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Modelling Woody Vegetation Suitability in Saloum Delta Ramsar Site (West-Africa): Implications for Conservation and Land Restoration

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ABSTRACT: Woody vegetation is crucial in maintaining ecological balance, supporting biodiversity, and contributing to carbon storage. However, these ecosystems face increasing threats from deforestation, climate change, and human activities. Despite the current challenges, diagnostics and preliminary information for guiding regreening interventions to restore ecosystems are notably lacking. This study employed Species Distribution Models (SDMs) to predict the spatial distribution and suitability of four woody tree covers (Mangroves, Close Woodlands, Open Woodlands, and Plantations). In each woody cover, a hundred occurrence points were used. The study used machine learning approaches such as Random Forest (RF), MaxEnt, and Generalized Linear Models (GLM) to analyse the relationships between woody cover occurrence data and environmental predictors, including climate, soil properties, anthropogenic factors, and natural disturbances. Results indicate that Salinity is the most significant driver affecting all vegetation types, particularly mangroves. Rainfall strongly influences Close Woodlands and Plantations, while fire disturbances shape Open Woodlands. Predicted suitability maps reveal potential habitat suitability, indicating areas of high restoration potential and underscoring the need for targeted conservation and restoration strategies. Comparison between current coverage and the predicted suitability revealed the smallest gap in Mangroves to cover the optimum suitable area (3.47%) while substantial areas still exist for Close woodlands, Open Woodlands and Plantations with 5,49, 6,03 and 6,41, respectively. Findings from this study provide essential insights for sustainable land management, regreening policy initiatives, and woody ecosystem restoration planning in West Africa's woody coastal areas. By integrating Geographic Information System (GIS) and ecological modelling, this research enhances decision-making for biodiversity conservation and climate resilience.

KEYWORDS: Woody Vegetation, Species Distribution Models, Ecological Restoration, Saloum Delta, Ramsar Site

1. INTRODUCTION

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

Soudano-sahelien has a dynamic interplay of climate variability, human activities, and ecological processes (Gonzalez, Tucker, and Sy, 2012; Cheng et al., 2023). A comprehensive, data-driven approach to inform land restoration strategies zones is critical. The assessment and monitoring of forest ecosystems rely increasingly on advances in geospatial technologies and ecological modelling (KOMBATE et al., 2023; Xue et al., 2019). Remote sensing tools, Geographic Information Systems (GIS), and predictive modelling

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techniques have revolutionised 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 and RAMSAR Site, is an ecologically and socioeconomically significant region characterised by diverse habitats, including Mangroves, savannas, and woodland ecosystems (Diop, 1998; Sambou, 2015). Woody tree cover in this delta is vital for maintaining ecological balance, supporting local communities, and contributing to global carbon storage. However, environmental and anthropogenic pressures, such as changing climate patterns, land use changes, and resource extraction, threaten these ecosystems (Dia, 2012). Site management interventions are often random and lack pre-diagnostic information to guide restoration efforts (Ntshotsho et al., 2015). Predicting the spatial distribution of woody cover and associated environmental drivers is key to identifying suitable or priority conservation and land restoration areas.
In this study, we apply SDMs to predict the environmental drivers and associated spatial distribution of woody tree cover and their area suitability in the Saloum Delta. By integrating spatial data and ecological modelling, this research seeks to inform optimum land restoration and enhance the effectiveness of restoration and future carbon sink policy initiatives in the region. The findings will contribute to sustainable land management, improved carbon stock pools, and conserving the Saloum Delta's ecosystems.

2. METHODOLOGY

2.1. Study site

This study was done in the Saloum Delta part of Foundiougne department. The region is between 13.85 and 16.15 degrees North latitude and 15.65 and 16.25 degrees West longitude, spanning approximately 3666 square km^2. The area is bordered to the east by the Kaolack region, to the west by the Atlantic Ocean, to the north by the Department of Mbour, and to the south by the Republic of Gambia (Figure 1). It comprises fourteen communes and three districts, including Djilor, Niodior, and Toubacouta, with a total estimated population of 279,436 for the 2013 Regional Census of Population. The insular section encompasses islands spanning 950 km^2 in total area. It is delineated by three primary rivers: the Saloum, the Diombos, and the Bandiala, all of which discharge into the Atlantic Ocean from Sangomar Point (Faye *et al.*, 2019). Fishing serves as the primary source of income for many residents. The delta's waters host a diverse range of fish species, establishing it as an essential area for fishing activities.
The Saloum Delta is located in a region with a Sudano-Sahelian climate, characterised by alternating air flows depending on the time of year. The region's climate is marked by two distinct seasons: from November to May, a dry season is observed, and a rainy season lasts five months, from June to October. Temperatures and insolation vary according to the seasons. Annual precipitation shows substantial variations, with a slight tendency towards dryness according to the Standardised Precipitation Index (SPI). This index reveals that 92% of years are very dry, 3% are extremely dry, and 4% are extremely wet (Tine *et al.*, 2020). Presently, the Saloum Estuary comprises a network of rias formed by the rivers in the region and numerous narrow rivers or streams, with minimal freshwater input due to rainfall variability (Faye *et al.*, 2019).
The main activity in the area is agriculture. Pearl millet (Pennisetum glaucum) is the most essential food crop, and groundnut (Arachis hypogea) is the leading commercial crop (Diop *et al.*, 2011). Fishing and salt extraction provide a means of livelihood for a large portion of the population in coastal areas (Bineta *et al.*, 2018). Tourism contributes to local communities' livelihoods (Sarr *et al.*, 2012).
Situated at the meeting point of the Sine and Saloum rivers, The Saloum Delta encompasses designated forests, community nature reserves, marine protected areas, and a Natural Park. The Saloum Delta is recognised by UNESCO as a World Biosphere Reserve and designated a wetland of international significance (IUCN, 2011).

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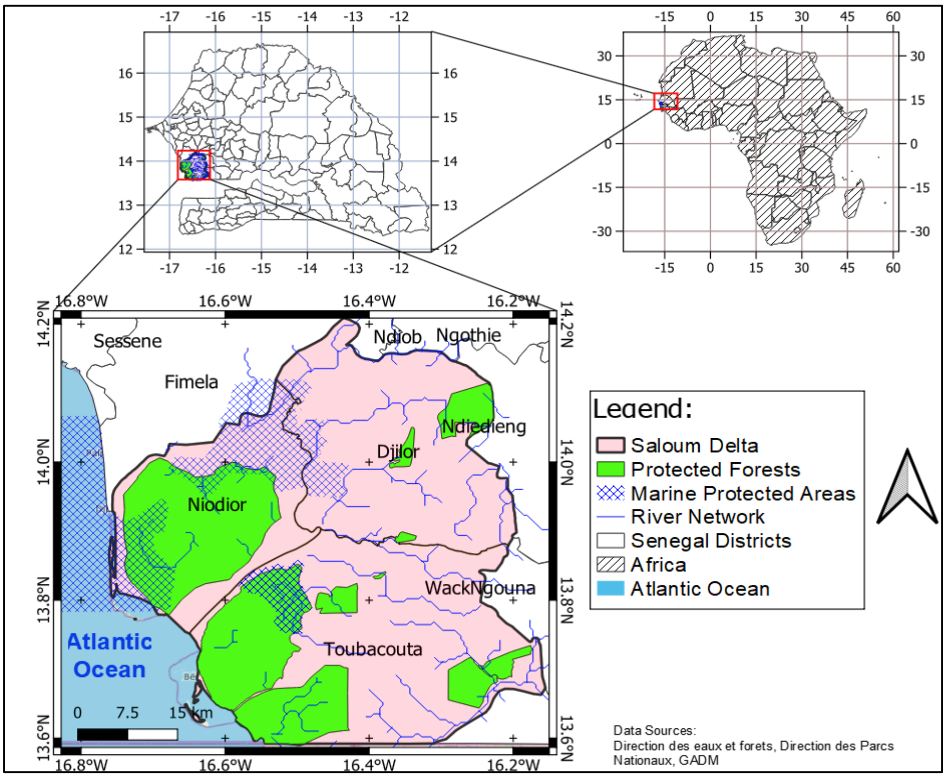

Figure 1: Map of the study area

2.2. Species Distribution Models

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.

2.3. Data Inputs

2.3.1. Occurrence Data

SDM usually require data on species occurrence to determine their ecological niche or suitability (Franklin, 2023). In this study, we didn't focus on a single species but the ecological community. An ecological community is a group or association of populations of two or more species simultaneously occupying the same geographical area (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). To ensure reliability and accuracy of the current species occurrence, the occurrence data of each woody cover was obtained using the ground sampling GPS coordinates collected for woody cover classification and coordinates from plot inventory (Table 1). Therefore, the sampled points represent the occurrence of the ecological community defined by the woody cover type, a community of species but not individual species. In each woody vegetation, we selected 100 points to represent species occurrence, which were considered as the current distributional data. Figure 2 shows the spatial distribution of each woody cover occurrence.

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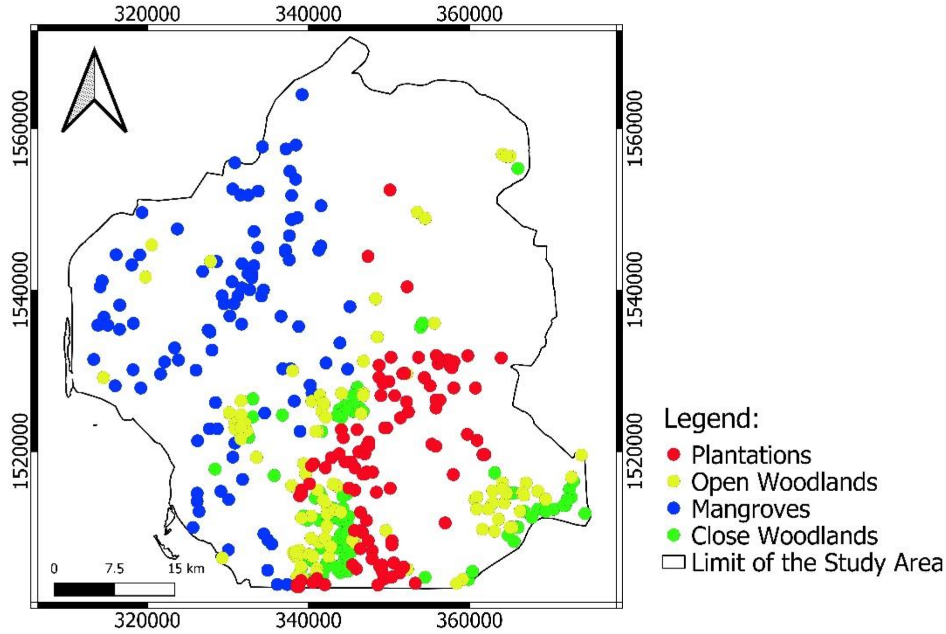

Figure 2: Occurrence Coordinate of the Woody Cover communities

Table 1: Occurrences Coordinate Samples of the Woody Trees

Occurrences of the Woody Trees	Mangroves	Close Woodland	Open Woodlands	Plantations
Number of Occurrence Points from Ground Sampling	83	57	62	60
Number of Occurrence Points from Plot Inventory	17	43	38	40

2.3.1.1. Environnemental Variables

We selected ten environmental variables grouped into five categories: 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 2.

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

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

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

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

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

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2.4. Model Processing

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

Environmental predictors (Table 2) 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. Background (pseudo-absence) data was generated by randomly sampling the study area to support robust model training, a common practice in species distribution modelling (Descombes et al., 2022).

Machine learning algorithms were applied to model species distributions, including Random Forest, Generalized Linear Models, and Maximum Entropy. These algorithms have been widely recognised for handling complex ecological data (Chollet et al., 2023; Zhang & Li, 2017; Zhao et al., 2022). An advanced cross-validation technique, such as subsampling and bootstrapping (Tsamardinos et al., 2018), was applied to enhance model reliability.

Predicted habitat suitability maps were generated for the study area and visualised through plots to illustrate suitable areas for each woody tree cover. Area statistic calculations were done to compare the actual coverage of the woody tree cover (2002), the suitable coverage from the model prediction, and the gap between the two. The workflow of the methodology is presented in Figure 3.

Table 2: 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) 2015
Other data	Burn Area Index	500m	MODIS
	River network		HydroSHEDS

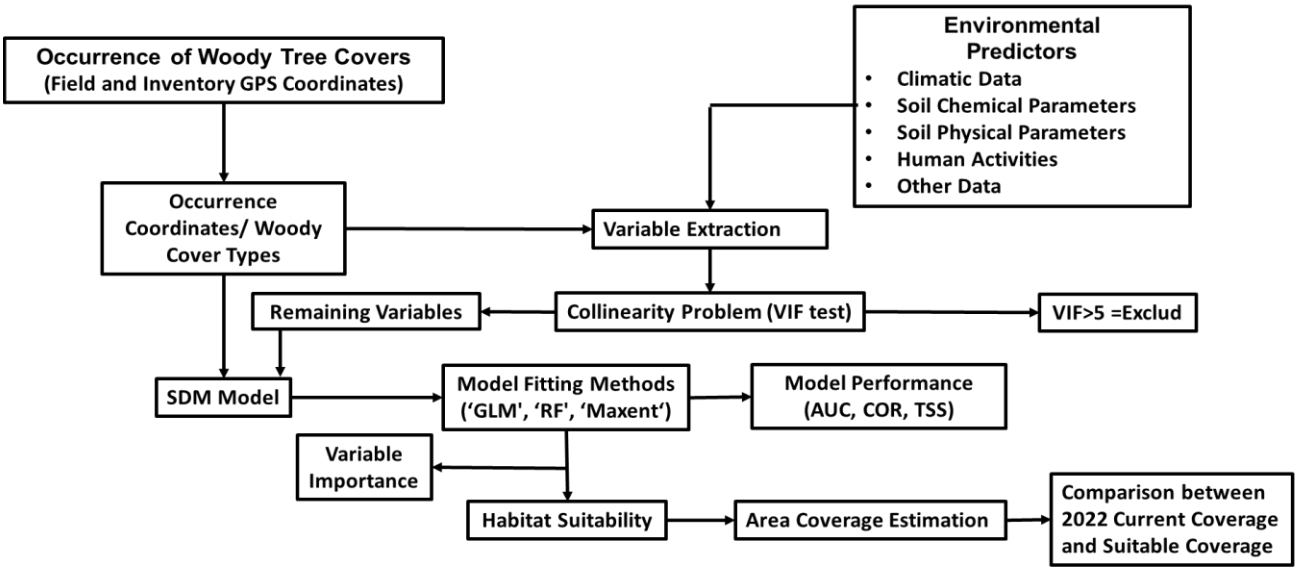

Figure 3: Workflow of the model prediction

2.5. RESULTS

2.5.1. Variable Importance

Figure 4 shows the relative importance of the drivers in predicting the woody cover distribution. The analysis reveals that the most critical drivers for Mangroves are Salinity, followed by Bulk density and coarse fragments. Salinity is the primary factor in Close Woodlands, followed by Rainfall and Burned Areas. For Open Woodlands, Salinity and Burned Areas are 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.

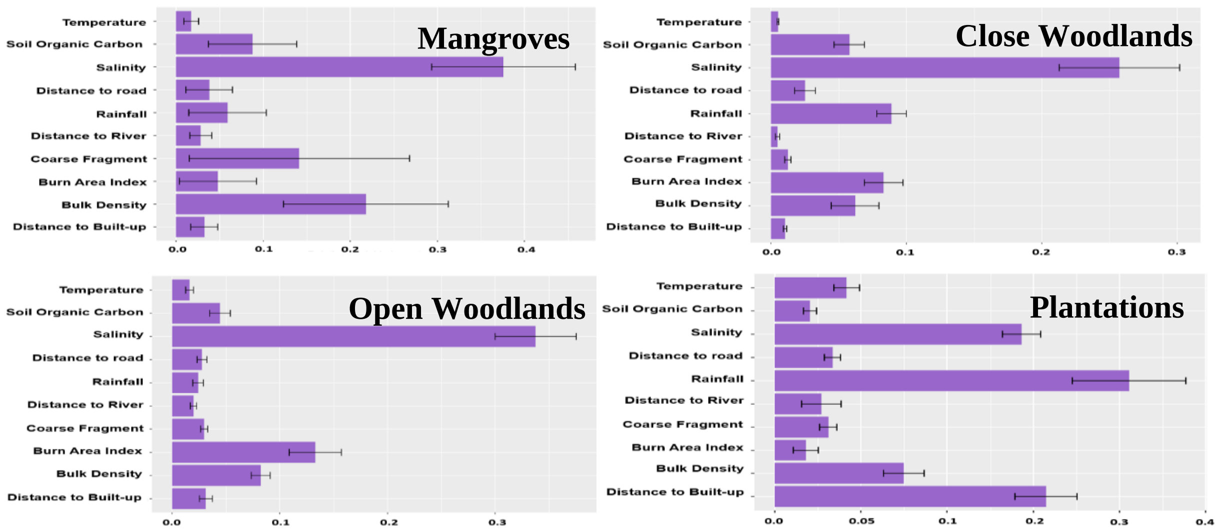

Figure 4: Variable importance of the woody cover drivers

2.5.2. Environmental Range Suitable for Woody Tree

Figure 5 illustrates the habitat suitability, indicating that Mangroves thrive within an environmental range characterised by the lowest Salinity Index (600 and 800) and a low to medium Bulk Density (0 and 60 g/cm³).

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

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

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

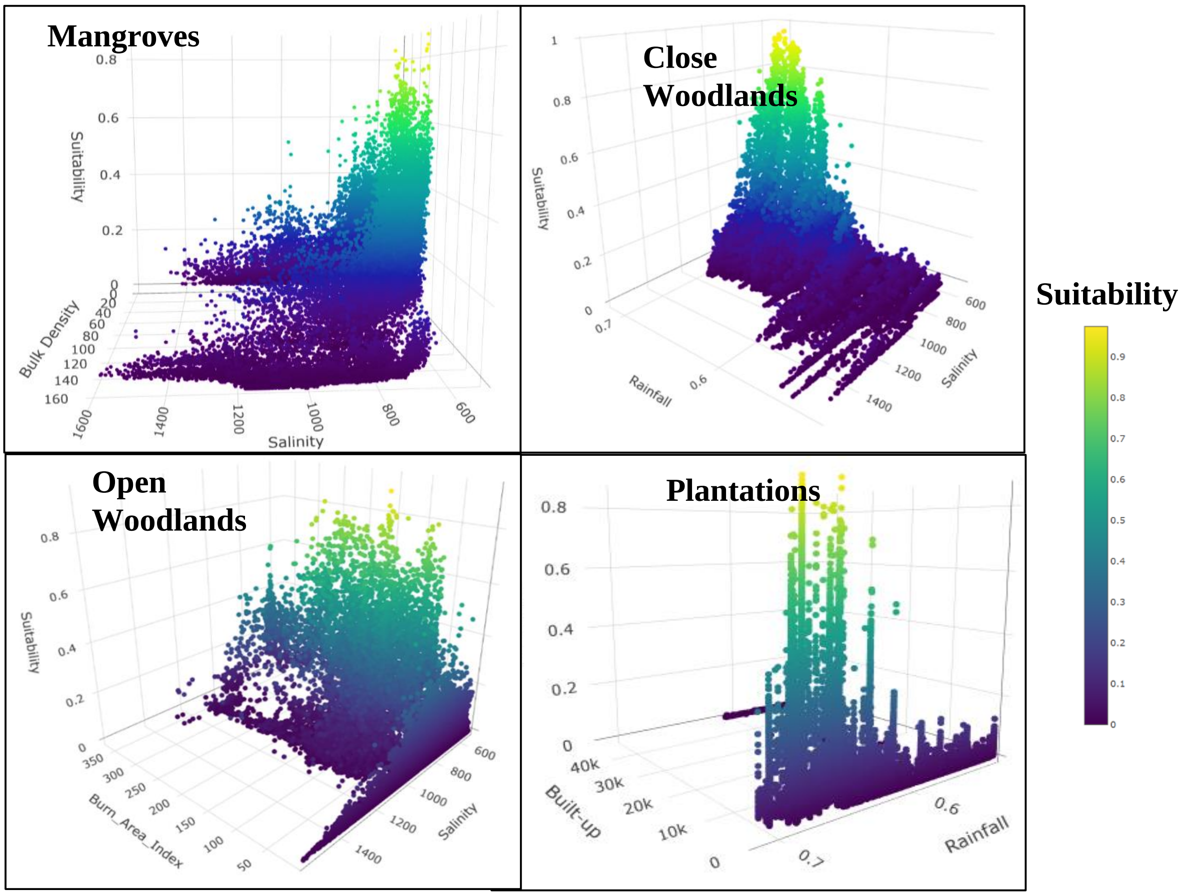

Figure 5: Habitat suitability from two main drivers in different woody cover

2.5.3. Habitat Distribution

The suitability of woody communities across the study area is illustrated in Figure 6. For Mangroves, the results indicate that their distribution aligns closely with the regions of maximum suitability. However, there is a notable absence of Mangroves along the northern edge of the study area, as reflected in the 2022 coverage data. For Close Woodlands, the highest suitability is observed within the protected areas, closely corresponding to their actual coverage. Additionally, the suitability extends beyond the boundaries of the protected forests, indicating a broader potential habitat. For Open Woodlands, the results suggest a significant overlap with the coverage of Close Woodlands, albeit in different high-suitability zones. These areas are particularly associated with regions where burn scars are more prevalent.

Lastly, the plantation's 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.

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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 7 that in 2022, mangroves will 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.

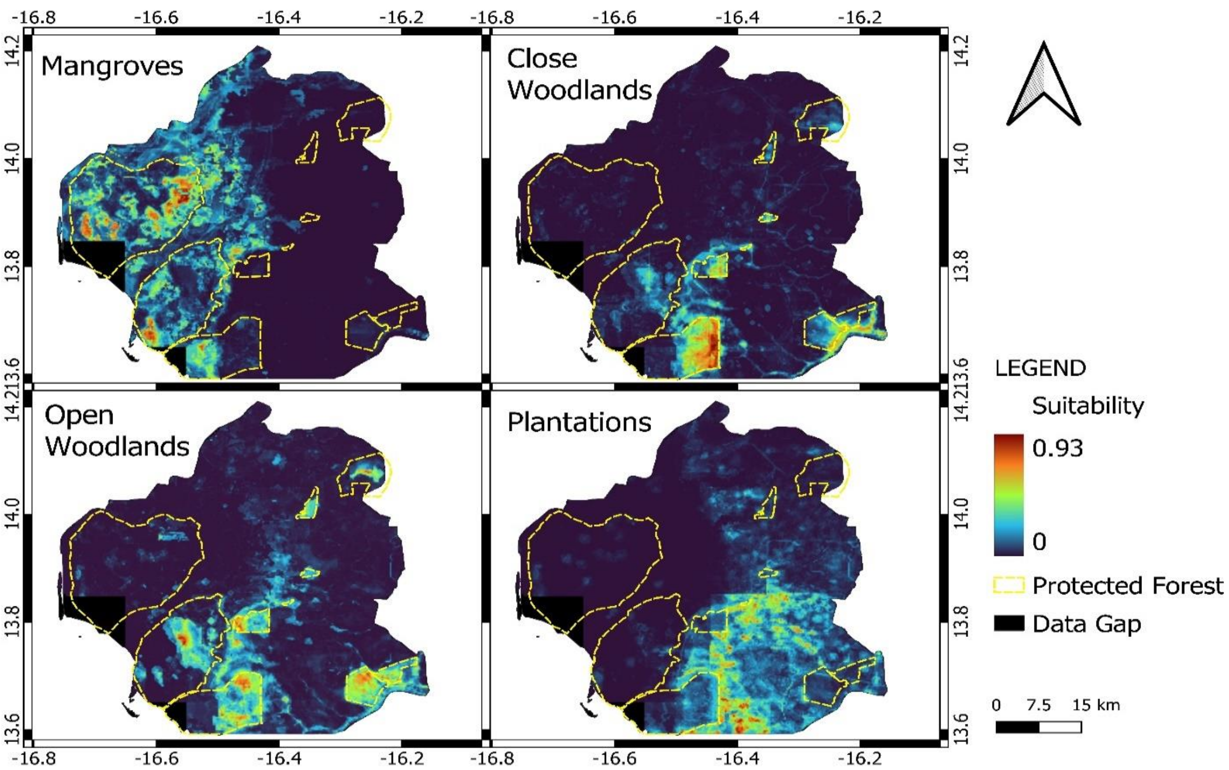

Figure 6: Map prediction of the habitat distribution in different woody cover

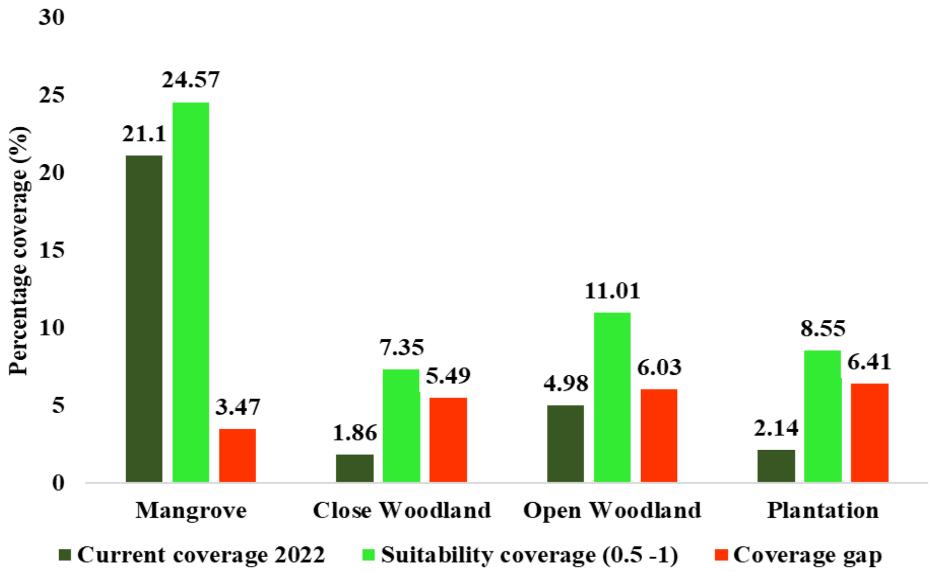

Figure 6: Comparison between current coverage and predicted suitable coverage

DISCUSSION

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

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

Interestingly, variables such as Temperature, Distance to Rivers, and 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 favourable environmental ranges for each vegetation type. Mangroves, for instance, thrive within a salinity index range of 600 to 800 and a Bulk Density between 0 and 60. This finding is consistent with studies indicating that Mangroves are adapted to specific Salinity ranges and soil conditions (Barik et al., 2018).

Close Woodlands prefer lower salinity levels and moderate Rainfall, while Open Woodlands are associated with specific 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 (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 mangrove coverage, particularly in the northern region of the study area. This indicates that, despite the high salinity levels characteristic of this region, mangrove regeneration has been notably successful. Such resilience highlights the importance of conserving and promoting mangrove 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. Prioritising the expansion and formation of Close Woodlands should take precedence, especially considering its ecological importance. This prioritisation may need to come at the expense of Open Woodlands, which is heavily influenced by burn scars and other disturbances. Addressing the factors driving the expansion of Open Woodlands, particularly those linked to fire, will be crucial for achieving a balanced and sustainable landscape that supports diverse woody communities.

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

CONCLUSION

This study highlights the critical environmental drivers influencing the spatial distribution of woody tree cover in the Saloum Delta. The analysis of variable importance underscores the role of Salinity as a key driver for Mangroves and woodland ecosystems. At the same time, Rainfall emerges as a critical factor for Close Woodlands and Plantations. Other factors, such as bulk density and the burn area index, also significantly determine habitat suitability for specific vegetation types. Conversely, predictors like Temperature and distance to rivers contribute minimally across most vegetation types, indicating their limited influence in this context. Ecological niche analysis further refines our understanding by defining environmental ranges within which different vegetation types thrive. Mangroves are primarily influenced by salinity and bulk density, while Close Woodlands depend more on a combination of Salinity and Rainfall. Open Woodlands and Plantations exhibit unique environmental requirements, with the burn area index and proximity to built-up areas playing pivotal roles. These findings have significant implications for conservation and management strategies in the Saloum Delta. The prominence of Salinity as a key driver suggests the need to develop adaptive management strategies to address Salinity as a key driver of landscape change by prioritising the use of resilient tree species and salt-tolerant plants, such as Eucalyptus spp. and Tamarix spp.(Thiam et al., 2021). These efforts should focus on restoring degraded areas, enhancing ecosystem resilience, and promoting sustainable land-use practices to mitigate the impacts of Salinity on biodiversity and livelihoods. Maintaining appropriate soil conditions and mitigating saltwater intrusion are crucial for Mangroves' conservation. In Open Woodlands, implementing effective fire management practices is essential to sustain ecological balance.

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