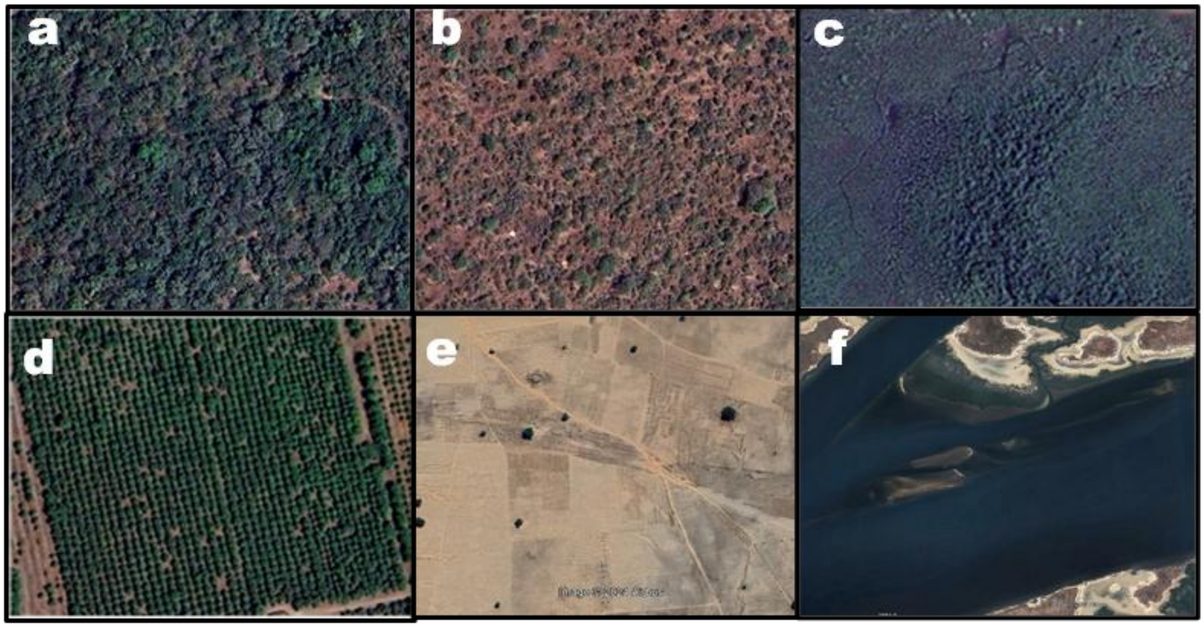


Figure 3.1: High-resolution orthophoto of different woody vegetation cover in the study area

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, which are found in the intertidal zone of sheltered tropical and subtropical coasts (Alongi, 2002).	MG
Close Woodlands	A Close Woodlands, alternatively referred to as 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 the penetration of light 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 penetration of sunlight to the ground. Crown cover is less than 80% (ABARES, 2020).	OW
Plantations	A forest stand 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. Additionally, a temporal filter was applied to select images from the chosen dates (January to December). The mask function was applied for bad 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 used for the image classification was obtained from Google Earth Pro (GE) and combined with GPS field coordinates as shown in Figure 3.2. A total of 4008 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 vigor. NDVI is important in 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 vegetations (Tolentino & de Lourdes Bueno Trindade Galo, 2021). Six surface reflectance bands (Blue, Green, Red, Near-infrared, SWIR-1, and SWIR-2) were used. These bands allow for accurate analysis of vegetation structure, health, and cover changes, which are key components for the study of 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		Tucker 1979
NDWI		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 involves using metrics such as mean, median, and min/max derived from time series images (Hu, 2019; D. R. Richards & Belcher, 2019). In this study, a median filter was used to merge the image collection. The reason for using the median is that 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 ensures the final composite image better represents the true surface reflectance for each year. Landsat composites have been obtained for each of the years 2002, 2007, 2017 and 2022 and subsequently used to do the image classification.

3.2.3. Classification of the Landsat Images

The 65% of the samples were used to run the classification. 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 Phan et al. 2020). The number of decision trees chosen showed good performance in previous studies and 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 further refine the classification results. 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, and kappa coefficient (Mathewos et al. 2022), area calculations were determined in R using the following equations.

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

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

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

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

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

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

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

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.

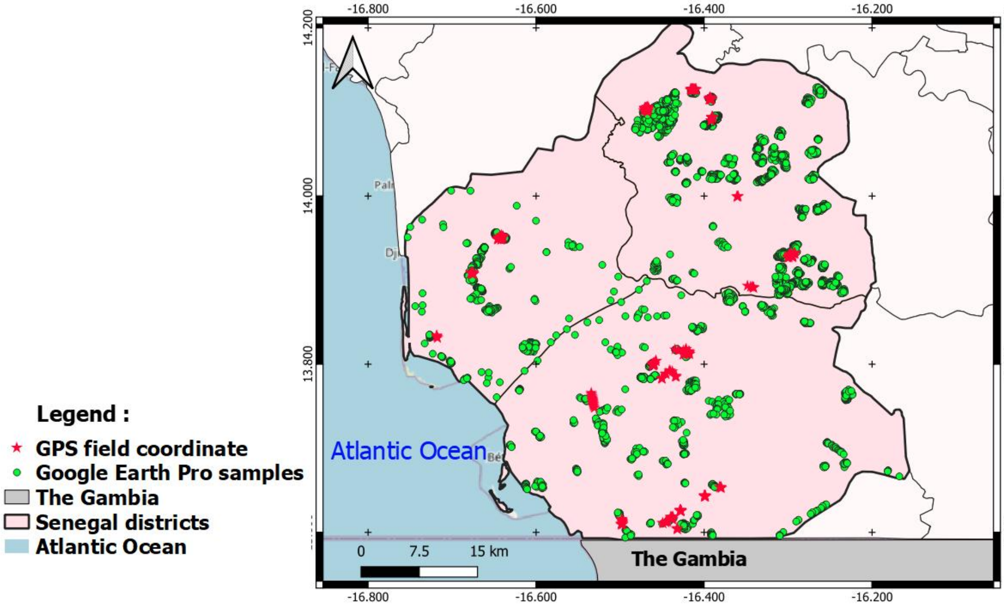


Figure 3.2: Spatial distribution of the ground truthing samples

3.2.5. Transition Statistics

Transition matrices were formulated to examine shifts in land cover values over time. To process the statistics inside and outside 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 circlize package available in R software.

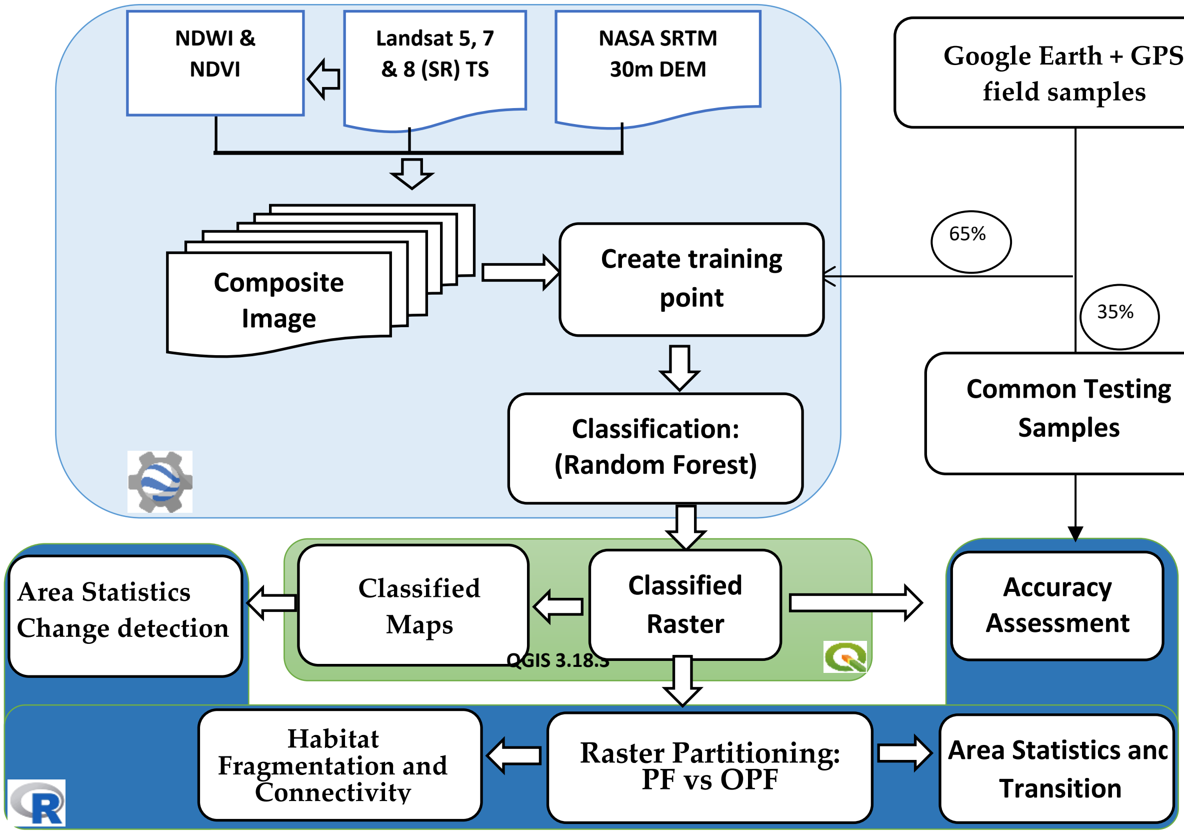


Figure 3.3: Schematic workflow used for the classification and pattern analyses

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). To assess the fragmentation/connectivity pattern of the woody cover the R's landscapemetric package was used. It contains several metrics for assessing landscape structure and fragmentation (Kumar et al., 2018). The metrics were chosen based on the review on the common used one in landscape restoration studies (Rosa et al. 2017; Sertel et al. 2018; Kumar et al. 2018). Four class-level metrics and one patch-level metric 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, we use the patch area metric (pa). Patch metrics offer insights into the configuration and spatial distribution of landscape patches (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). Output map of the patch area metric provided by R software comes as an image; in order to spatially target the concerned coverage, we used the 2022 coverage map as a reference.

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	$\text{lpi} =(\frac{\text{Amax,x}}{\text{AT}}) \times 100$
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.	$\text{ed} = \frac{\text{Ex}}{\text{AT}}$
Perimeter Area Fractal (pafrac)	Reflects the complexity of patch shapes, approaching 1 for simple shapes and increasing with more complex, fragmented patches.	$\text{pafrac} = \frac{2\ln(0.25 \times \text{P})}{\ln(\text{A})}$
Aggregation Index (ai)	Quantify the degree of spatial aggregation or clumping of patches within a landscape	$\text{ai} = \frac{g_x}{\text{Max}(\text{g}_x)} \times 100$
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	$\text{pa} = \frac{A_y}{10000}$

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 shows a significant increase mostly 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).

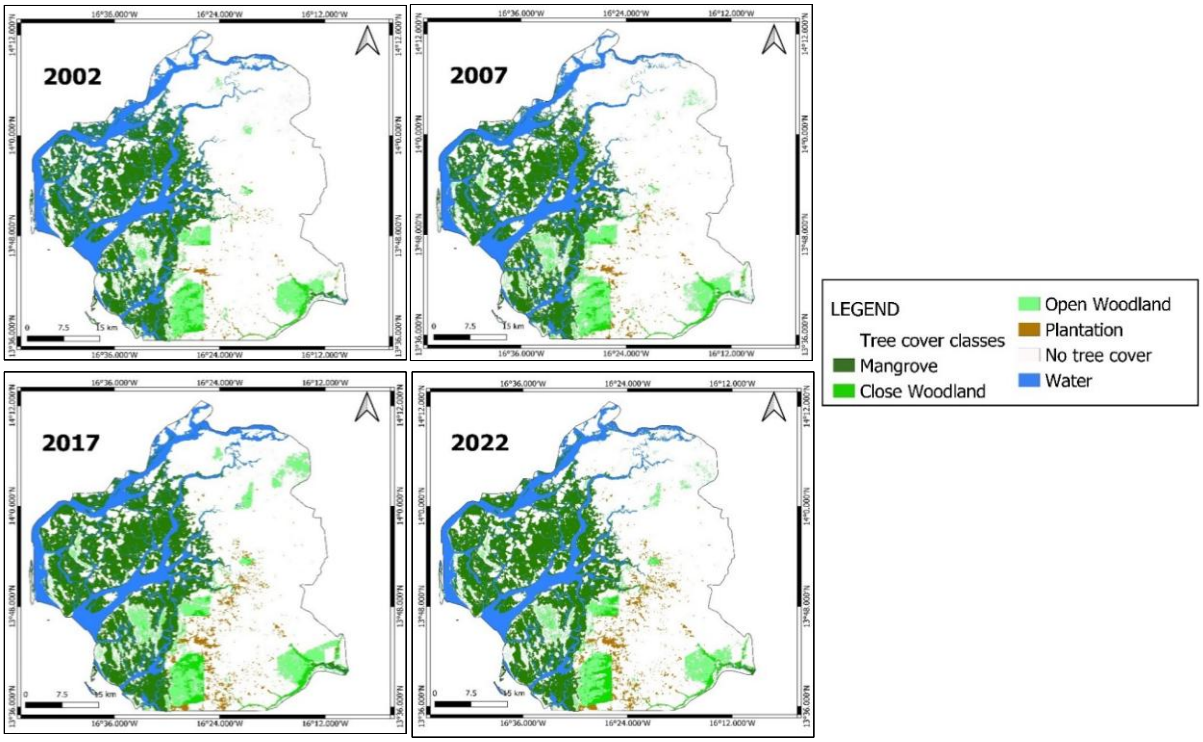


Figure 3.4:Woody tree cover map in the study landscape

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 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 in 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 significant dynamic from 0.80% to 3.03%.

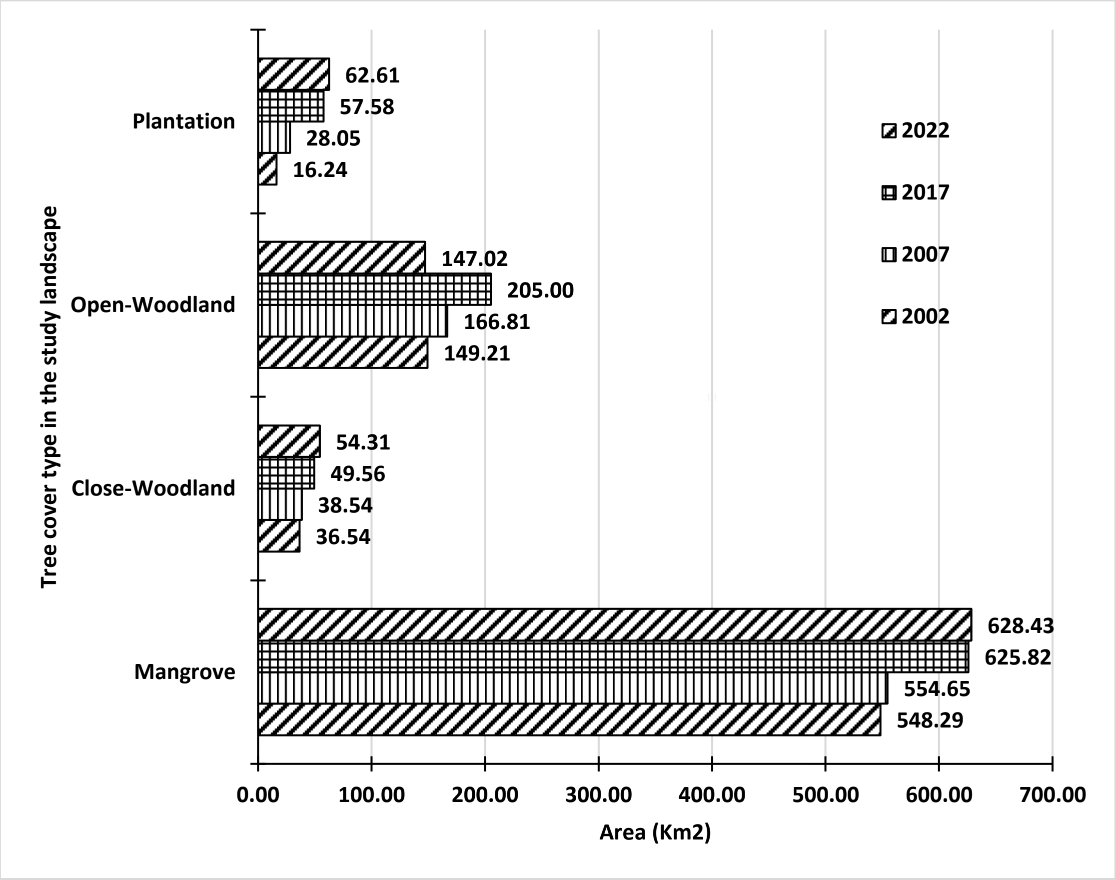


Figure 3.5: Woody tree cover distribution of the study landscape

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 Woodlands PF gain from No Woody Cover with 11.50, 22.67 and 6.73% respectively for the three times intervals. Vice-versa, No Woody Cover gain also from Open Woodlands with 20.15, 14,37 and 32.15% of its coverage. Open Woodlands is subjected to significant conversion with No Woody Cover with and slightly 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 respectively 1.01, 2.07 and 1.07%.

Results shows a slightly gain of Open Woodlands from No Woody Cover during the 2002-2007 study period and a slightly gain from Close Woodlands during the 2007-2017 study period.

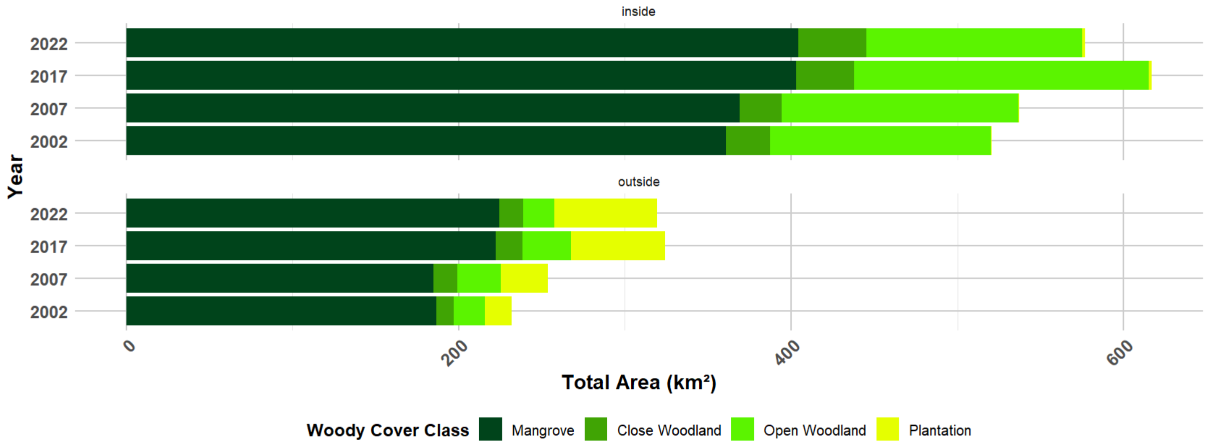


Figure 3.6: Woody coverage inside and outside protected forests

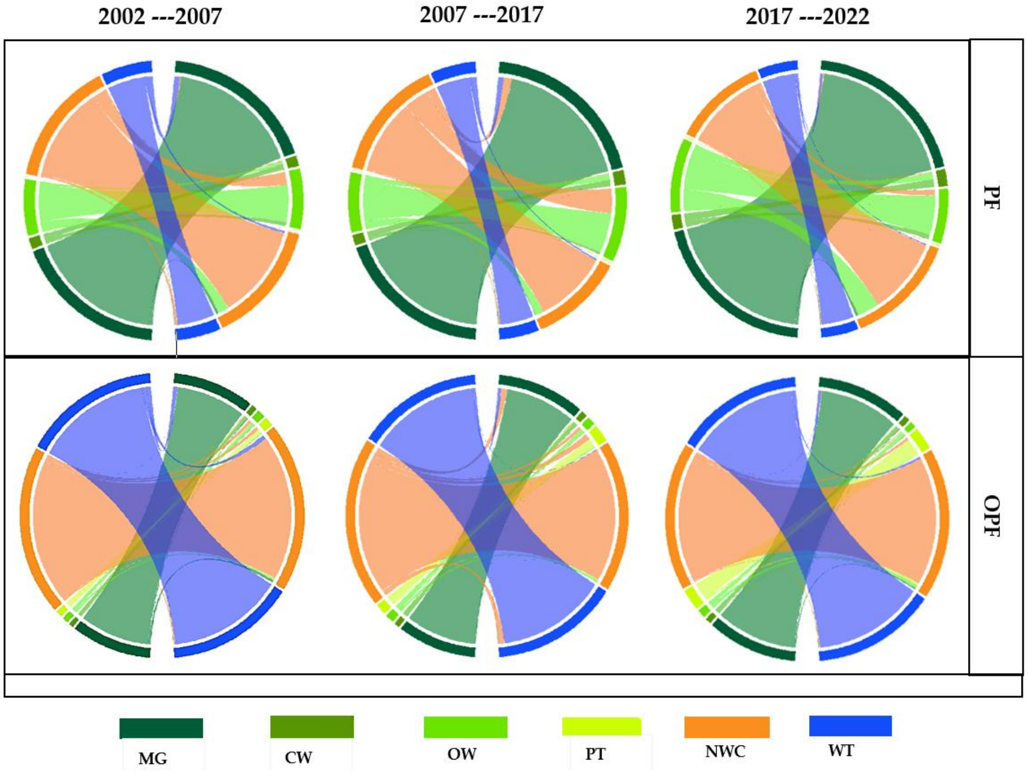


Figure 3.7: Chord diagram of woody vegetation conversion from 2002 to 2022

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

The Figure 3.8 shows that in Mangroves PF, the largest patch index (lpi) strong 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, indicating a shift from a fragmented, dispersed landscape to a more clustered and connected one.

In Close Woodlands PA, the 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.

In Open Woodlands PA, the largest patch index (lpi) strongly decreased from 2002 to 2022. Edge density (ed) strongly increased from 2002 to 2017, indicating greater 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.

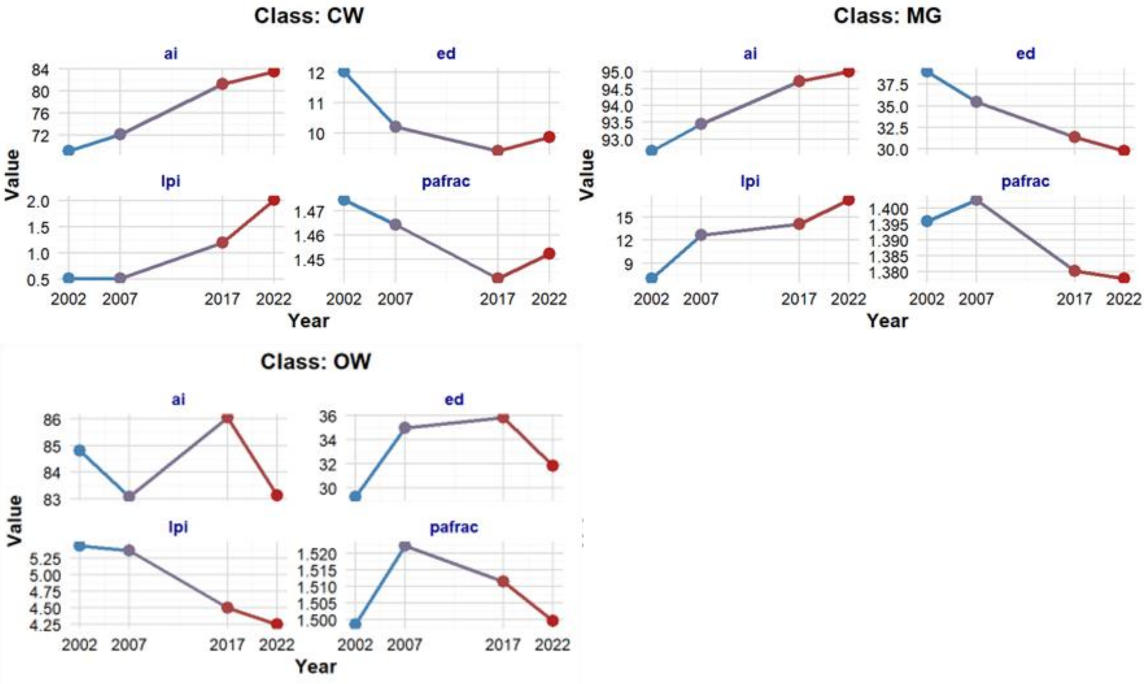


Figure 3.8: Pattern analysis from 2002 to 2022 in Protected Forests classes

3.3.4.2. Pattern Outside Protected Forests

The 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 over time. 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, indicating a shift 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) strongly declined from 2002 to 2017, indicating a less regular shape. However, an increase in 2022 suggested a more regular shape had emerged by that time. 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 then strongly 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 very slight increase observed in 2022. The aggregation index (ai) strongly increased during the study period, indicating a shift from a fragmented, dispersed landscape to a more clustered and connected one.

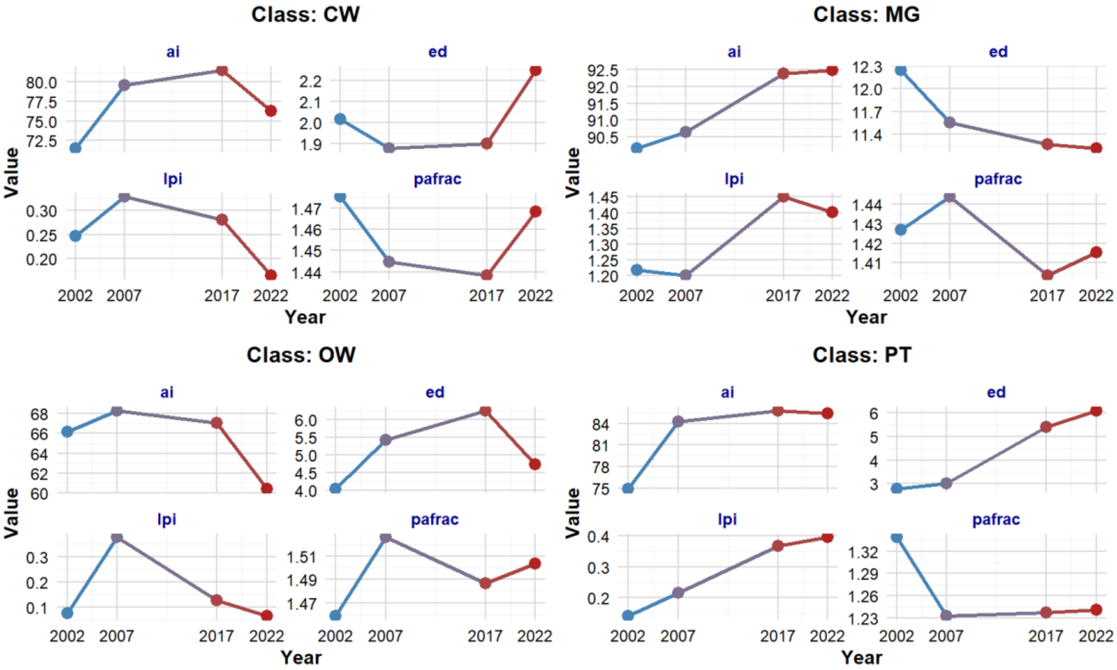


Figure 3.9: Pattern analysis from 2002 to 2022 Outside Protected Forests classes

3.3.4.3. Habitat Connectivity

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 Mangroves patches were mainly observed at the eastern part of its coverage. From 2002 to 2022, an increase in the largest patch has been noticed northward, with a decrease observed in the year 2017. Plantations are mainly found in OPF, with a significant increase in the smallest patches across the study period. The Plantations patches were mainly progressing eastward.

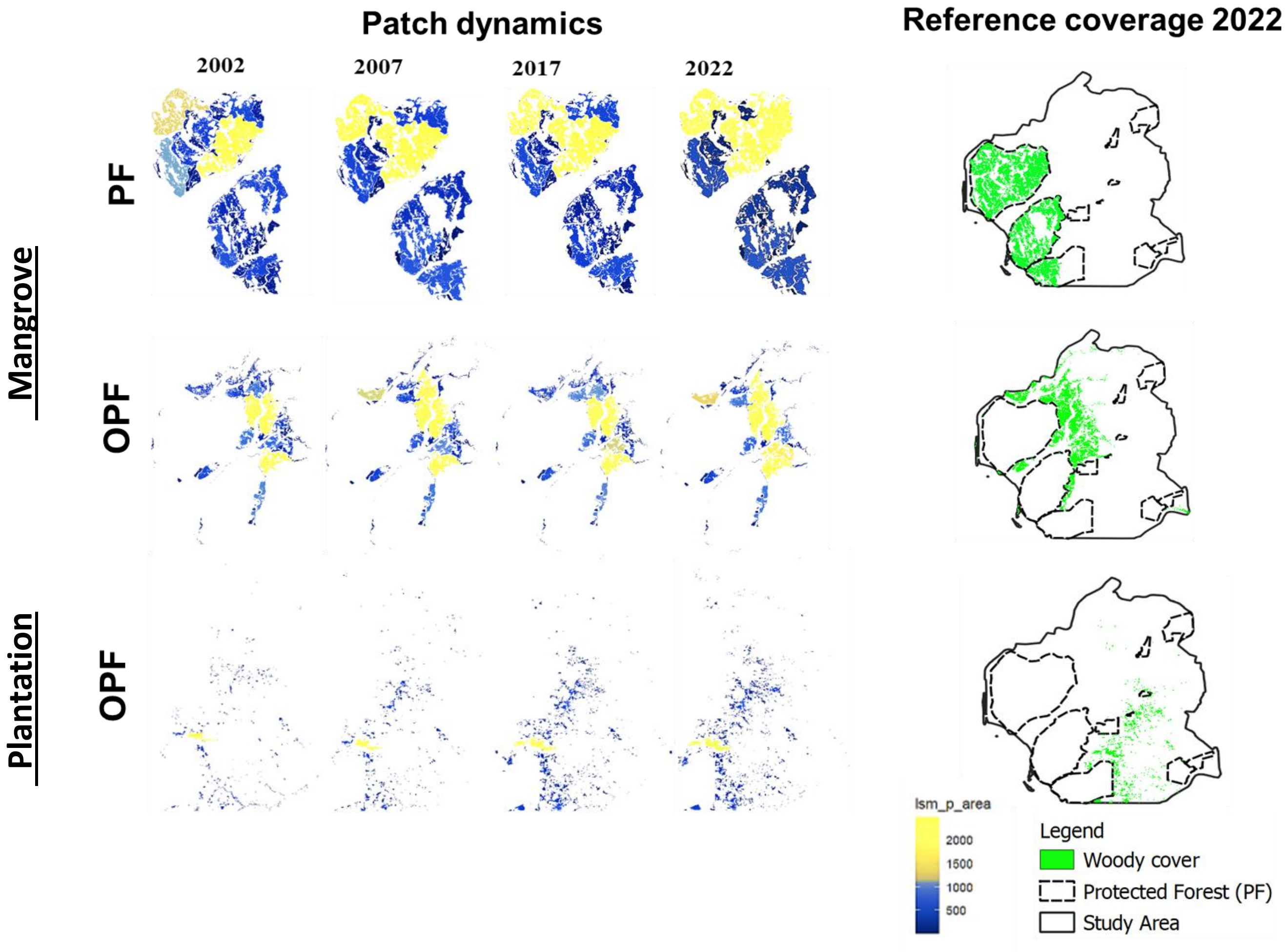


Figure 3.10: Patch area dynamic for most significant changes

3.4. DISCUSSION

Our findings show a slight increase of 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 and is 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). Although 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 certain 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, adjacent savannah areas typically exhibit lower levels of woody vegetation coverage on average. The depletion and looming disappearance of woodlands and pastures between villages in Senegal's groundnut basins underscore the challenges confronting these ecosystems as a result of human activities (Badji et al. 2014).

Mangroves in the study area and in the specific period of our study has shown an increase, 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, owing in part to initiatives like mangroves 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 the preservation and optimal utilization of mangroves 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, shown 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 greatly increasing from 2002 to 2022. High Plantations densities, yields, and the socioeconomic aspects of cashew cultivation are 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 play a crucial role in driving mangrove forest dynamics, underscoring the importance of trait plasticity in shaping community structure and function (Olagoke, 2016).

Results have shown in Open Woodlands 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 compared to 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 with different sizes and shapes (Rivas, 2022).

Our findings show that the Plantations is characterized by continuous small patch 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, primarily in the northern area, increased, 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 both biodiversity and local livelihoods.

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

4.1. INTRODUCTION

Woody cover are essential ecosystems, providing critical services such as carbon sequestration, biodiversity conservation, and support for livelihoods (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) emphasize the importance of 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.

In Soudano-sahelien there is a dynamic interplay of climate variability, human activities, and ecological processes (Gonzalez, Tucker, and Sy 2012; Cheng et al. 2023). This 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 modeling (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, pose a threat to these ecosystems (Dia, 2012). Predicting the spatial distribution of woody cover and associated environmental drivers is key to identifying suitable or priority areas for conservation and land restoration.

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 modeling, 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 occurrence of species 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 different species occupying the same geographical area at the same time (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 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 woody cover is directly influenced by climatic conditions. 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). A parameter such as Salinity was taken into because the Saloum Delta has been experiencing by occurrence of salt-affected land (Descroix et al., 2020; Thiam et al., 2021).

The importance of the chosen soil physical parameter is due to the fact that the physical properties of soil determine water infiltration, retention, and root penetration (S. J. 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 (van Straaten et al., 2019).

4.2.2. Model Processing

Woody tree cover occurrence data and predictor variables were integrated into a modeling framework. Occurrence data for woody tree covers, including geographic coordinates of woody tree covers from field work 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, such as filtering out missing values, ensured the integrity of the dataset. Background (pseudo-absence) data was generated by randomly sampling the study area to support robust model training, a common practice in species distribution modeling (Descombes et al., 2022)

Machine learning algorithms, including Random Forest, Generalized Linear Models, and Maximum Entropy, were applied to model species distributions. These algorithms have been widely recognized for their ability to handle complex ecological data (Chollet et al., 2023; Zhang & Li, 2017; Zhao et al., 2022). Advanced cross-validation techniques, such as subsampling and bootstrapping, were employed to enhance 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-M et al., 2021)

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

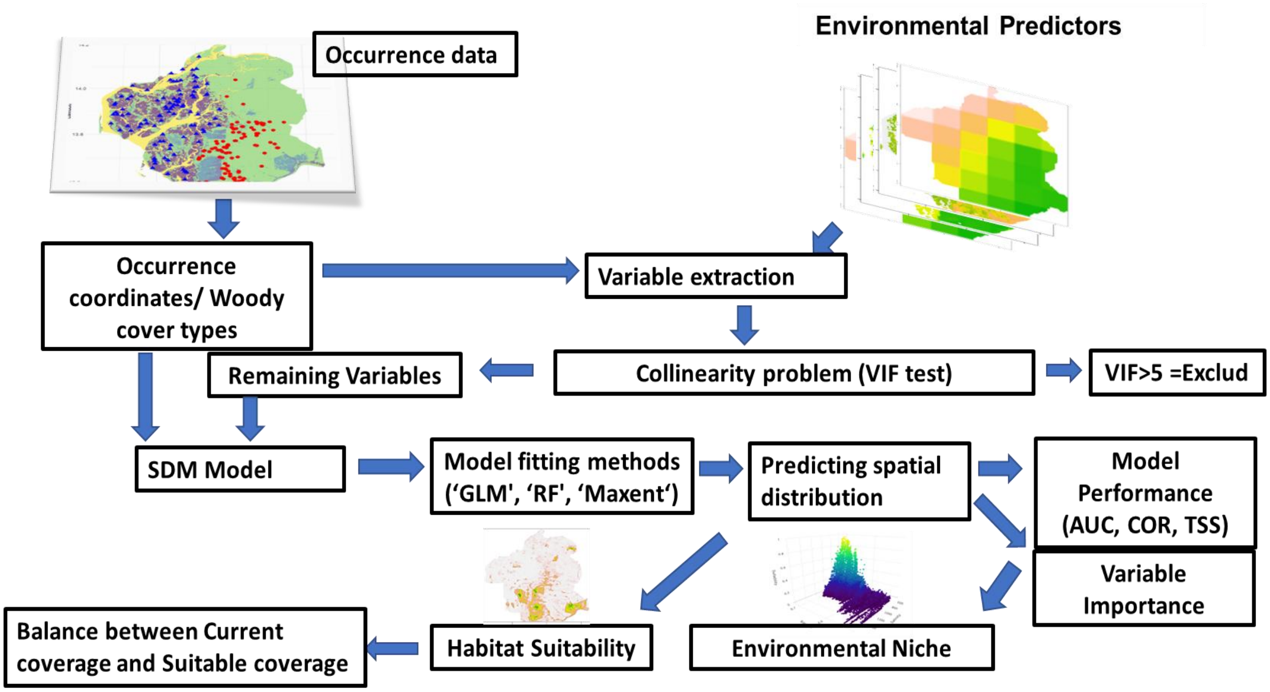


Figure 4.1: Workflow of the model prediction

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 for both, 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 again lags behind, with 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. Maxent, while maintaining a decent AUC of 0.91, suffers from a higher Deviation of 0.56. GLM is the weakest performer, with lower metrics across all categories, including an AUC of 0.89 and a COR of 0.47, along with a notable Deviation of 0.44.

Across all vegetation types, the Random Forest (RF) performs better than the other models. Maxent achieves good results in terms of AUC and TSS but is less dependable due to greater 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 important drivers for Mangroves are salinity, followed by bulk density and coarse fragments. In Close Woodlands, salinity emerges as the primary factor, followed by rainfall and burned area. For Open Woodlands, salinity and burned area are identified as the key drivers. 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.

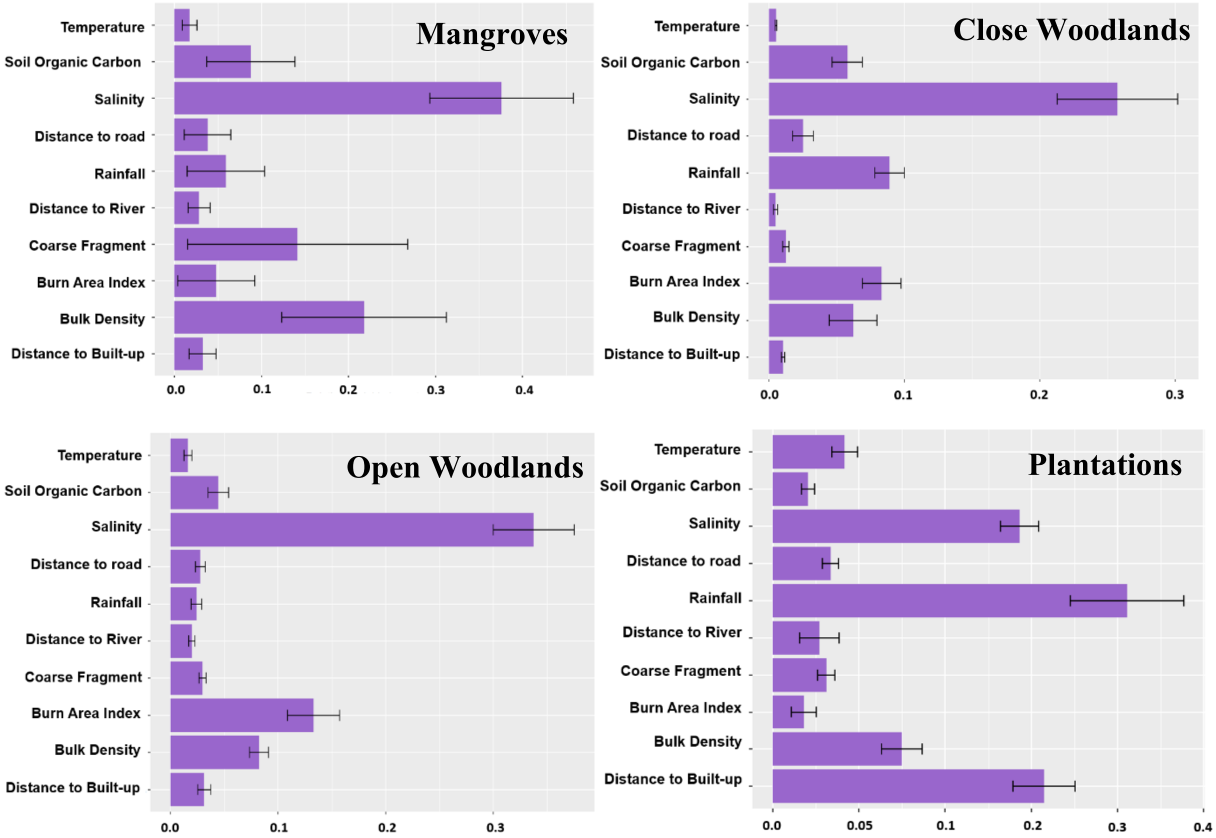


Figure 4.2: Variable importance of the woody cover drivers

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 lowest Salinity Index (between 600 and 800) and a low to medium Bulk Density (between 0 and 60 g/cm³).

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

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

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

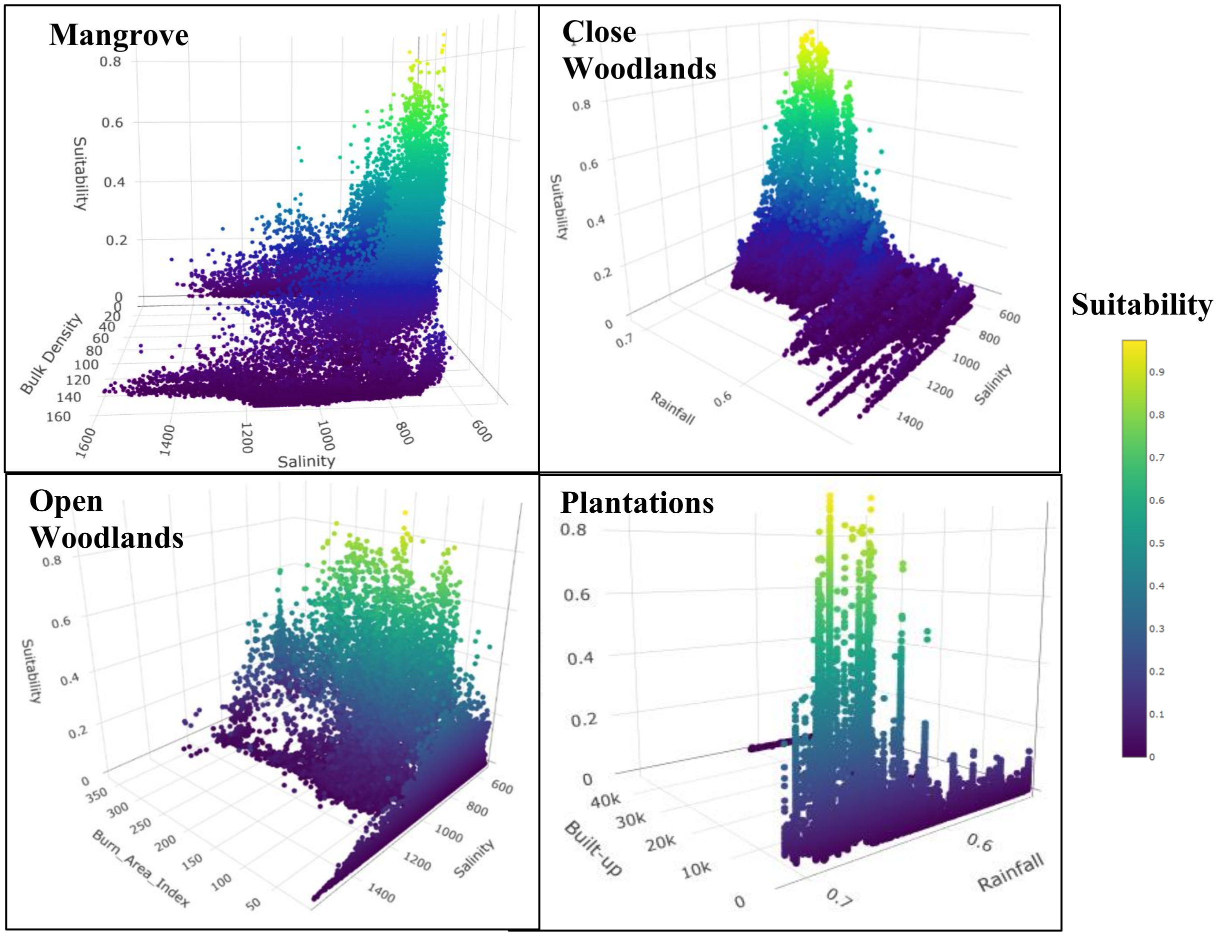


Figure 4.3: Habitat suitability from two main drivers in different woody cover

4.3.4. Habitat Suitability

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 areas 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 suitability in different woody cover

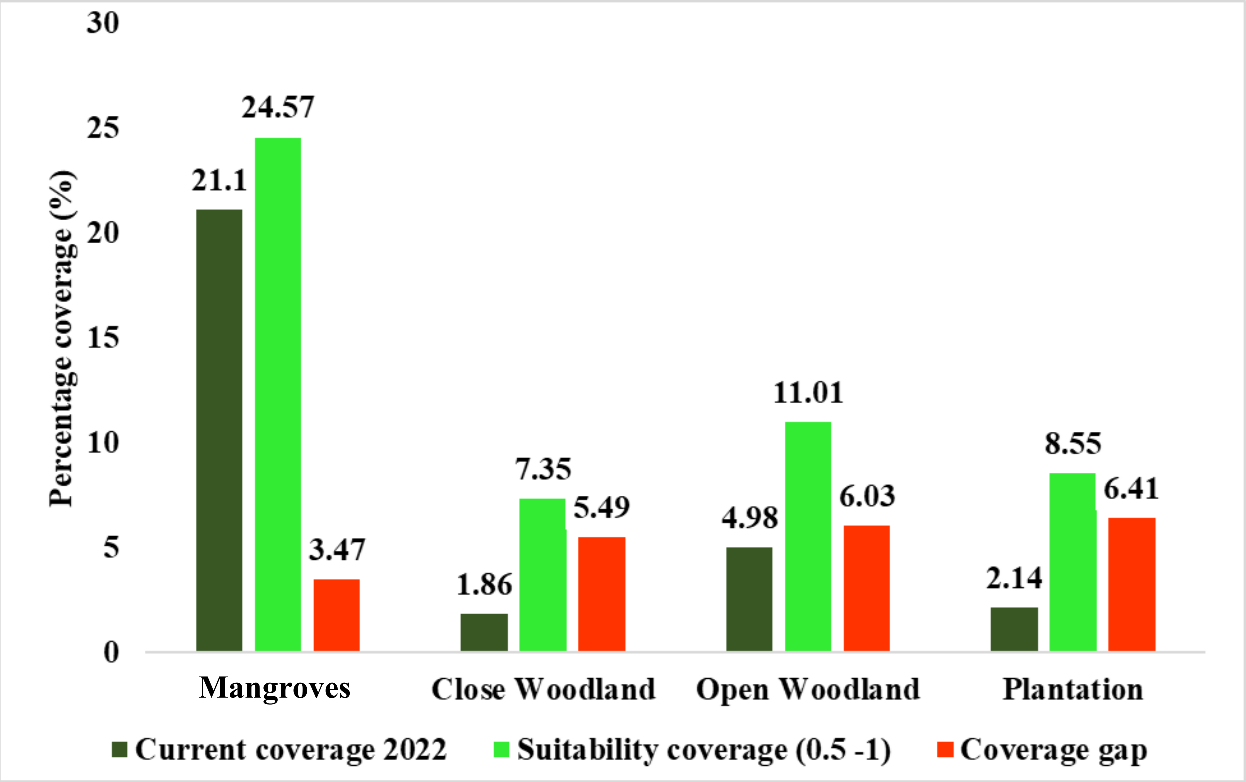


Figure 4.5: Comparison between current coverage and predicted suitable coverage

4.4. DISCUSSION

This study evaluates the efficacy of three modelling techniques, Random Forest (RF), Generalized Linear Model (GLM), and Maxent, in predicting the spatial distribution of various vegetation types in the Saloum Delta. The findings indicate that RF consistently outperforms the other models across all vegetation categories, as evidenced by higher Area Under the Curve (AUC), Correlation Coefficient (COR), and True Skill Statistic (TSS) values, coupled with lower deviation scores. This superior performance of RF is consistent with existing literature, which highlights its robustness in handling complex ecological datasets and its ability to model non-linear relationships effectively (Drew et al. 2011). In contrast, Maxent, while achieving commendable AUC and TSS scores, exhibits greater variability, as indicated by higher deviation values. This instability may stem from Maxent's reliance on presence-only data, which can introduce sampling biases and affect predictive reliability (Valavi et al., 2021).

GLM demonstrates the weakest performance among the three models, likely due to its limitations in capturing complex, non-linear ecological relationships, a challenge well-documented in ecological modelling studies (Mushagalusa et al. 2024).

The analysis of variable importance 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, Nielsen, and Rasmussen 2000).

Interestingly, variables such as temperature, distance to rivers, and proximity to road exhibit minimal contributions across most vegetation types. This suggests that, within the Saloum Delta, these factors may play a secondary role. This observation is consistent with the concept of 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 specific environmental ranges favorable for each vegetation type. Mangroves, for instance, are found to thrive within a salinity index range of 600 to 800 and a bulk density between 0 and 60. This 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 ranges of salinity and annual burnt count, reflecting their adaptability to fire regimes (Veenendaal et al., 2018). Research found that nearly 99.82% of the total settlement area has been identified as suitable for home gardens (R. 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 indicates that, despite the high salinity levels characteristic of this region, Mangroves 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 regions. This 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 a 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 and left 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 economic viability of cashew cultivation in the Sokone area. This dual benefit underscores the value of cashew trees in both 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 terms of 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, while rainfall emerges as a critical factor for Close Woodlands and Plantations. Other factors, such as bulk density and the burn area index, also play significant roles in determining 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 are more dependent 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. For Mangroves, maintaining appropriate soil conditions and mitigating saltwater intrusion are crucial for their 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 plays a crucial role 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 (X. 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 the adoption of 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 policy 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 is a relevant aspect 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. There is limited resources and scarcity of region-specific allometric equations (Walker et al. 2016). New advances in technology with recent advancements in remote sensing technologies, such as lidar and airborne laser scanning (ALS), provide reliable, non-invasive 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 (Y. 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), allow 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. Addressing this limitation, our study focused on different woody tree cover within the Saloum Delta. 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

To estimate the number of survey plots required, a pre-inventory was carried out with three plots for each woody cover type. 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) reported also in (Heyojoo & Nandy, 2015) as followed. A total of 138 plots were established.

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

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 , 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) were 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. For unidentified woody species, samples 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.

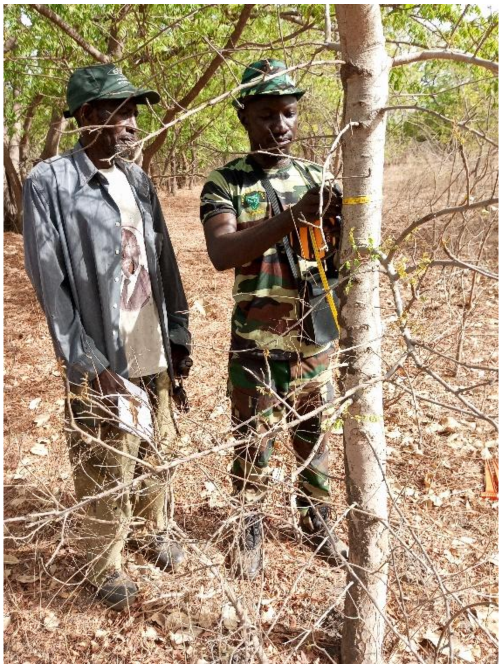


Figure 5.1: DBH Measurement of trees

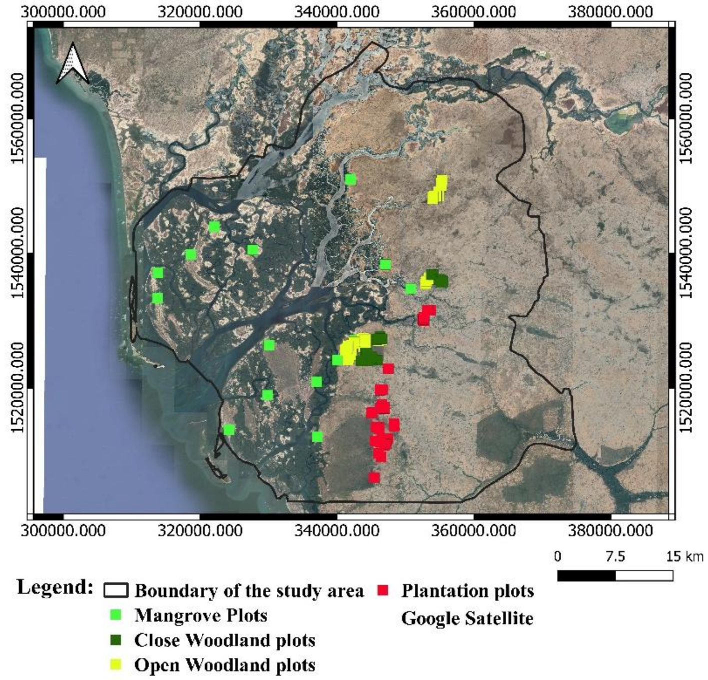


Figure 5.2: Spatial Distribution of the plots

5.2.3. Above-Ground Biomass Estimation

Given the scarcity of species-specific allometric equations, previously validated one for Open Woodlands (OW) and Close Woodlands (CW), specifically the one of Mbow et al. (2014) were employed. In Plantations, mainly composed by mango (*Mangifera spp.*) and cashew (*Anacardium spp*) species specific allometric equation were used. For Mangroves areas, to avoid overestimations, the estimation relied on equations proven suitable in prior studies done in one part of 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	$\mathrm{AGB}_1 = \exp(-2.6554) \times \mathrm{DBH}{}^\wedge 2.26$	(Dao et al. 2021)
***Annacardiun Spp.:*AGB_2**	$\mathrm{AGB}_2 = exp\,[-1{,}85645+0{,}01656+2{,}02288*ln\,(Dbh)]$	(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 data 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 mostly using a trial-and-error method, starting from the most common to the least common 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 comprises also vegetations in coastal areas where water may have an influence on 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. A total of 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 in relation to 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 (Chandrashekar and Sahin, 2014), 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 for training 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 utilized a combination of 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). Comprehensive descriptions of these methods, along with their tuning parameters, are presented in Table 5-2. All the process was done in R software as shown in Figure 5.3.

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)

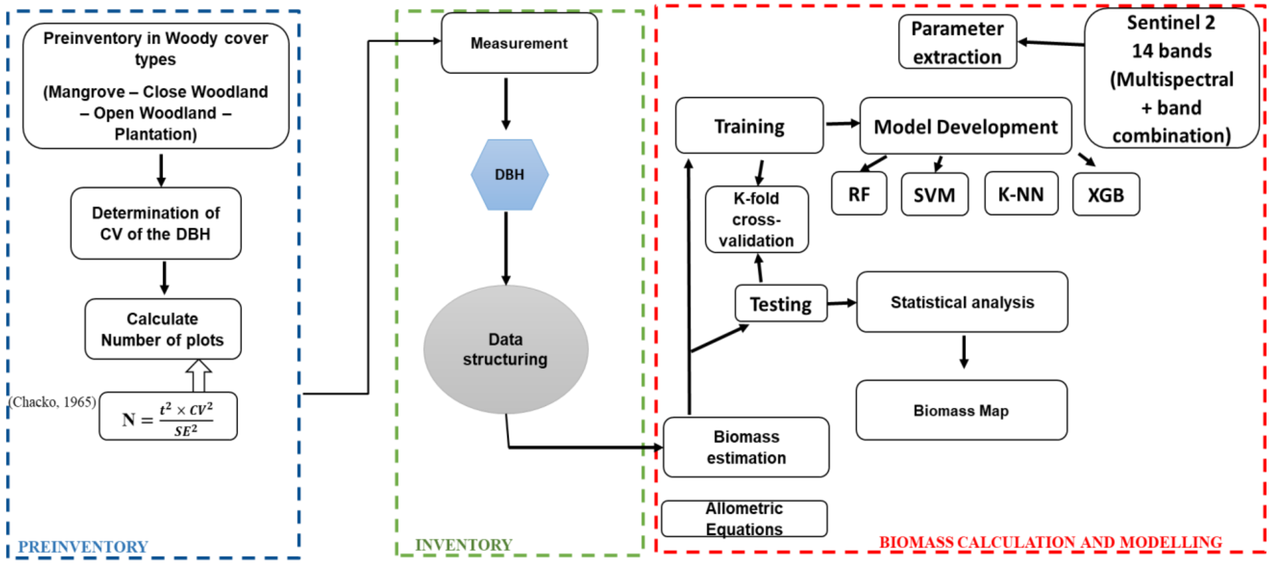


Figure 5.3: Workflow of the machine learning process

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 of 2.32. Mangroves (MG) and Plantations (PT) recorded the lowest species richness, with only 2 species each. The Shannon indices for MG and PT were 0.58 and 0.64, respectively.

The structural characteristics of woody vegetation using DBH class are illustrated in Figure 5.5. In Mangroves, the diameter at breast height (DBH) 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.

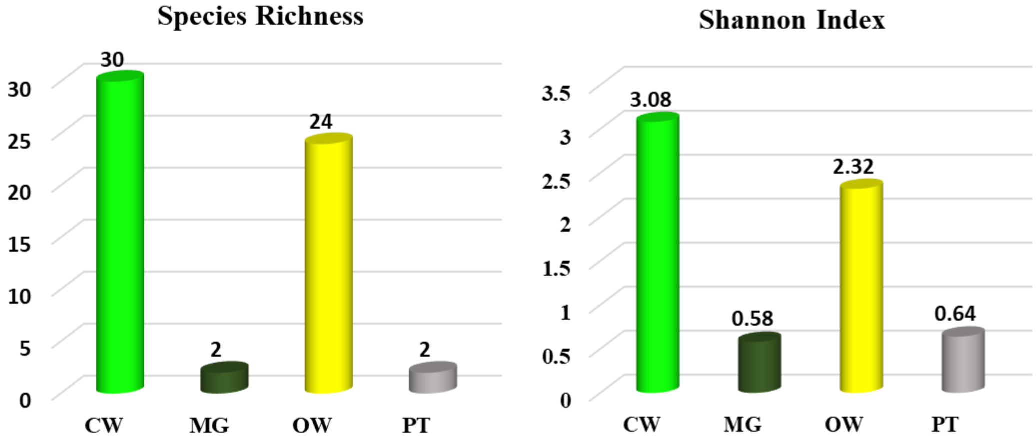


Figure 5.4: Biodiversity indices in the different woody cover

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

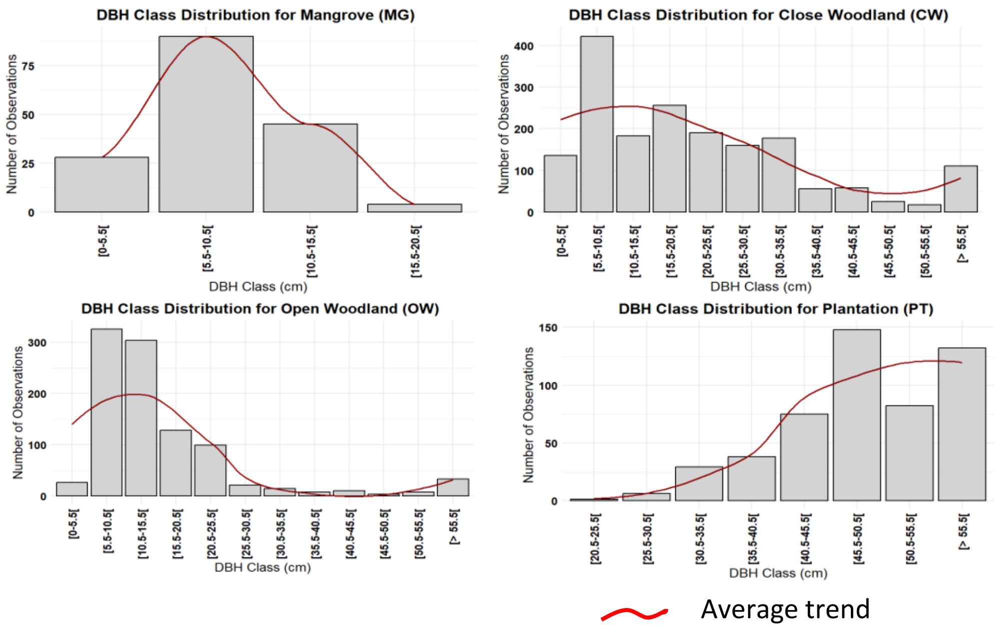


Figure 5.5: DBH Class in the different woody cover

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

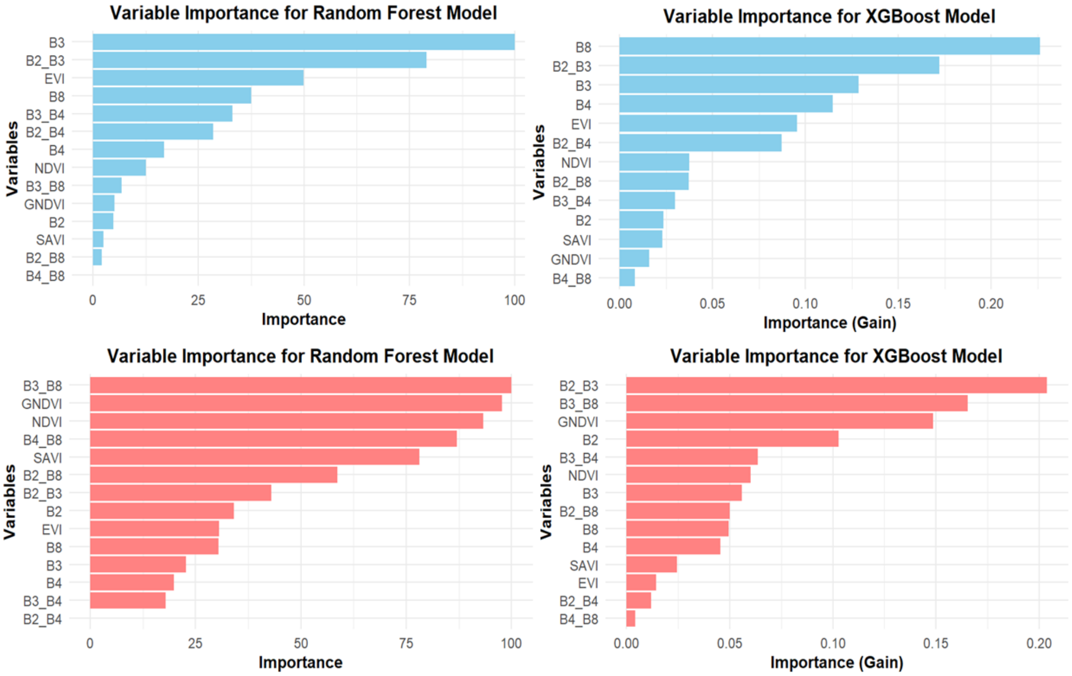


Figure 5.6: Variable importance of the model for RF and XGB

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 tend to overestimate at low in-situ AGB values, while underestimation predominantly occurs at the highest in-situ AGB values. 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.

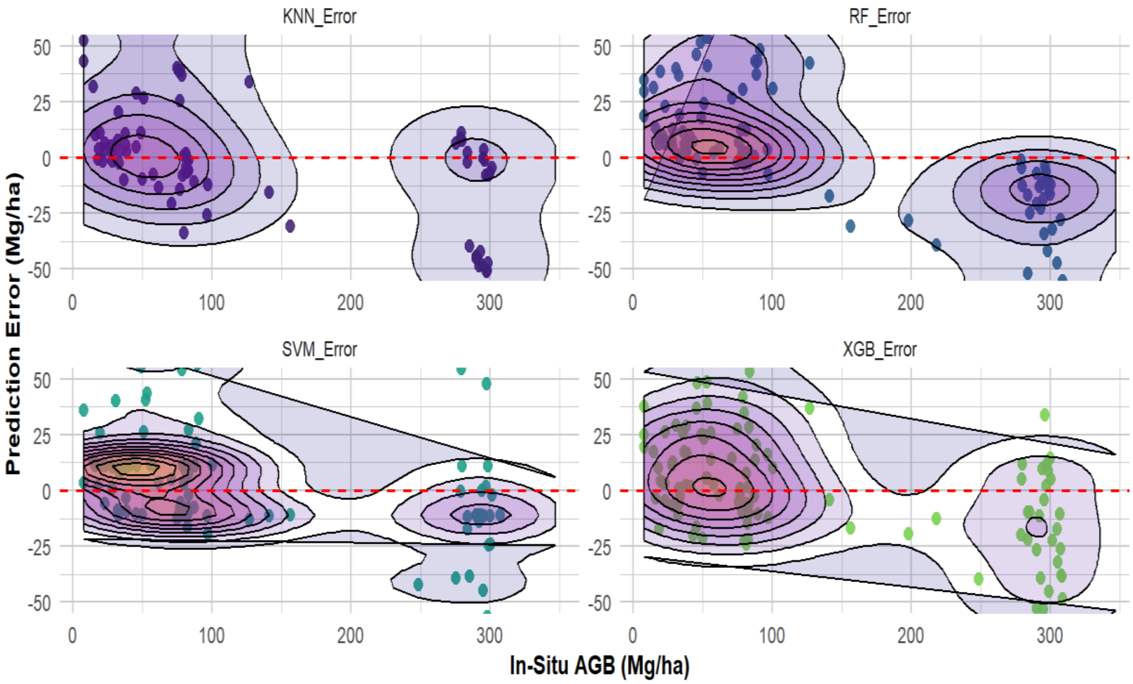


Figure 5.7: Density plot comparison of in-situ AGB and Predicted Error

5.3.3.4. Spatial Distribution of AGB

Figure 5.8 shows the RF, SVM, K-NN and XG-Boost prediction maps. The maps accurately reflect the spatial heterogeneity of the area, displaying areas of both low and high biomass. The spatial distribution of biomass for RF was more closed 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.

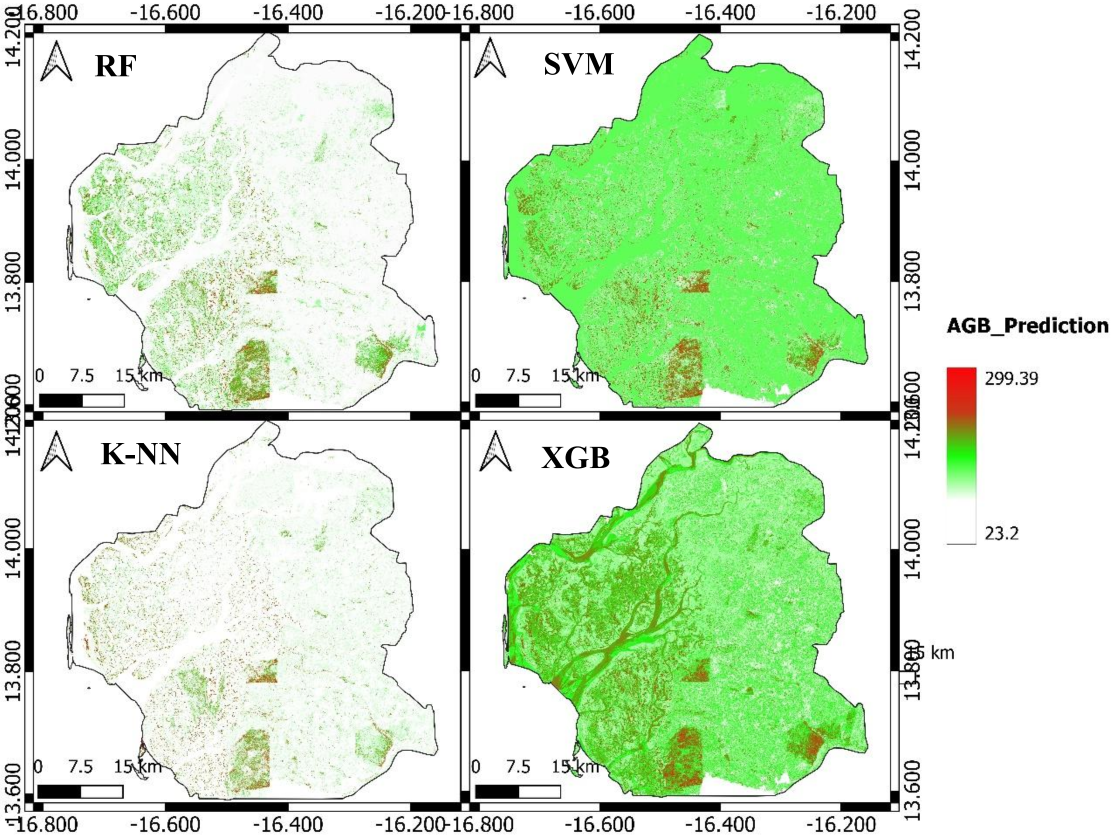


Figure 5.8: AGB Predicted map for the different models

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, with an average of 295.08 ± 9.54 Mg/ha. This was followed by Open Woodlands 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 cashew, 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. Greater value lies in leveraging advanced technologies for biomass assessment, enabling more accurate estimations across larger areas, which highlights 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 compared to 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 the intra- and inter-annual dynamics of carbon stocks. 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, coupled with frequent bushfires during the dry season, significantly reduces 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; B. 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 both the Random Forest (RF) and XGBoost models, emphasizing its importance for prediction accuracy. This result aligns with previous findings that band combination 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 modeling.

These findings collectively underscore the importance of leveraging diverse data sources, including spectral bands and VIs variables, to optimize AGB predictions across varying 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 ability to model AGB across seasons, supported by its capacity to integrate a wide range of predictor variables. Notably, 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 provides a summary of the key findings, conclusions, and recommendations aligned with each specific 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 dynamic and pattern of the woody covers, identifying challenge and opportunities for restoration and to balance 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 regions of moderate rainfall and salinity. 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 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

Firstly, 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 larger, connected patches, whereas Outside Protected Forests (OPFs) experienced greater fragmentation. Land use pressures such as agriculture and urbanization were significant contributors 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 driver 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 achieved following the habitat suitability map. The mismatching of suitability between Close Woodlands and Open Woodlands remains obvious. Consequently, the manager would rather decide to go for Close Woodlands, paying full attention to Open Woodlands drivers like fire burn. The use of species distribution models (SDMs) demonstrated that Random Forest (RF) consistently outperformed other models in predicting vegetation types. Adaptive management strategies, including the introduction of 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 equation 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 compared to the dry season. The model's effectiveness was further validated by strong adjusted R-squared and RMSE values, highlighting its ability to incorporate diverse predictor variables. Notably, 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 gab 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 both 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 both 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 focused 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 environmental 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 restoration and conservation plans that are robust under future climate uncertainties.

For Research Objective 3, which involved assessing and modeling 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.

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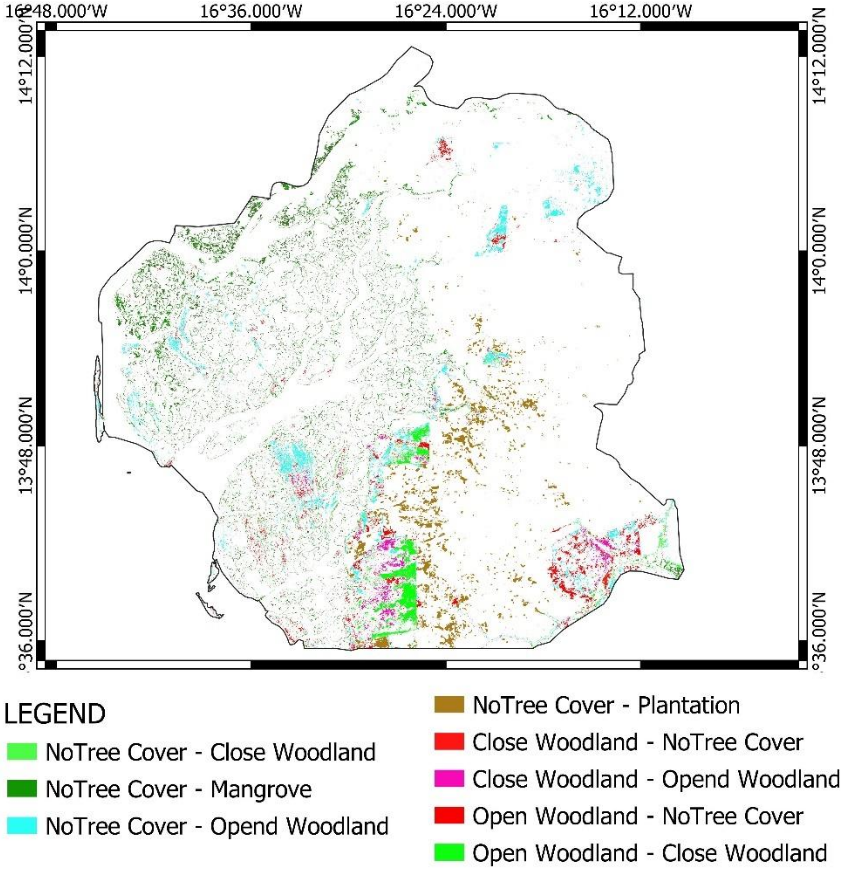
APPENDICES

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)							
		No tree cover	Close Woodlands	Mangrove	Open Woodlands	Plantation	Water	Total	Loss
Change to final year 2007 (Km^2)	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)							
		No tree cover	Close Woodlands	Mangrove	Open Woodlands	Plantation	Water	Total	Loss
Change to initial year 2017	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		

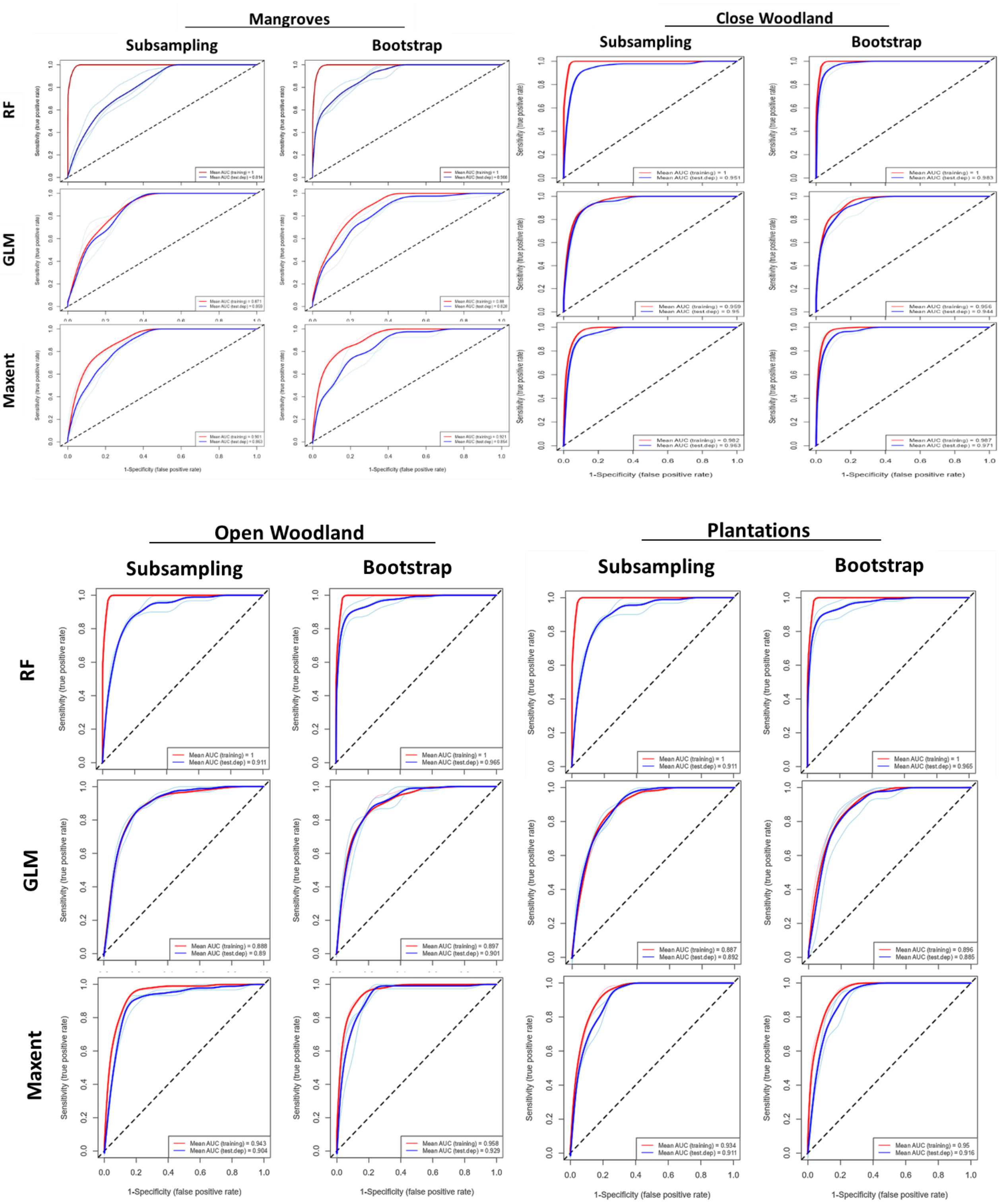
Appendix 5: Transition matrix from 2017 to 2022 in the study landscape

		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		

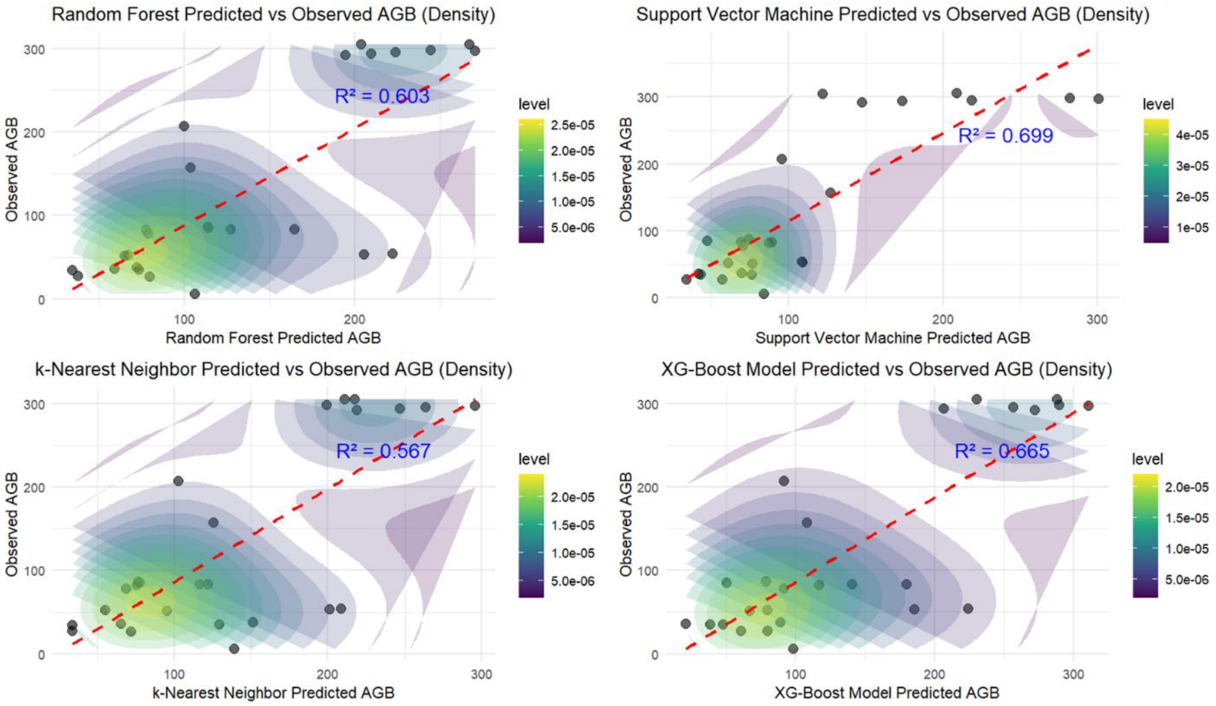
Appendix 6: Transition matrix from 2002 to 2022 in the study area

		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		

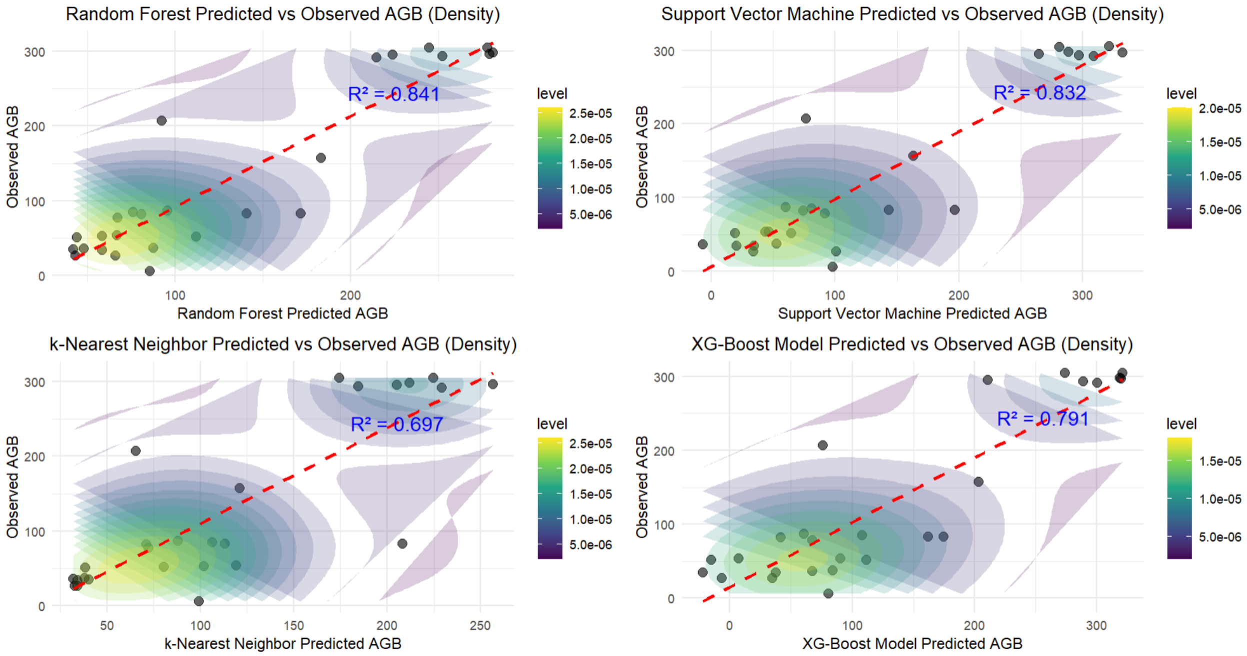
Appendix 7: Mean AUC of Sub-sampling and Bootstrap for different model in each woody communities. (red=training) ; (blue=testing)



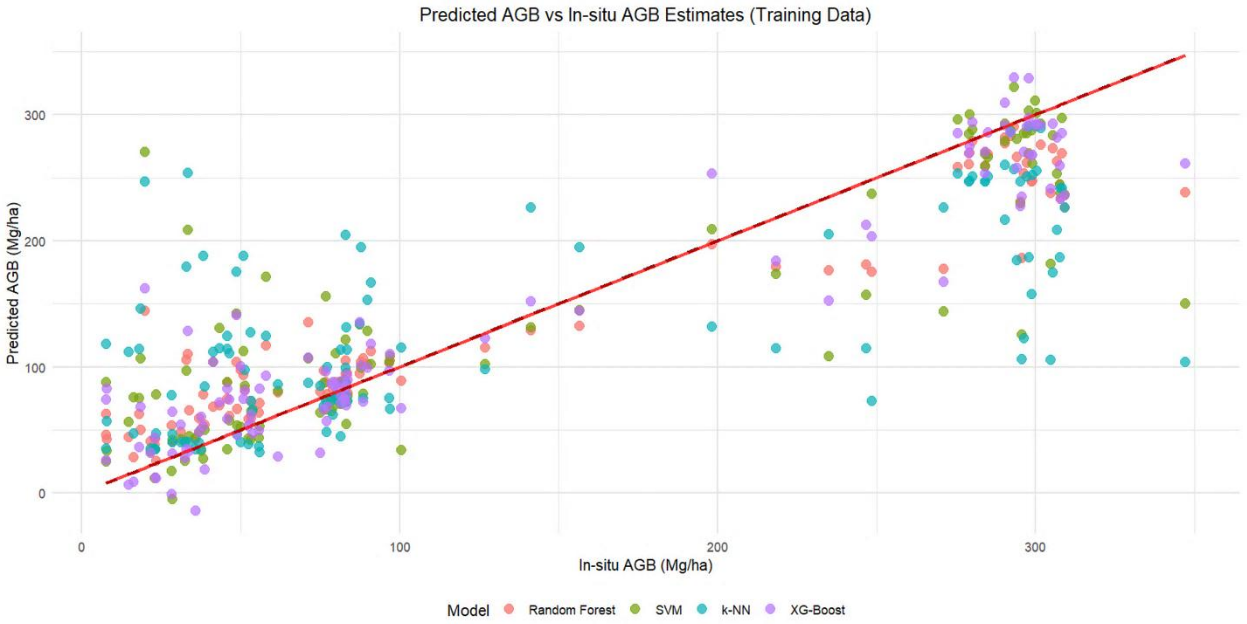
Appendix 8: Predicted AGB vs Observed AGB and related Rsquare for the dry season



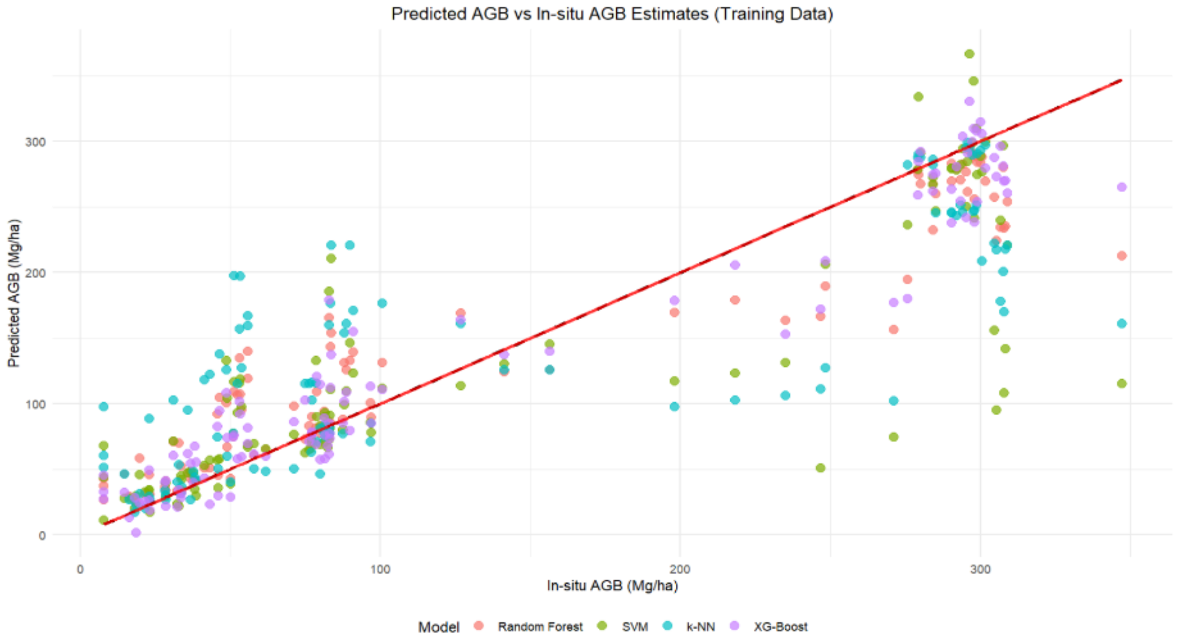
Appendix 9: Predicted AGB vs Observed AGB and related Rsquare for the wet season



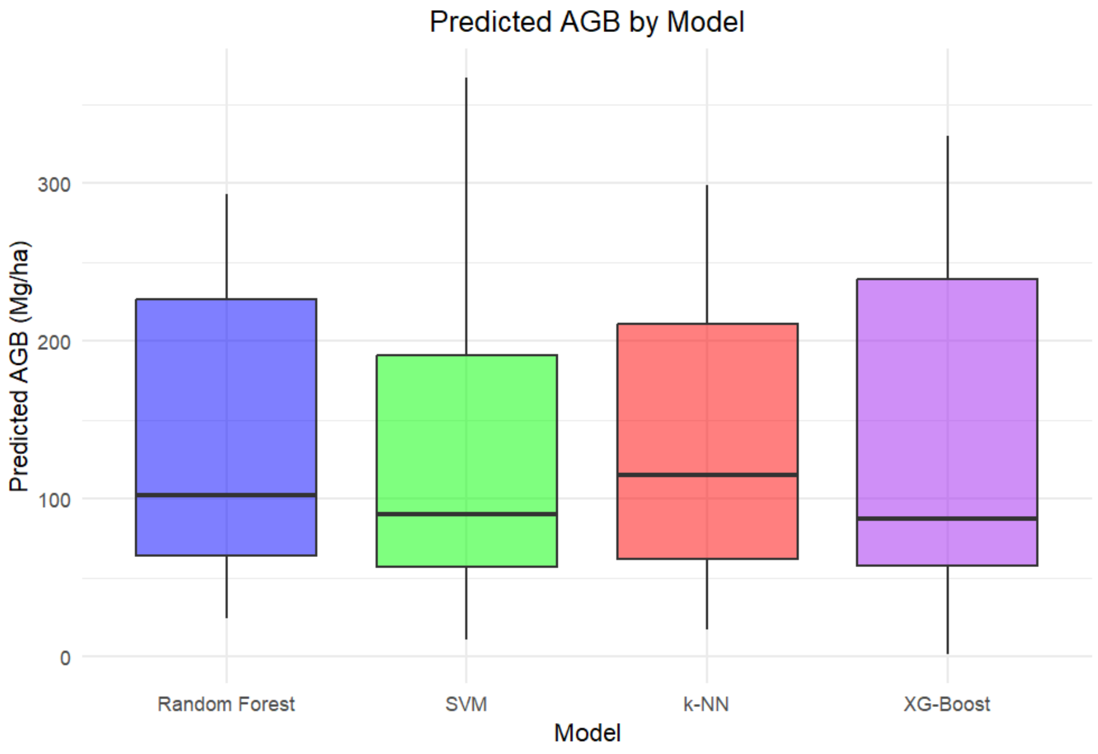
Appendix 10: Predicted vs Observed AGB for all models in dry season



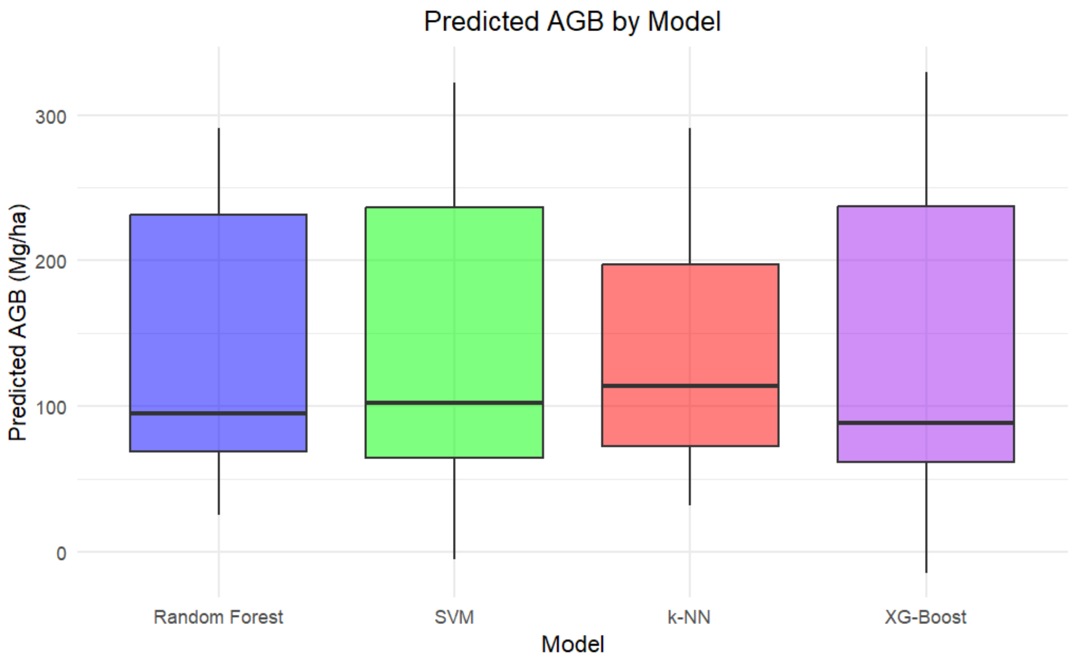
Appendix 11: Predicted vs Observed AGB for all models in wet season



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