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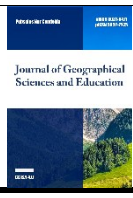

[Research Article]

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Valuing Blue Carbon for Ecological Sovereignty: Dynamics and Projections of Seagrass Stock in Teluk Saleh

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Abstract

Limited quantitative data and a 7% annual rate of seagrass degradation hamper efforts to optimize Indonesia's blue carbon absorption potential within global climate change mitigation strategies. This study aims to quantify seagrass blue carbon stock and project its future dynamics in Teluk Saleh, West Nusa Tenggara. Seagrass distribution from 2019 to 2025 was mapped using Sentinel-2 satellite imagery and a Support Vector Machine (SVM) classification approach. Carbon stock projections until 2035 were conducted using the Autoregressive Integrated Moving Average model. The results show significant temporal variability, with carbon stocks decreasing by approximately 16,000 tons (2022) and then increasing by 36,000 tons (2023). Projected peak recovery potential is approaching 50,000 tons (2028), but this projection remains sensitive to ongoing anthropogenic pressures. These findings underscore the importance of blue carbon quantification in supporting data-driven coastal management and climate mitigation policies, and highlight its potential to inform sustainable, non-extractive economic pathways.

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Abstrak

Keterbatasan data kuantitatif dan degradasi lamun sebesar 7% per tahun menghambat optimalisasi potensi penyerapan karbon biru Indonesia dalam strategi mitigasi perubahan iklim global. Penelitian ini bertujuan untuk mengkuantifikasi stok karbon biru lamun serta memproyeksikan dinamika masa depannya di Teluk Saleh, Nusa Tenggara Barat. Distribusi lamun periode 2019–2025 dipetakan menggunakan citra satelit Sentinel-2 dan pendekatan klasifikasi Support Vector Machine. Proyeksi stok karbon hingga tahun 2035 dilakukan menggunakan model Autoregressive Integrated Moving Average. Hasil penelitian menunjukkan adanya variabilitas temporal yang signifikan, dengan penurunan stok karbon hingga sekitar 16.000 ton (2022), kemudian meningkat menjadi 36.000 ton (2023). Proyeksi potensi puncak pemulihan mendekati 50.000 ton (2028), namun proyeksi ini masih sensitif terhadap tekanan antropogenik yang berkelanjutan. Temuan ini menegaskan urgensi kuantifikasi karbon biru untuk memperkuat kebijakan mitigasi perubahan iklim berbasis data sekaligus mendorong transisi menuju model ekonomi berkelanjutan non-ekstraktif.

INTRODUCTION

The acceleration of global climate change is one of the most pressing challenges in contemporary environmental management and is closely linked to the systemic failure of development models that rely on the intensive exploitation of natural resources (Giglio et al., 2025). In In the Indonesian archipelago, coastal ecosystems face mounting pressures from rapid infrastructure development, aquaculture expansion, and unsustainable fishing practices that have collectively degraded over 30% of the nation's seagrass meadows in the past two decades (Christianen et al., 2014). Teluk Saleh, situated in West Nusa Tenggara Province, exemplifies this vulnerability: its rich marine biodiversity, including extensive seagrass beds, coral reefs, and mangrove forests, is increasingly threatened by mainland runoff from agricultural intensification, blast fishing in adjacent reef zones, and unplanned coastal settlement expansion (Supriyadi et al., 2024).

Nature-based Solutions (NbS) in the context of climate change mitigation have gained increasing global attention, particularly through the protection and restoration of blue carbon ecosystems such as mangroves, tidal marshes, and seagrass meadows. As the world's largest archipelagic country, Indonesia plays a strategic role in global blue carbon storage, with substantial carbon reserves distributed across its coastal ecosystems (Serrano et al., 2019). Among these ecosystems, seagrass meadows exhibit exceptionally high carbon storage capacity per unit area, despite their relatively smaller spatial extent compared to terrestrial ecosystems, making them a critical component of the global carbon balance (Qiu et al., 2014). Nevertheless, seagrass ecosystems in many Indonesian coastal regions are currently under severe pressure from coastal development and other anthropogenic activities, resulting in widespread and accelerating degradation.

This study focuses on Teluk Saleh (Saleh Bay), West Nusa Tenggara, a coastal area of high ecological significance that is experiencing intensive anthropogenic pressure. Seagrass meadows in this region provide essential ecological functions, including natural protection of shorelines against erosion and storm impacts, habitat for spawning and nursery grounds of economically important fish species, and the maintenance of coastal water clarity and quality (Al-Asif et al., 2022).

Teluk Saleh faces a combination of localized anthropogenic stressors that directly threaten its seagrass ecosystems: 1) terrestrial sediment and nutrient loading from intensified agriculture and aquaculture ponds in the upper bay catchment, which reduce water clarity and increase turbidity; 2) destructive fishing practices, including blast (bomb) fishing and cyanide use targeting reef fish, which cause collateral physical damage to adjacent seagrass beds; and 3) progressive coastal settlement expansion and infrastructure development that alter natural hydrological patterns and increase direct physical disturbance to nearshore meadows (Rahmawati et al., 2022). Understanding which of these pressures most significantly drives carbon stock variability is essential for designing targeted management interventions.

The degradation of seagrass ecosystems may trigger cascading impacts, including increased coastal erosion threatening coastal settlements, declining fisheries productivity, and disturbances to adjacent coastal ecosystems, particularly coral reefs, due to deteriorating water quality (Dunic et al., 2021).

Beyond their ecological functions, seagrass meadows also serve as significant blue carbon reservoirs. The loss of seagrass not only alters coastal ecosystem structure and function but also releases stored carbon into the atmosphere. In this context, blue carbon valuation is increasingly important as a scientific approach to translating ecosystem carbon stocks into quantitative metrics relevant for spatial planning and climate change mitigation policies. Recent national policy developments, such as Presidential Regulation No.98 of 2021 on Carbon Economic Value, provide an institutional framework that supports the use of carbon stock data as an evidence base for ecosystem management and climate policy formulation.

Specifically, this study aims to quantify blue carbon stocks and their associated values within seagrass ecosystems in Teluk Saleh; analyze the dynamics and future projections of carbon stock changes using historical data and potential degradation risks; and present the results as a scientific foundation for coastal zone management and climate change mitigation strategies. Through this approach, the study is expected to contribute to the advancement of coastal geographical research, particularly in enhancing the spatial understanding of seagrass ecosystem dynamics and their role in climate change mitigation.

In this study, we conceptualize 'ecological sovereignty' as the capacity of a coastal community to govern, protect, and derive sustainable economic benefits from its local marine ecological assets, particularly blue carbon stocks, without reliance on external extractive industries. This framing positions seagrass ecosystems not merely as environmental features, but as strategic national resources that underpin Indonesia's energy and food security independence, aligning with the national development agenda of sustainable development as articulated in RPJMN 2020–2024 (BAPPENAS, 2020). By quantifying blue carbon stocks and projecting their dynamics, this research provides the empirical foundation for Teluk Saleh's communities to exercise such ecological sovereignty through evidence-based coastal management.

METHOD

Study Area

This study focuses on the shallow marine areas surrounding Teluk Saleh, Sumbawa Island, West Nusa Tenggara Province, Indonesia. The selection of this study area is based on the abundant seagrass ecosystems along the coastal zone, which constitute a key component of blue carbon ecosystems (Sitorus et al., 2022). Teluk Saleh was chosen for its high potential as a blue carbon sink and storage area, supported by previous studies that have estimated carbon stocks in the region's seagrass biomass. Sitorus et al. (2022) reported very high seagrass density in Teluk Saleh, with an average of 491 shoots m^{-2}, as well as a mean seagrass biomass carbon value of 881.86 g C m^{-2}. These underscore Teluk Saleh's importance as a highly suitable site for quantifying blue carbon.

Although Sitorus et al. (2022) characterized the seagrass conditions in Teluk Saleh as generally favorable, their assessment was inherently static, capturing conditions at a single point in time without accounting for temporal variability. Seagrass ecosystems are highly dynamic, experiencing seasonal and interannual fluctuations driven by oceanographic variability, monsoon-driven shifts in turbidity, and episodic disturbances such as La Niña-induced freshwater flooding (Kennedy et al., 2010). Without time-series modeling, such fluctuations remain invisible, and management decisions based on snapshot data risk being ill-informed during periods of rapid decline or recovery. Moreover, projecting carbon stock dynamics to 2035 is critical to aligning this research with Indonesia's Nationally Determined Contribution (NDC) targets under the Paris Agreement, which require quantifiable projections of the carbon sequestration potential of coastal ecosystems (Government of Indonesia, 2022).

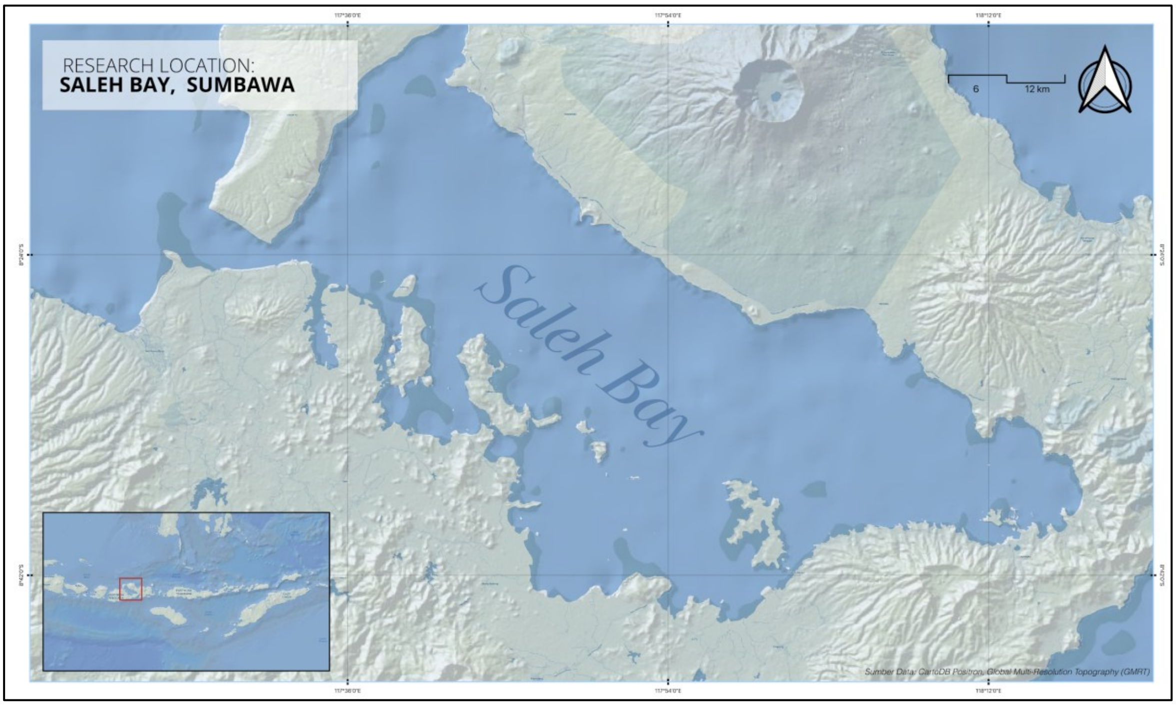

Figure 1. Map of the Study Area in Teluk Saleh, West Nusa Tenggara, Indonesia

Materials and Data

This study utilized various data sources, with remote sensing data serving as the primary dataset. The remote sensing data were processed to derive several vegetation and water-related indices, which were subsequently used for data delineation and validation. Following the remote sensing data processing stage, carbon stock estimation and economic valuation were derived from an extensive literature review.

The economic valuation of seagrass blue carbon stocks in this study employs a multi-benchmark approach (Table 1). Carbon stock values are first estimated using the IPCC Tier 1 default carbon price methodology, which provides a conservative baseline for global comparability (IPCC, 2014). To contextualize these values within the Indonesian policy framework, we also refer to the Nilai Ekonomi Karbon (NEK) mechanism established under Peraturan Presiden No. 98 Tahun 2021, which sets the domestic carbon pricing floor at IDR 39,000 per ton of CO_2 equivalent (rising to IDR 75,000 by 2025).

Furthermore, we compare our results with voluntary carbon market prices for blue carbon credits, which ranged from USD 10 to 30 per ton of CO_2 in 2024 (Ecosystem Marketplace, 2024), to illustrate potential revenue streams from international carbon trading mechanisms. This multi-scale approach demonstrates how Teluk Saleh's seagrass carbon assets can be integrated into both national regulatory frameworks and international carbon markets.

Table 1. Materials and Data Used in This Study

No.	Data Category	Data Source	Resolution/ Frequency	Acquisition Period	Purpose of Use	Reference
1	Sentinel-2 Satellite Imagery	Copernicus	10 m	January 1, 2024 – December 31, 2024	Calculation of vegetation and water-related indices; seagrass cover mapping	Vieiras-Yanes et al., 2023; Davies et al., 2024; Gasparovic et al., 2022
2	Field Data	Satellite image interpretation and field data from previous studies	-	2018 – 2022	Training data for the machine learning model	Kennedy et al., 2021; Rajandran et al., 2022
3	Sea Depth	National Bathymetry	183 m	-	Depth-based area limitation	-
4	Benthic Habitat Distribution	Allen Coral Atlas	5 m	January 1, 2018 – January 1, 2021	Validation of seagrass cover classification results	Allen Coral Atlas, 2020
5	Carbon Stock Reference Values	Supplement of 2013 to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories: Wetlands	-	-	Basis for carbon stock distribution and total carbon stock calculation	Wahyudi et al., 2020

Data Analysis Techniques

This study employed an integrated geospatial and spatio-temporal analytical framework that combined remote sensing, GIS-based spatial modeling, and time-series forecasting to analyze seagrass distribution and blue carbon dynamics in Teluk Saleh. Data processing and analysis were conducted using Google Earth Engine (GEE) and OriginPro 2025b. The analysis of each data is described as follows

Satellite Data Acquisition and Preprocessing

Sentinel-2 Surface Reflectance imagery (Copernicus/S2_SR_Harmonized) was used as the primary remote sensing dataset. Preprocessing steps included cloud and cloud-shadow masking to ensure data quality and minimize spectral noise in shallow-water environments. Prior to classification, Sentinel-2 imagery was subjected to atmospheric correction using the Sen2Cor processor (version

2.11, ESA) to convert Top of Atmosphere (TOA) reflectance to surface reflectance, thereby removing the effects of atmospheric scattering and absorption (Main-Knorn et al., 2017). All image processing was performed within the GEE platform.

Spectral Indices and Water Correction

To enhance seagrass detection in coastal waters, a set of spectral indices and water-related corrections was applied. Sun glint correction followed the method of Hedley et al. (2005), utilizing the relationship between Near-Infrared (NIR) and green-band reflectance. Water-column effects were reduced using the Lyzenga depth-invariant approach, yielding the Depth-Invariant Index (DII), which served as a proxy for seagrass density.

A water column correction was applied using the DII approach based on the Lyzenga (1981) algorithm, which compensates for the differential attenuation of spectral bands by water. This two-step correction process is essential for benthic habitat studies because the water column significantly alters the spectral signature of submerged seagrass, which can lead to misclassification if left uncorrected (Pahlevan et al., 2017).

Additional vegetation and water indices, including Normalized Difference Vegetation Index, Normalized Difference Ammonia Vegetation Index, Normalized Difference Chlorophyll Index, Normalized Difference Turbidity Index, and a Soil-Adjusted Spectral Index, were derived to capture the physical and biological characteristics of seagrass meadows. These indices served as input variables for land-cover classification and carbon-stock modeling.

Land Cover Classification and Accuracy Assessment

Coastal land cover classification was performed using the Support Vector Machine (SVM) algorithm, selected for its robustness to high-dimensional, spectrally complex coastal data. Classification followed the Allen Coral Atlas habitat scheme, including seagrass meadows, coral reefs, sand, and open water.

While earlier studies relied primarily on field surveys and simple interpolation techniques (Sitorus et al., 2022), this research employs an SVM classifier, specifically chosen for its superior performance in handling high-dimensional spectral data with limited training samples (Melgani & Bruzzone, 2004), to process Sentinel-2 multispectral imagery for seagrass habitat mapping. The SVM's kernel-based approach is particularly effective for distinguishing between spectrally similar benthic classes (e.g., sparse seagrass vs. bare sand, mixed seagrass-coral substrates) that commonly confound traditional Maximum Likelihood classifiers in optically complex tropical waters (Traganos et al., 2018).

Ground truth samples derived from image interpretation and previous field surveys were divided into training (70%) and validation (30%) datasets. Model performance was evaluated using Overall Accuracy (OA), Kappa Coefficient, and Confusion Matrix metrics. The trained model was then used to generate quarterly land cover maps for the period 2019-2025, from which seagrass extent was extracted.

Spatial Estimation of Seagrass Blue Carbon

Seagrass distribution maps from each time step were used as the spatial basis for blue carbon estimation. The normalized DII was employed to represent relative seagrass density and spatial variability. Carbon stock estimation followed the IPCC 2013 Wetlands Supplement Tier 1 approach, using a national default seagrass carbon stock value of 1.0452 t C ha^{-1} on Equation 1 (Wahyudi et al., 2020):

$$C = A \times CS \quad (1)$$

where C is total carbon stock (tons), A is the seagrass area (ha), and CS is the default carbon stock value.

The spatial accuracy of the seagrass classification was evaluated using three complementary metrics derived from the confusion matrix constructed from the 35 validation points:

1) Overall Accuracy representing the proportion of correctly classified pixels across all classes;
2) The F1-Score, computed as the harmonic mean of Producer's Accuracy (PA, or user's perspective of commission error) and User's Accuracy (UA, or producer's perspective of omission error), providing a balanced measure of classification performance that accounts for both false positives and false negatives; and
3) Cohen's Kappa coefficient (κ), which adjust

OA to account for chance agreement, thereby providing a more rigorous assessment of classification quality (Cohen, 1960; Pontius & Millones, 2011).

These metrics were calculated following the standardized accuracy assessment protocol recommended by Olofsson et al. (2014) for remote sensing land cover classifications. Annual carbon sequestration was estimated using a national mean sequestration rate of 7.01 t C $ha^{-1}yr^{-1}$ based on Equation 2, calculated as:

$$S = A \times SR \quad (2)$$

where S is annual carbon sequestration (t C yr^{-1}), A is the seagrass area (ha), and SR is the sequestration rate.

To address the spatial heterogeneity of carbon distribution while maintaining consistency with the IPCC Tier 1 framework, a weighted spatial disaggregation approach was implemented. Initially, a total carbon pool for the study area was established by multiplying the total seagrass extent by the national default value (1.0452 t C ha^{-1}). This total stock was then distributed at the pixel level using a relative-density proxy derived from the DII. Specifically, the contribution of each pixel was determined by the ratio of its individual DII value to the cumulative sum of DII values across the entire seagrass meadow.

This ratio served as a weighting factor, which was subsequently multiplied by the total carbon pool to assign a pixel-specific carbon value. Consequently, this method ensures that while the aggregate carbon stock remains aligned with standardized Tier 1 estimates, the spatial output reflects the biophysical variability and density gradients of the seagrass beds, avoiding the limitations of a uniform (flat) spatial representation.

Spatio-temporal Forecasting of Carbon Stock

Temporal dynamics of seagrass carbon stock were analyzed using quarterly time-series data (2019-2025). Forecasting was conducted using the Autoregressive Integrated Moving Average (ARIMA) model in OriginPro 2025b.

The optimal ARIMA model was selected using a systematic three-stage approach. First, candidate models were identified by evaluating combinations of autoregressive (p), differencing (d), and moving average (q) parameters within the ranges p = 0–3, d = 0–2, and q = 0–3. Second, each candidate model was fitted to the observed time series (2019–2025), and model performance was assessed using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), which balance model fit and complexity. The model with the lowest AIC and BIC values was considered the most appropriate.

Third, residual diagnostics were conducted using the Ljung–Box test to verify that no significant autocorrelation remained in the residuals. The results indicate that the selected model, ARIMA (0,1,0), satisfies these criteria, as it provides the most parsimonious representation of the data while ensuring that the residuals behave as white noise.

OriginPro 2025b for exploratory analysis and model fitting. OriginPro was selected for this study due to its integrated graphical output capabilities, which facilitated the simultaneous visualization of time-series decomposition, Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots, forecast intervals, and residual diagnostics within a unified interface. All ARIMA computations were independently verified using R (version 4.3.1, with “forecast” package v8.22) to ensure computational accuracy and reproducibility.

Parameter Estimation and Diagnostic Verification

The tentative model identified in the previous stage was subsequently subjected to parameter estimation. Diagnostic verification was conducted to evaluate the adequacy and reliability of the development model. This estimation is performed using significance tests and residual analysis.

Model parameters (autoregressive or moving average terms) were considered statistically significant when their probability values (p-values) were lower than the selected significance level (0<0.05). Insignificant parameters were removed to achieve a more parsimonious model.

A well-specified model is expected to produce residuals that behave like white noise, characterized by randomness, independence, and the absence of systematic patterns. This condition was assessed by examining the ACF and PACF plots of the residuals. The absence of statistically significant spikes in these plots indicates that the residuals are random and that the model adequately captures the underlying data structure.

Forecasting

After the optimal ARIMA model was identified and validated, it was applied to forecast future seagrass carbon stock values. The forecasting results were presented graphically and accompanied by 95% confidence intervals, providing an estimated range of potential future values and conveying the uncertainty associated with the projections.

The 10-year projection horizon (2026–2035) was selected to align with Indonesia's NDC target year and SDGs 2030 milestones, providing policy-relevant forward-looking scenarios despite the relatively short six-year calibration period. The ARIMA model captures a cyclical disturbance-recovery pattern consistent with known monsoon-driven seagrass dynamics in tropical Indonesia (Ralph et al., 2007), whereby each observed cycle within the short record represents a quasi-replicate of the underlying ecological process. The projections are further qualified by the model's naturally widening confidence intervals, which transparently communicate increasing uncertainty for more distant horizons. We frame these projections as exploratory baseline scenarios under an adaptive management approach, intended to be systematically refined as new annual observations become available (Fourqurean et al., 2012).

RESULT AND DISCUSSION

Land Cover Classification Model Evaluation

The performance of the SVM model was quantitatively evaluated using standard accuracy assessment metrics. The evaluation results are presented as a Confusion Matrix, OA, and Kappa Coefficient. The following confusion matrix presents the classification results of coastal land cover generated using the SVM algorithm (Table 2).

Table 2. Confusion Matrix

	Class	Actual				
		Seagrass	**Coral Reef**	**Sand**	**Water**	**Total**
Predicted	Seagrass	12	0	0	1	13
	Coral Reef	3	9	0	3	15
	Sand	2	1	0	0	3
	Water	0	0	0	4	4
	Total	**17**	**10**	**0**	**8**	**35**

The interpretation of the confusion matrix is described as follows (Table 2). A total of 12 samples were correctly identified as seagrass (true positive for Class 0). One sample was misclassified as water (a false negative for Class 0 and a false positive for Class 3), while no samples were misclassified into other classes.

Nine samples were correctly classified as coral reef (true positives for Class 1). However, three seagrass samples were incorrectly classified as coral reef (false positives for Class 1), and three water samples were also misclassified as coral reef

The model demonstrated relatively weak performance for the sand class. Of the three actual sand samples, none were correctly predicted. Two samples from the seagrass class and one from the coral reef class were incorrectly classified as sand. This indicated that the model had difficulty distinguishing pure sand from other benthic cover types, or that the training data for sand were insufficiently representative. Four samples were correctly identified as water. One seagrass sample was incorrectly classified as water.

The overall accuracy of the SVM model was 0.7143 (71.43%), indicating that approximately 71.43% of the total validation samples were correctly classified. The obtained Kappa coefficient was 0.5742, indicating a moderate level of agreement between the predicted and actual classifications after accounting for chance agreement. This value can be considered acceptable for satellite image classification in complex coastal environments, although improvements are needed, particularly for the sand and coral reef classes.

Spatial Distribution Map of Seagrass Carbon Stock in Teluk Saleh

This section presents the spatial distribution and temporal dynamics of seagrass carbon stock in Teluk Saleh (Figure 2). The analysis provides deeper insight into areas of high carbon concentration and zones most vulnerable to change. These findings are important for designing targeted and effective management and conservation strategies.

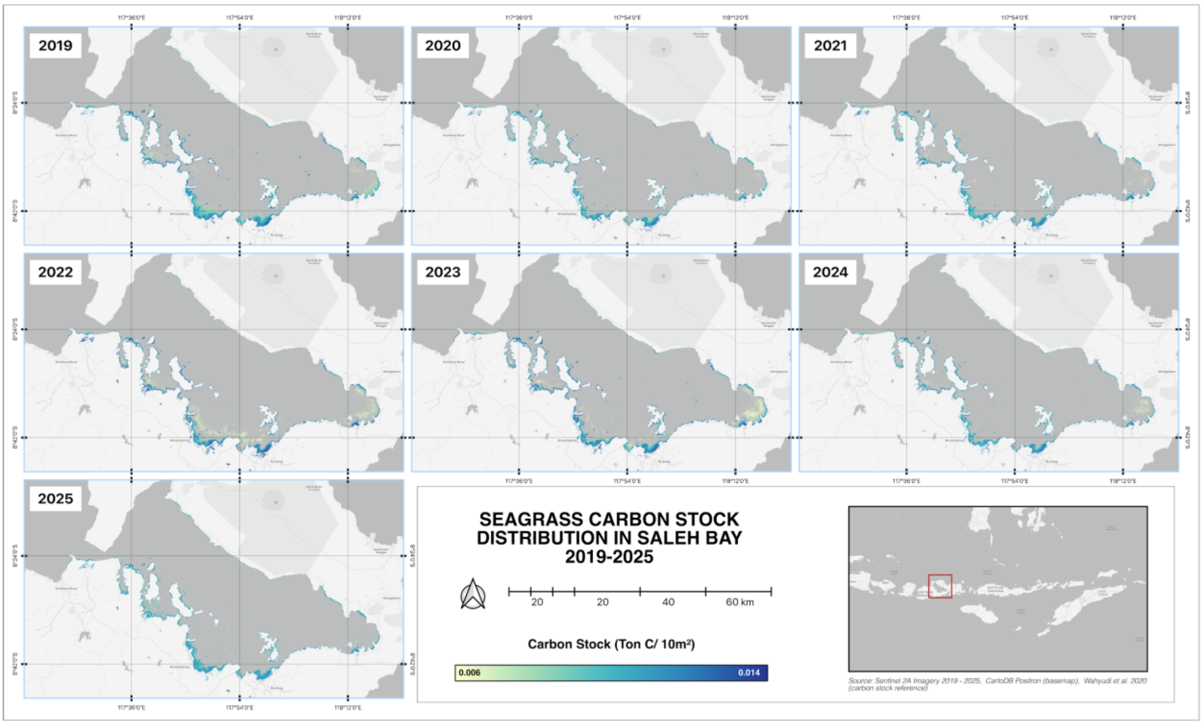

Figure 2. Spatial Distribution of Seagrass Carbon Stock in Teluk Saleh (2019 – 2025)

The spatial distribution map of seagrass carbon stock in Teluk Saleh from 2019 to 2025 reveals significant interannual spatial dynamics, visually confirming the fluctuations identified in the previous time-series analysis. Based on the legend (Figure 2), dark blue areas represent the highest carbon stock density (up to 0.014 tons C per 10 m^2 or 14 t C ha^{-1}), while light green to yellow areas indicate lower densities (down to 0.006 tons C per 10 m^2 or 6 t C ha^{-1}). In general, the highest and most persistent carbon stock concentrations are found along relatively shallow, sheltered coastal zones in the central to eastern parts of Teluk Saleh.

In 2020, which represents one of the peaks in the historical dataset, an extensive and intensive distribution of dark blue areas is evident, indicating healthy seagrass meadows with optimal carbon storage capacity. In contrast, 2022, identified as the lowest point in carbon stock, shows substantial spatial degradation. Areas previously dominated by dark blue tones drastically shrank and shifted to light green or even yellow in several locations, reflecting a significant decline in seagrass density and potential carbon release. A strong recovery in 2023 is spatially reflected by the re-expansion of dark blue areas, suggesting ecosystem resilience. However, a declining trend reappears in 2024 and 2025, with a reduction in the extent of areas characterized by high carbon density.

This spatial analysis highlights that although the ecosystem demonstrates recovery potential, it remains highly vulnerable to external anthropogenic pressures. The sharp decline observed in 2022 may be associated with increased environmental stressors, such as sedimentation from terrestrial activities or coastal pollution. Seagrass areas near river mouths or centers of human activity are more vulnerable. Therefore, achieving the projected future recovery depends largely on effective management of these critical zones, ensuring that drivers of degradation are minimized and that the ecosystem's natural recovery capacity can function optimally.

The sharp decline in seagrass carbon stock observed in 2022 (decreasing to approximately

16,000 tons from a peak of over 30,000 tons) can be contextualized within the broader climatic conditions affecting the Indonesian archipelago during this period (Figure 3). The years 2021 to 2022 coincided with a prolonged La Niña event, one of the strongest in recent decades, which brought above-average rainfall to much of eastern Indonesia, including the Nusa Tenggara region (BMKG, 2022). This intensified precipitation regime would have increased terrestrial runoff into Teluk Saleh, elevating suspended sediment loads, reducing water-column transparency, and decreasing salinity in the inner bay, all of which are known stressors on seagrass photosynthesis and growth (Ralph et al., 2007).

Increased sedimentation may have also directly smothered seagrass shoots, particularly in shallow meadows near river mouths. Similar La Niña-driven seagrass declines have been documented in other Indonesian bays, where prolonged turbidity events reduced light availability below the minimum threshold required for seagrass survival (approximately 10–20% of surface irradiance for most tropical species) (Collier et al., 2016).

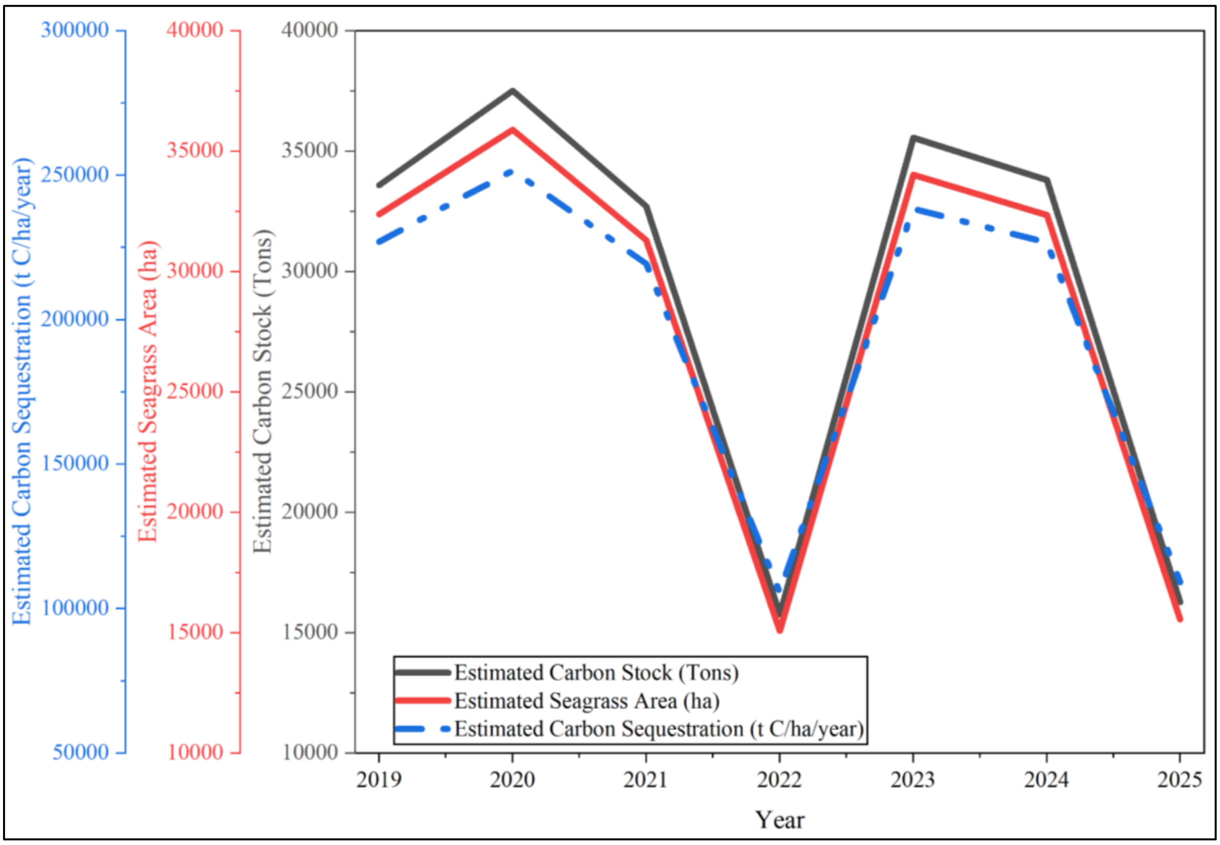

Figure 3. Graph of Estimated Seagrass Carbon Stock, Seagrass Area, and Carbon Sequestration from 2019 to 2025

The analysis of estimated seagrass ecosystem metrics in Teluk Saleh from 2019 through the 2025 projection reveals significant temporal dynamics (Figure 3), with a strong positive correlation among seagrass area (ha), total carbon stock (tons), and carbon sequestration rate (t C ha-1 yr-1). The graph illustrates a synchronized fluctuation pattern in which all three variables peaked in late 2020 and late 2023, followed by a pronounced decline that reached its lowest point in mid-2022.

At its peak in late 2023, the seagrass area reached 34,017.61 hectares, with an estimated carbon stock of 35,555.20 tons. Conversely, during the lowest phase in 2022, seagrass extent declined sharply to 15,076.19 hectares, reducing the total carbon stock to 15,757.63 tons. This variability reflects the relatively high vulnerability of the seagrass ecosystem in Teluk Saleh to environmental pressures, whether driven by natural processes or anthropogenic activities (Arriesgado et al., 2024). Nevertheless, the observed recovery following the decline indicates a certain degree of ecological resilience, allowing the seagrass ecosystem to restore its structure and function within a relatively short period.

A closer examination of the carbon sequestration curve (blue line) provides important insight into the dynamic function of the ecosystem as a carbon sink. The sequestration rate, expressed in tons of carbon per hectare per year, represents the capacity of seagrass meadows to actively absorb CO_2 from the water column through photosynthesis and store it within biomass (Hertyastuti et al., 2020). This sequestration capacity is directly influenced by seagrass health and vegetation density (Hetharia et al., 2024).

The peak in carbon sequestration coinciding with maximum seagrass area indicates that when the ecosystem is in optimal condition, its climate mitigation capacity is at its highest. Conversely, the sharp decline observed in 2022 signifies a substantial loss of carbon sequestration function, reducing the ecosystem's ability to store new carbon and potentially increasing the risk of previously stored carbon being released from sediments.

The carbon sequestration rate, therefore, is a critical metric that reflects the direct contribution of seagrass meadows to the blue carbon cycle and provides a scientific basis for understanding the environmental value of ecosystem services (Pasupalati et al., 2017).

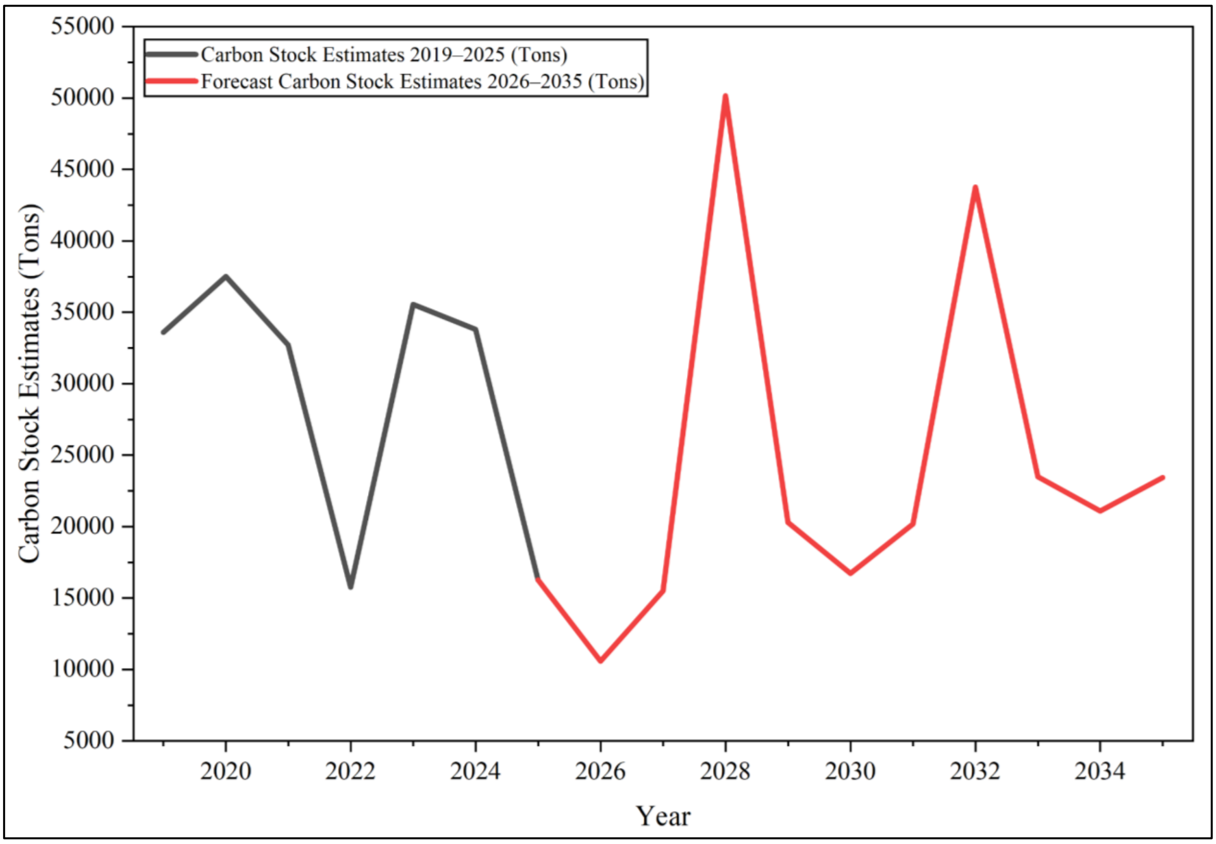

Figure 4. Forecast of Estimated Seagrass Carbon Stock from 2019 to 2035

The forecasting analysis of seagrass carbon stock in Teluk Saleh for the period 2019–2035 suggests temporal variability that is important for understanding both the ecosystem's potential and its vulnerability (Figure 4). The projection was generated using an ARIMA model implemented in OriginPro 2025b.

The Augmented Dickey-Fuller (ADF) test indicated that the original time series was non-stationary (p-value = 0.366), thus first-order differencing was applied. Initial model estimation suggested a statistically significant seasonal autoregressive component (p-value = 0.00681; standard error = 0.22629). However, further diagnostic analysis using ACF and PACF plots of the differenced series showed no significant autocorrelation.

Therefore, a more parsimonious model, ARIMA (0,1,0), was selected as the final specification because it adequately captures the time series's stochastic nature without overfitting. The forecast results are presented with 95% confidence intervals to account for uncertainty in the projections.

Historical data (2019–2025) indicate substantial fluctuations, with carbon stock peaking at approximately 37,000 tons in 2020 before declining sharply to around 16,000 tons in 2022. A recovery phase followed, with values increasing again to approximately 36,000 tons in 2023. The forecasting model extends this cyclical pattern, projecting a further decline to a minimum of approximately 11,000 tons in 2026, followed by a strong recovery, potentially reaching a peak of around 50,000 tons in 2028 (Figure 4). However, these projections should be interpreted as probabilistic outcomes within a 95% confidence interval, rather than precise predictions of future states.

While the model indicates the possibility of substantial recovery, this projection is contingent upon several key assumptions: 1) the environmental carrying capacity of Teluk Saleh remains intact; 2) no ecological tipping points are exceeded; and 3) external forcing factors such as coastal development, climate variability, and pollution remain within the range observed during the training period (2019–2025). Importantly, ARIMA is a purely statistical model that captures temporal dependencies without incorporating ecological processes, environmental thresholds, or spatial feedback mechanisms (Liu et al., 2022).

Therefore, the projected increase to approximately 50,000 tons should be interpreted as a best-case scenario under stable environmental conditions, rather than a guaranteed outcome. The actual trajectory of seagrass carbon stocks will depend on the interaction between natural recovery processes and anthropogenic pressures that are not explicitly represented in the model. This highlights the need for future studies to integrate process-based ecological models or include exogenous variables such as sea surface temperature, rainfall, and land-use change.

Despite these limitations, the projected recovery potential reflects the inherent resilience of seagrass ecosystems and their critical role in supporting ecosystem services, including blue carbon storage and coastal fisheries productivity (Ilma & Supriadi, 2022). However, this recovery is highly sensitive to human activities. Increasing pressure from coastal development, industrial activities, and unsustainable fishing practices could significantly alter the projected trajectory (Katwijk et al., 2024).

If such pressures are not effectively managed, the lower bounds of the forecast, such as those projected around 2026 and 2030, may become more pronounced and persistent, indicating deeper phases of degradation. In a worst-case scenario, sustained anthropogenic stress could push the ecosystem beyond a critical tipping point, potentially leading to irreversible decline (Chefaoui et al., 2018).

Therefore, the forecasting graph should not be interpreted merely as a statistical projection but as an indication that the future condition of seagrass ecosystems in Teluk Saleh depends strongly on effective coastal management and mitigation of human-induced pressures.

Limitations and Future Research

This study acknowledges several methodological limitations that should be considered when interpreting the results. First, the use of IPCC Tier 1 default carbon values introduces global average assumptions that may not accurately reflect the species-specific carbon storage characteristics of the seagrass communities in Teluk Saleh, particularly given the region's high species diversity, including Enhalus acoroides, Thalassia hemprichii, and Cymodocea rotundata (Fourqurean et al., 2012).

Future studies should develop site-specific allometric equations through systematic biomass harvesting campaigns to enable Tier 2 or Tier 3 carbon assessments. Second, the SVM classification accuracy of 71%, while acceptable for exploratory analysis, falls below the threshold recommended for operational seagrass monitoring programs (>85%; Roelfsema et al., 2013). Improving classification accuracy could be achieved by incorporating: a) multi-temporal feature stacking from Sentinel-2 time series; b) integration of Synthetic Aperture Radar data from Sentinel-1 to overcome cloud cover limitations; and c) ensemble machine learning approaches (e.g., Random Forest and XGBoost) that may better handle spectral variability. Third, the ARIMA forecasting model, while statistically robust, is a univariate time-series extrapolation method that does not incorporate exogenous environmental variables.

Future research should explore ARIMAX or dynamic regression models that integrate water quality parameters (chlorophyll-a, turbidity, sea surface temperature), rainfall data, and spatial planning policy indicators as predictive covariates. Additionally, the limited temporal resolution of annual observations constrains the model's ability to capture intra-annual variability; quarterly or monthly observations would significantly enhance forecasting precision.

CONCLUSION

This study makes three principal contributions to the seagrass blue carbon literature in Indonesia. First, it represents the first integrated application of Sentinel-2 remote sensing with Support Vector Machine classification and ARIMA time-series forecasting to quantify and project seagrass carbon stock dynamics in an Indonesian bay, establishing a replicable methodological framework that can be transferred to other tropical seagrass ecosystems. Second, it provides the first multi-year (2019–2025) spatio-temporal carbon stock assessment for Teluk Saleh, revealing significant cyclical fluctuations (from ~16,000 to ~36,000 tons) that were previously undocumented in this region.

Third, by contextualizing the results within Indonesia's NEK policy framework, this study bridges the gap between ecological science and national climate mitigation policy, demonstrating how remote sensing-derived carbon stock data can be directly operationalized for coastal governance and carbon market participation. These contributions collectively advance the field from static seagrass mapping toward dynamic, predictive blue carbon assessment, a critical evolution for evidence-based coastal management in the era of climate change.

From a research perspective, future studies are recommended to move beyond purely statistical forecasting by incorporating biophysical and socio-economic drivers into more process-based models. Improving classification accuracy through advanced technologies such as Light Detection and Ranging (LiDAR) or hyperspectral imagery is also essential to reduce uncertainty in carbon estimates. Additionally, expanding the analytical scope to include other ecosystem services, particularly fisheries productivity, will enhance the relevance of seagrass ecosystems within broader socio-ecological and policy contexts.

Additionally, the SVM classification accuracy of 71% represents a notable constraint on the reliability of the spatial carbon estimates. At this accuracy level, approximately 29% of pixels may be misclassified, potentially leading to systematic over or underestimation of seagrass area and, consequently, carbon stocks. The classification errors were particularly concentrated at the boundaries between sparse seagrass and bare sand classes, as well as between dense seagrass and mixed seagrass-coral substrates. These boundary misclassifications are expected in optically complex tropical waters but should be transparently communicated. Future improvements could incorporate LiDAR bathymetry data to enhance depth discrimination, or hyperspectral imagery to improve the spectral separation of benthic classes.

Overall, this study underscores the importance of transitioning from static assessments toward predictive and policy-relevant blue carbon frameworks, positioning seagrass ecosystems as critical assets for climate mitigation, sustainable coastal management, and community-based economic development.

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