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Research Article

Mapping Aboveground Carbon in Rehabilitated Mangrove: Evaluating the Performance of Regression Modelling with Satellite-Derived Vegetation Indices and Kriging Interpolation

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Abstract
Mangroves are vital ecosystems in combating climate change, primarily through their exceptional capacity for carbon sequestration and long-term storage. To effectively manage and conserve these valuable resources, accurate carbon stock mapping is crucial. Given the inherent variability of mangrove biophysical characteristics, selecting appropriate mapping methodologies is essential. This study aimed to evaluate two distinct approaches: regression modeling using satellite-derived vegetation indices and kriging interpolation, within the Angke Kapuk mangrove area of Jakarta. Regression models were constructed utilizing forest canopy density (FCD) and its constituent indices (derived from Landsat 8), alongside normalized difference vegetation index (NDVI), advanced vegetation index (AVI), and soil adjusted vegetation index (SAVI) from Sentinel 2A, as predictor variables. Field-based carbon stock data, obtained from 50 square plots (10 m × 10 m) using established allometric models, served as the response variable. The study revealed substantial heterogeneity in carbon storage, ranging from 34.76 to 236.87 tons/ha, with a mean of 135.31 tons/ha and a standard deviation of 50.09 tons/ha. Regression modelling, however, demonstrated limited predictive power, achieving a maximum R^2 value of only 0.03, indicating a poor fit between the predictor variables and observed carbon stocks. Kriging interpolation yielded moderate accuracy, as evidenced by a coefficient of variation of root mean square error (CV RMSE) of 0.39. This disparity in performance can be attributed to several factors, including the homogeneity of the rehabilitated mangrove canopy, which limited the ability of vegetation indices to accurately represent carbon stock variations. Furthermore, kriging's capacity to model spatial autocorrelation proved advantageous in this context. Based on these findings, this paper discusses the influence of mangrove characteristics on modelling performance and provides practical recommendations for area managers regarding future carbon stock mapping initiatives.

Keywords: ecosystem services, carbon storage, forest canopy density, spatial modelling

1. INTRODUCTION

Forest carbon stock mapping is crucial for understanding the spatial distribution of carbon within a forest, considering its diverse biophysical characteristics. Given the vital role forests play as carbon sinks and stores, accurate spatial information on carbon stocks is essential for strategic forest management. This mapping serves various purposes, from assessing the ecological benefits of forests for humans (e.g., mapping forest ecosystem services) [1][2] and monitoring the success of forest restoration efforts on degraded lands [3][4], to analysing the impact of deforestation and identifying areas of carbon loss due to land conversion [5][6]. Furthermore, carbon mapping data informs land-use planning based on ecosystem services, enabling the development of optimal conservation policies [7][8]. Carbon mapping also underpins payment for ecosystem services (PES) schemes [9][10], allowing those who protect forests to receive compensation for the valuable environmental services they provide, particularly carbon sequestration, which significantly contributes to climate change mitigation.

Mangrove forests are exceptionally effective carbon sinks [11][12], making them a critical component of climate change mitigation strategies. Their unique ability to sequester and store high amount of carbon, particularly as soil carbon within their organic-rich sediments, classifies them as vital "blue carbon" ecosystems [13][14]. Mapping these carbon stocks is essential for effective mangrove protection and management. Accurate maps highlight the crucial role mangroves play in mitigating climate change [15][16], strengthening

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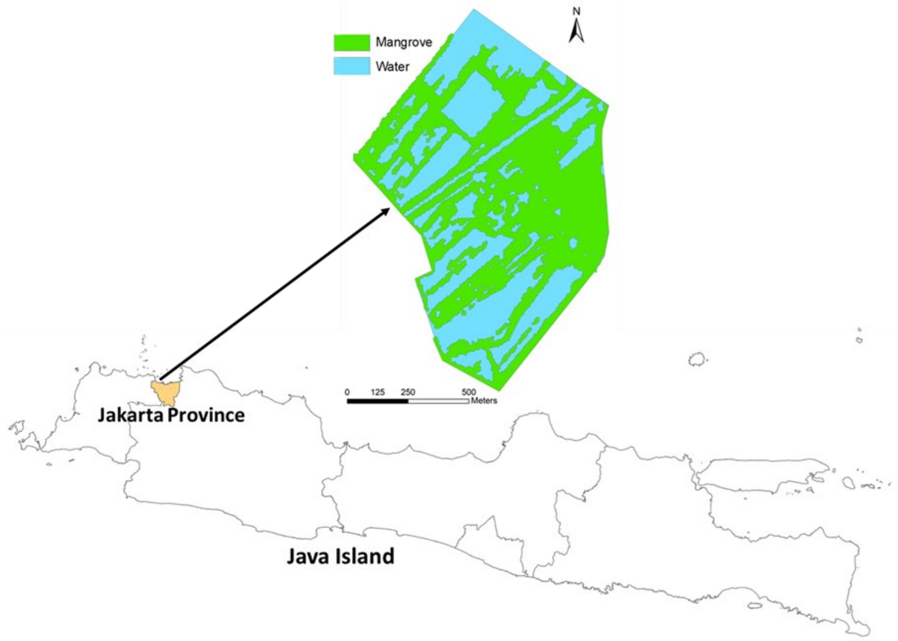

Figure 2. Boxplot of carbon storage across sampled plots (ton C/ha).

conservation and restoration policies. Furthermore, such mapping enables the monitoring of mangrove restoration programs aimed at enhancing carbon sequestration and ecosystem function in degraded areas [17], ensuring that conservation and rehabilitation efforts are targeted and data-driven.

Numerous methods exist for mapping mangrove forest carbon stocks, with remote sensing techniques playing a dominant role due to their efficiency and ability to cover large areas with increasing accuracy [18][19]. Medium- and high-resolution satellite imagery, such as Landsat and Sentinel, are frequently employed [20][21], offering the advantage of open access and facilitating widespread use in regional and global studies. Vegetation indices derived from these images, such as the normalized difference vegetation index (NDVI) and the enhanced vegetation index (EVI), are commonly used to assess mangrove forest health, density, and ultimately, carbon stocks [22][23]. Complementing satellite data, drone technology is increasingly utilized, especially when high spatial resolution is required. The superior detail of drone imagery allows for more precise mapping of mangrove stand structure, contributing to more accurate carbon stock estimations [24][25].

While remote sensing has significantly advanced the efficiency and accuracy of mangrove forest carbon stock mapping, its effectiveness can be limited in certain situations. Specifically, in mangrove forests with low canopy variability, remote sensing data may struggle to capture subtle differences in carbon stocks. This potentially leads to less accurate estimations, particularly if variations in stand density and structure are poorly represented in satellite or drone imagery. Inaccurate carbon mapping poses a significant risk to effective monitoring and management, as it can result in misleading representations of carbon storage distribution. In such cases, field-based mapping methods offer a valuable alternative for achieving higher accuracy. Direct field measurements allow for more precise carbon stock data collection, accounting for individual tree characteristics and their immediate environment. Interpolation methods, which utilize field measurement points to estimate carbon distribution across larger areas, are often employed in this context and have demonstrated promising results in several studies [26][27]. This approach is particularly well-suited for smaller mangrove areas (e.g., around 100 ha) where field surveys remain feasible. Therefore, field-based interpolation can potentially improve carbon mapping accuracy in areas where remote sensing data is either limited or insufficient to capture existing carbon stock variations. There remains a lack of studies that directly evaluate regression modeling using satellite image-based vegetation data alongside interpolation techniques for mapping aboveground carbon in rehabilitated mangrove ecosystems using the same dataset. Addressing this gap will provide valuable scientific evidence to guide the selection of the appropriate method for monitoring aboveground carbon in these restored environments.

This study aims to investigate the effectiveness of regression modelling using satellite image-based vegetation indices and interpolation for mapping carbon stocks in mangrove forests exhibiting low vegetation variability. The study area, encompassing approximately 100 hectares of mangrove forest in Jakarta, allowed for efficient and systematic field surveys, enabling detailed data collection. We hypothesize that variations in carbon stock within this mangrove environment are weakly explained by satellite-based vegetation data. This research provides empirical evidence with the potential for broader application in carbon mapping of similar mangrove ecosystems and can support more data-driven management and conservation strategies.

2. MATERIALS AND METHODS

2.1. Study Area

This study was conducted in the Angke Kapuk mangrove forest, a 99.8 ha recreational park located in Jakarta (Figure 1). Mangroves comprise approximately 57% of the park's area. This area experienced severe mangrove deforestation in the past, with approximately 90% converted to illegal aquaculture ponds two decades ago. A continuous mangrove rehabilitation program has since reforested the area.

2.2. Data Collection and Analysis

This study integrated field measurements of biomass and carbon stocks, satellite data analysis to derive vegetation information, regression analysis to establish relationships between remotely sensed vegetation data and mangrove carbon storage, and Kriging interpolation for mapping mangrove carbon storage. The following sections detail the data collection and analysis procedures for each of these four components.

2.2.1. Carbon Storage Measurement

Field data for carbon storage estimation were collected from 50 square plots measuring 10 × 10 m² each, which were proportionally distributed across locations using a cluster sampling approach. The study area was stratified into five clusters, each representing a different class of water depth. Within each plot, detailed information on species and the diameter at breast height (DBH) of all mangrove trees present were recorded. To estimate above-ground biomass (AGB), this study applied species-specific allometric equations (Table 1), which are widely used for biomass estimation based on tree dimensions. These equations account for variations in species characteristics and growth patterns. Once the AGB of each tree was determined, this study applied a conversion factor of 0.47 to estimate the carbon storage in the above-ground biomass. This ratio is based on standard methodologies used in forest carbon assessments, reflecting the proportion of biomass composed of carbon.

2.2.2. Remote Sensing Data Analysis

This study utilized Landsat 8 OLI (30 m spatial resolution) and Sentinel-2A (10 m spatial resolution) satellite imagery acquired in 2024 to assess mangrove forest vegetation condition. Landsat 8 OLI imagery was used to derive forest canopy density (FCD), a key indicator of forest cover density. FCD was calculated using four component indices: the advanced vegetation index (AVI), shadow index (SI), bare soil index (BSI), and thermal index (TI) [32]. These indices collectively capture vegetation characteristics,

Table 1. Allometric equations for estimating AGB of mangroves.

Mangrove Tree Species	Allometric Equations	Sources
Avicennia marina	$0.308D^{2.11}$	[28]
Avicennia alba	$0.2901D^{2.2605}$	[29]
Rhizopora apiculata	$0.3836D^{2.2348}$	[30]
Rhizopora mucronata	$0.105D^{2.68}$	[31]

Table 2. Equations for generating satellite image-based vegetation data.

Satellite Imagery	Indices	Equations
Landsat 8 OLI	AVI	$\sqrt[3]{(NIR+1)*(1-Red)*(NIR-Red)}$
	SI	$\sqrt[3]{(1-Blue)*(1-Green)*(1-Red)}$
	BSI	$\frac{(SWIR1+Red)-(NIR+Blue)}{(SWIR1+Red)-(NIR+Blue)}*100+100$
	TI	$\left(\frac{K2}{\ln\left(\frac{K1}{CV_R}+1\right)}\right)-272.15$
	FCD	$\sqrt[2]{VD*SSI+1}-1$
Sentinel-2A	NDVI	$\frac{(NIR-Red)}{(NIR+Red)}$
	AVI	$\sqrt[3]{NIR*(1-Red)*(NIR-Red)}$
	SAVI	$\frac{(NIR-Red)}{(NIR+Red+L)}\times(1+L)$

NIR: near infrared; SWIR: short-wave infrared; K1 and K2: thermal band constants; CVR: radian value in the thermal band; VD: vegetation density, created by performing principal component analysis (PCA) on AVI and BSI; SSI: scaled shadow index, created by performing PCA on SI and TI; L: soil correction factor.

shadow presence, bare soil, and surface temperature, providing a more comprehensive understanding of the forest. Sentinel-2A imagery was used to calculate additional vegetation indices, including the NDVI, AVI, and soil adjusted vegetation index (SAVI). All index calculations were performed using Google Earth Engine (GEE), a cloud-based platform for efficient spatial data analysis. Table 2 presents the equations used to generate the indices.

2.2.3. Regression Analysis

Regression modelling was employed to map forest carbon stocks. Carbon stock values measured in 50 field plots served as the response variable, while remotely sensed vegetation data acted as predictor variables. These predictors included AVI, SI, BSI, TI, and FCD derived from Landsat imagery, as well as NDVI, AVI, and SAVI derived from Sentinel imagery. Model accuracy was assessed using the coefficient of determination (R^2), which quantifies the proportion of variance in the response variable explained by the predictors. All regression analyses were conducted using the R statistical software.

2.2.4. Krigring Interpolation

Ordinary kriging, based on geostatistical analysis of carbon data from 50 plots, was used for interpolation. Initially, the spatial structure of the carbon data was analyzed using variogram analysis, performed with the gstat library in R [33]. The parameters (partial sill, range, and nugget) of the selected variogram model were then used for ordinary kriging interpolation within the Spatial Analyst toolbox of ArcGIS 10. Model accuracy was assessed via cross-validation (leave-one-out method) by calculating the coefficient of variation (CV) of the root mean square error (RMSE). The CV RMSE represents the deviation of prediction error from the mean of the input data, with 0 indicating perfect accuracy.

3. RESULTS AND DISCUSSIONS

3.1. Carbon Storage from Sample Plots

Biomass measurements across the research plots in TWA Angke Kapuk exhibited considerable variability, indicative of differing mangrove growth conditions. Carbon storage values ranged from 34.76 to 236.87 tons/ha, with an average of 135.31 tons/ha. This range highlights the heterogeneity of factors influencing carbon storage capacity. The relatively large standard deviation of 50.09 tons/ha confirms substantial differences in carbon storage among the sampled plots. A boxplot in Figure 2 visually represents the distribution of carbon storage values across the studied plots.

3.2. Regression Models

Table 3 presents the results of linear, polynomial, and exponential regression modelling for carbon storage distribution estimation, using indices derived from Landsat and Sentinel satellite imagery. Landsat-derived canopy density data was incorporated as a predictor in three distinct approaches: direct use of the FCD value, separate utilization of its component indices (AVI, SI, BSI, TI), and a multiple regression model combining these components.

The regression models presented in Table 3, utilizing vegetation indices from Landsat and Sentinel imagery as predictors, failed to achieve statistical significance (all p values > 0.05). This suggests a lack of robust correlation between the chosen predictor variables and mangrove forest carbon stocks. Moreover, the models exhibited poor predictive performance, as evidenced by the low R^2. The maximum R^2 value of 0.03 indicates that only about 3% of the carbon stock variability could be explained. These findings demonstrate the limitations of regression models based on satellite-derived vegetation indices for accurately estimating mangrove carbon stocks in this study area, showing their inadequacy for accurate carbon stock mapping in this mangrove ecosystem. Therefore, alternative methodologies, including the interpolation technique also assessed herein, warrant further investigation.

3.3. Kriging Interpolation

Figure 3 presents the empirical variogram, illustrating the spatial structure of carbon stock distribution across 50 sample plots. This variogram depicts the relationship between semivariance and distance (in degrees latitude/longitude). Semivariance quantifies the dissimilarity in carbon stock values between locations separated by a given distance. Variogram analysis indicated the spherical model as the best fit for the empirical data (Figure 3). This model was selected for its ability to capture the spatial pattern characteristics of carbon stocks, particularly the transition in carbon values with increasing distance. The model produced a RMSE of 52.03 tons, indicating the average deviation between predicted and observed carbon storage values. The CV RMSE was 0.39, which provides a normalized measure of error relative to the mean carbon storage values. There is no universally standardized classification for CV RMSE. However, in principle, a lower CV RMSE indicates higher predictive accuracy [34]. The typical range for CV RMSE falls between 0 and 1, although values greater than 1 may occur in predictions with substantially high error. Using the common range, a CV RMSE of 0.39 can be reasonably considered as moderate. This level of accuracy suggests that while the model appropriately represents the overall spatial distribution of carbon, there is room for improvement in reducing prediction error. The spherical model parameters—nugget 0, range 0.00082, and partial sill 3062.1—were used in the kriging interpolation, generating the predicted carbon stock distribution map shown in Figure 4.

3.4. Modelling Performance

This study demonstrated that vegetation indices derived from Landsat and Sentinel satellite imagery exhibited poor accuracy in predicting mangrove carbon storage distribution. While some studies have reported high performance for remote sensing-

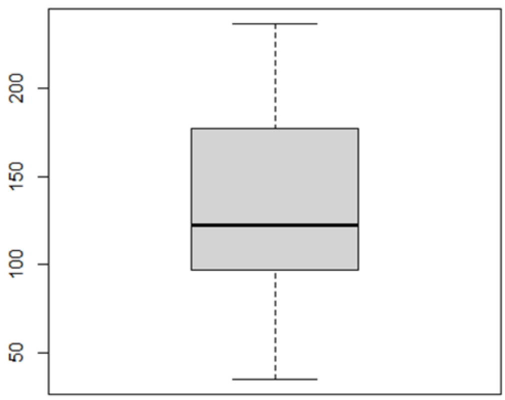

Figure 2. Boxplot of carbon storage across sampled plots (ton C/ha).

Table 3. Performance of regression models based on Landsat and Sentinel vegetation data for carbon stock estimation.

Satellite Image	Indices as Predictors	Regression types	P value	R^2
		Linear	0.3308	0.019710
Landsat	FCD	Polynomial	0.6232	0.019920
		Exponential	0.5329	0.008152
		Linear	0.7258	0.002587
	AVI	Polynomial	0.8757	0.005632
		Exponential	0.4476	0.012070
		Linear	0.319	0.020690
	SI	Polynomial	0.599	0.021570
		Exponential	0.4685	0.011000
		Linear	0.2968	0.022660
	BSI	Polynomial	0.5356	0.026220
		Exponential	0.3139	0.021120
		Linear	0.3693	0.016820
	TI	Polynomial	0.6337	0.019230
		Exponential	0.5800	0.006427
	AVI+SI+BSI+TI		0.8436	0.030060
		Linear	0.2819	0.024080
Sentinel	NDVI	Polynomial	0.5203	0.027420
		Exponential	0.2695	0.025340
		Linear	0.5611	0.007085
	AVI	Polynomial	0.8376	0.007513
		Exponential	0.4478	0.012050
		Linear	0.4682	0.011010
	SAVI	Polynomial	0.7252	0.013580
		Exponential	0.3838	0.015840

based vegetation indices in forest biomass and carbon stock prediction [35][36], others have highlighted their limitations [37]. Several factors may explain the inadequacy of these indices in accurately predicting mangrove carbon storage. Primarily, vegetation indices measure canopy greenness, which does not directly correlate with biomass or carbon content. In certain contexts, this relationship is weak, hindering the ability to discern variations in biomass and carbon storage. This phenomenon was observed in the study area, where the mangrove canopy exhibited homogeneity, as evidenced by low variability in Landsat-derived FCD (CV = 0.06) and Sentinel-derived NDVI (CV = 0.16). These values were significantly lower than the variability in carbon storage (CV = 0.38). Furthermore, optical satellite sensors, which primarily detect surface reflectance and have limited canopy penetration, may fail to capture below-canopy biomass. Additionally, the medium spatial resolution of Landsat and Sentinel imagery may not adequately represent small-scale variations in mangrove biomass, resulting in generalized and less accurate carbon storage estimations.

The application of kriging interpolation in this study yielded a moderate level of accuracy. This finding underscores the adequacy of spatial interpolation techniques in capturing the inherent variability of carbon stocks within the study area. A primary factor contributing to this outcome is the specific ecological context of the rehabilitated mangrove ecosystem. Approximately 25 years ago, the area was subjected to illegal conversion into aquaculture ponds, resulting in significant deforestation [38]. Subsequent rehabilitation efforts have been implemented progressively, leading to mangrove stands with relatively homogeneous growth conditions in adjacent locations, as these areas were rehabilitated within similar timeframes. This homogeneity aligns with the fundamental principle of spatial interpolation, where distance serves as the primary determinant of interpolated value variability.

The strength of kriging lies in its ability to model the spatial autocorrelation of the data, meaning that values closer together are more likely to be similar. By constructing a variogram, kriging estimates the spatial dependence structure and uses this information to predict values at unmeasured locations. This is particularly advantageous in ecosystems where environmental factors influencing carbon storage. In the context of rehabilitated mangroves, these factors are likely to be spatially correlated due to the relatively uniform rehabilitation practices in a rehabilitation block. The spatial structure of the carbon stocks, as revealed by the variogram analysis, likely reflected this spatial autocorrelation.

Furthermore, kriging relies on the spatial distribution of field-measured carbon stocks, which are more representative of the actual carbon content, including below-canopy biomass and carbon. The moderate accuracy achieved by kriging suggests that further refinements, such as increasing the number of sample plots or incorporating auxiliary environmental data, could potentially improve the accuracy of carbon stock mapping in this rehabilitated mangrove ecosystem. The results of this study are consistent with previous research that has demonstrated the feasibility and effectiveness of kriging interpolation in mapping forest carbon stocks [39][40], highlighting its potential as a valuable tool for carbon monitoring and management in similar ecosystems.

3.5. Implication to Management

Regular mangrove carbon storage mapping within conservation areas like Angke Kapuk is essential for quantifying the critical ecosystem services these forests provide, particularly in carbon sequestration and storage. Such mapping efforts are also vital for monitoring the efficacy of management strategies, including the evaluation of rehabilitation program success. This study demonstrated the suitability of kriging interpolation for mangrove carbon mapping, given the existing mangrove characteristics. Area managers should consider adopting this method for future carbon storage mapping activities. Kriging offers a more robust approach in environments where spatial

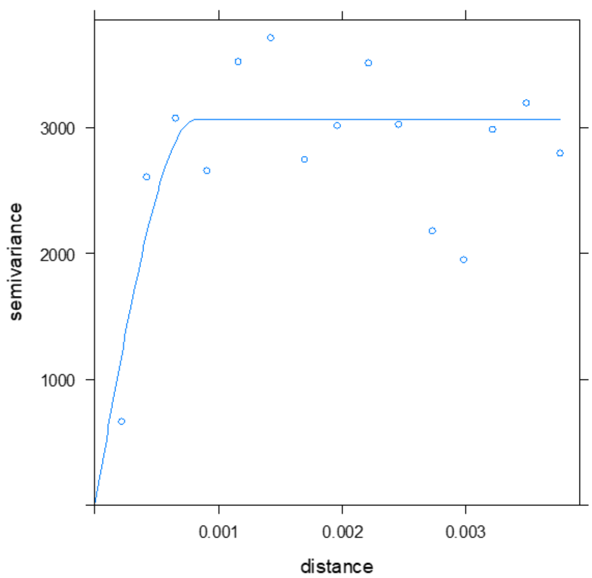

Figure 3. Empirical variogram and Spherical fitted variogram model of AGC distribution.

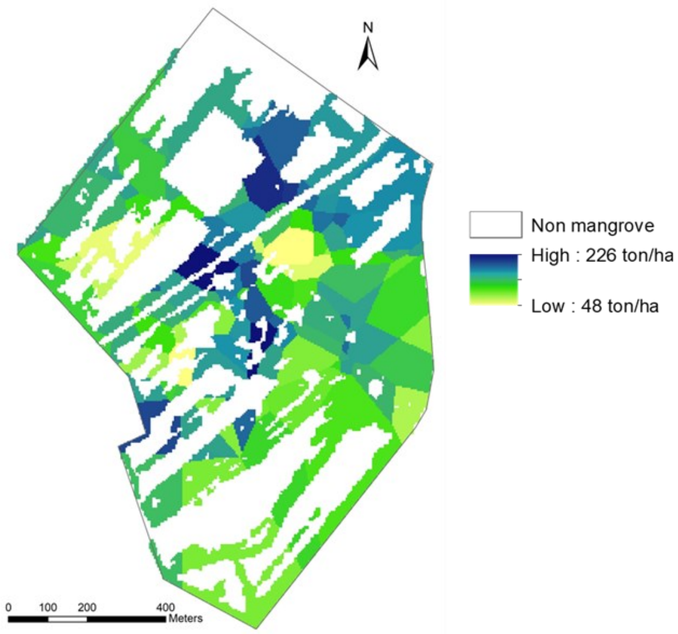

Figure 4. Map of AGC generated from kriging interpolation.

dependencies are significant, as seen in rehabilitated mangrove ecosystems. However, it is crucial to acknowledge that the kriging interpolation method did not achieve optimal accuracy in this study. This suggests substantial room for improvement in refining the mapping process.

Enhancing mapping accuracy through kriging interpolation in the Angke Kapuk mangrove forest can be significantly achieved by increasing the number of sample plots. Given the accessibility of the entire mangrove area for vegetation data collection, a strategic approach involves doubling the current sampling effort. To ensure robust and consistent carbon stock estimations, particularly with an annual mapping frequency, area managers should aim to establish 100 sample plots. This increase is feasible considering the available resources, including funding and manpower, allowing for a regular and systematic expansion of the sampling network. The rationale behind increasing sample plots lies in the fundamental principle of kriging interpolation: the more representative data points, the more accurate the spatial prediction. A denser network of sample plots provides a more granular understanding of the carbon stock distribution, capturing subtle variations that might be missed with fewer data points. Each additional plot contributes to a more comprehensive dataset, revealing the actual carbon storage values across the ecosystem. This enhanced dataset directly translates to improved variogram modelling, which is crucial for accurate kriging predictions. The variogram becomes more reliable with a higher density of data points, leading to more precise estimations of carbon storage in unmeasured locations. Furthermore, the increased spatial coverage of sample plots allows for a better representation of the heterogeneity within the mangrove ecosystem, accounting for variations in species composition, stand density, and environmental factors that influence carbon storage. This refined data input is essential for generating accurate and reliable carbon stock maps.

An alternative approach to enhance carbon stock mapping accuracy involves integrating drone technology to complement or replace traditional vegetation sampling. Drones offer significant advantages in terms of time and energy efficiency, enabling rapid data collection over large areas. However, successful implementation requires trained personnel capable of operating and maintaining these systems. While drones excel at capturing high-spatial-resolution imagery, revealing individual tree crowns with unparalleled detail, they also present certain limitations. Like other optical remote sensing technologies, drones primarily capture surface reflectance, limiting their ability to penetrate dense canopies and accurately assess below-canopy biomass. In areas with overlapping crowns, accurately delineating individual trees can be challenging, potentially affecting stand density estimations.

Despite these limitations, drones offer valuable capabilities, such as precise terrain elevation mapping, which can be leveraged to estimate tree height [41][42]. However, a critical challenge remains: the inability to directly measure tree diameters. This limitation hinders the accurate estimation of individual tree biomass and, consequently, carbon storage. To overcome this, future research should focus on developing robust models that correlate drone-derived vegetation indices with tree counts and diameters. These models could leverage spectral and textural information from drone imagery to infer tree dimensions, potentially incorporating machine learning techniques to enhance accuracy. If successful, such models would unlock the full potential of drone technology for mangrove carbon inventory and mapping. Drones could then become a standardized tool, enabling efficient and accurate carbon stock assessments across diverse mangrove ecosystems, significantly improving monitoring and management efforts.

4. CONCLUSIONS

This study found that regression modelling using vegetation indices derived from Landsat 8 and Sentinel 2A imagery demonstrated weak performance in estimating mangrove carbon stock distribution within the Angke Kapuk, Jakarta. The relatively homogeneous canopy green levels, a characteristic of the rehabilitated mangrove ecosystem, appear to be the primary limitation of relying solely on vegetation indices for carbon stock estimation. Kriging interpolation was examined as an alternative mapping approach and was found to provide moderate accuracy. While further efforts are needed to enhance the performance of regression modeling such as the use of machine learning, the findings suggest that kriging interpolation may be the more suitable method for future carbon mapping in homogeneously rehabilitated mangrove ecosystems. To further enhance accuracy, an increase in the number of field sample plots is recommended, providing a more robust dataset for spatial interpolation. The integration of drone technology also presents a promising avenue for improvement. While drones offer efficient data collection and high-resolution imagery, their limitations in accurately identifying tree counts and diameters must be addressed. Future research should focus on developing and testing models that correlate drone-derived data with these critical parameters.

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Conflicts of Interest

All authors agree with this submission and there is no conflict of interests in regard to the research, authorship, and/or publication of this manuscript.

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DECLARATION OF GENERATIVE AI

During the preparation of this manuscript the authors used ChatGPT and Gemini 1.5 Flash to enhance text editing and readability. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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