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AI–Driven Carbon Stock Estimation: Analysis Framework for Indonesia's Energy Transition

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Abstract

Indonesia faces a critical climate challenge as the world's sixth-largest carbon emitter, with coal accounting for more than 60% of its electricity generation. Achieving its ambitious net-zero target by 2060 requires urgent action. While Indonesia has introduced various carbon pricing mechanisms to advance carbon neutrality, these initiatives demand sophisticated optimization across the archipelago's diverse regions to balance emissions reduction with sustainable development goals. This research presents an innovative artificial intelligence framework that leverages geospatial big data to estimate carbon stock and inform pricing strategies while supporting Indonesia's transition away from coal dependency. The framework integrates three key components: (1) a remote sensing-based Measurement, Reporting, and Verification (MRV) model that accurately quantifies carbon stocks across varied ecosystems; (2) an automated reporting system powered by generative Artificial Intelligence that enhances transparency and reduces bias in carbon accounting; and (3) a comprehensive analytics dashboard that visualizes dynamic carbon stock data to inform policy decisions. By addressing Indonesia's geographical complexities through tailored carbon stock estimation policies and optimizing resource allocation across diverse ecological contexts, this framework provides a data-driven foundation for Indonesia to navigate its energy transition and meet its climate commitments through enhanced MRV systems and targeted green financing initiatives.

Keywords:
artificial intelligence, carbon pricing, geospatial analysis, green financing, MRV, remote sensing

1. Introduction

Indonesia stands at a critical juncture in the global climate crisis, ranking as the sixth-largest carbon emitter worldwide according to UNFCCC (2022), with coal powering more than 60% of its electricity generation. This position places Indonesia at the forefront of international climate action and as a key player in achieving the Paris Agreement's goal of limiting global temperature rise to 1.5°C (UNFCCC, 2015). The agreement requires Indonesia to reduce greenhouse gas emissions by 29% independently and up to 41% with international support by 2030 (MEF, 2022). In response to growing global pressure from organizations such as the G20, UNFCCC, and World Bank, Indonesia has committed to achieving Net Zero Emissions (NZE) by 2060, raising its carbon reduction target in the Enhanced Nationally Determined Contributions (NDCs) to 32% by 2030 (MEF, 2021).

Despite possessing the world’s third-largest tropical rainforest, a significant natural carbon sink, Indonesia faces substantial challenges in meeting its targets (Guillaume et al., 2018). The financial burden of transitioning to a green economy is immense, with MOF (2023) estimating that Indonesia requires approximately USD 280 billion for green financing through 2030. Only 30% of this amount can be covered by the state budget, leaving a funding gap of around USD 196 billion that must be secured from private and international sources. To address this gap, Indonesia is turning to green financing instruments such as carbon trading and offset mechanisms, which enable emission reductions through market mechanisms and compensation projects (MOF, 2023). A significant step forward occurred on January 20, 2025, when Indonesia officially launched international carbon trading through the sale of carbon credits from rainforest conservation projects, with an ambitious revenue target of USD 65 billion by 2028 (FSA, 2025).

Limitations in monitoring and transparency present major obstacles to the success of green financing initiatives (Quatrini & Costanza, 2023), as evidenced by documented challenges in programs such as Reducing Emissions from Deforestation and Forest Degradation Plus (REDD+) in Aceh and the jurisdiction-based REDD program in East Kalimantan. Such challenges are particularly critical in carbon trading and offset contexts, where the integrity of carbon credits depends heavily on robust verification and monitoring systems (Tang et al., 2018). Without transparent and reliable mechanisms, risks such as double counting, carbon leakage, or greenwashing can severely damage the credibility of green financing schemes (Ma & Duan, 2024), directly affecting investor confidence, which is strongly influenced by transparency and accountability in carbon emission measurements (Villena & Dhanorkar, 2020).

Currently, Measurement, Reporting, and Verification (MRV) systems for carbon emissions in Indonesia rely primarily on inventory methods based on industry self-assessment reports, which are prone to producing less transparent and accurate data. The Ministry of Environment and Forestry (MEF) employs these conventional approaches, which often struggle with inconsistent methodologies, limited spatial and temporal resolution, and insufficient verification processes. These limitations compromise the integrity of carbon accounting and reduce the effectiveness of carbon pricing mechanisms, which are essential market-based approaches that assign monetary value to emissions and incentivize reductions. Traditional carbon stock measurement methods, which calculate the amount of carbon stored in forests, soils, and other reservoirs, typically involve field-based measurements that are labor-intensive, time-consuming, and limited in spatial coverage.

The integration of cutting-edge technologies such as geospatial big data, remote sensing, and Artificial Intelligence (AI) offers a promising solution to these challenges. Remote sensing collects information about the Earth’s surface without direct physical contact, using sensors mounted on satellites, aircraft, or drones to measure radiation reflected or emitted by objects on the Earth’s surface (Rees, 2013; Toth & Jóźków, 2016). This technology can capture the geographical conditions and economic activities of a region with significant advantages in environmental data analysis, particularly in recording actual conditions at the grid level with rapid updates (Chen et al., 2015). Moreover, integrating remote sensing with AI’s ability to analyze large datasets and identify patterns enables precise, location-specific monitoring of carbon emissions data (Chen et al., 2021).

Generative AI represents a revolutionary tool for enhancing MRV systems by automating report generation, identifying patterns in emissions data, and providing more efficient and transparent recommendations for carbon market operations (Cogiel et al., 2026). Zhang et al. (2024) have shown that applying AI to remote sensing data can support Continuous Emission Monitoring Systems in power plants to accurately measure carbon emissions. The combination of these technologies not only addresses the limitations of current MRV methods but also strengthens the foundation for effective carbon pricing strategies that can drive Indonesia’s energy transition away from coal dependency toward renewable energy sources.

Our research introduces a novel approach to carbon stock calculation using satellite imagery and automatic report generation through Generative AI, aiming to develop an AI-powered framework that optimizes carbon pricing strategies across Indonesia's diverse regions. A remote sensing-based MRV model is developed for accurate carbon emissions verification and establishes an AI-powered dashboard, named CarbonNet, for monitoring, analyzing, and providing policy recommendations. This innovative approach will contribute significantly to Indonesia's energy transition by creating a data-driven foundation for carbon pricing optimization that balances environmental imperatives with economic realities. By establishing reliable carbon pricing mechanisms supported by robust MRV systems, Indonesia can accelerate its energy transition while managing socioeconomic impacts on coal-dependent regions. The different land cover types across Indonesia possess varying capacities to absorb carbon due to differences in vegetation and soil characteristics, making a geospatial analysis framework particularly valuable for optimizing carbon pricing in support of the country's dual objectives of reducing emissions and fostering sustainable development. This framework will enable policymakers to design geographically tailored carbon pricing strategies that accelerate the shift from coal to renewable energy sources while ensuring just transition pathways for affected communities, ultimately supporting Indonesia's progress toward achieving its NZE target by 2060.

2. Methods and Materials

2.1 Study Area

Riau Province, Indonesia, was selected as the primary study area due to its strategic importance in the country's carbon management landscape. Located on the central eastern coast of Sumatra Island as shown in Figure 1, Riau spans approximately 87,023.66 km² with diverse ecosystems including peatlands, tropical rainforests, and palm oil plantations. The province contains about 4.04 million hectares of peatland, accounting for 45% of its total area, and representing one of Indonesia's largest carbon sinks with significant potential for carbon sequestration and emission reduction (Putri et al., 2023). Riau has also been included in Indonesia's REDD+ pilot projects.

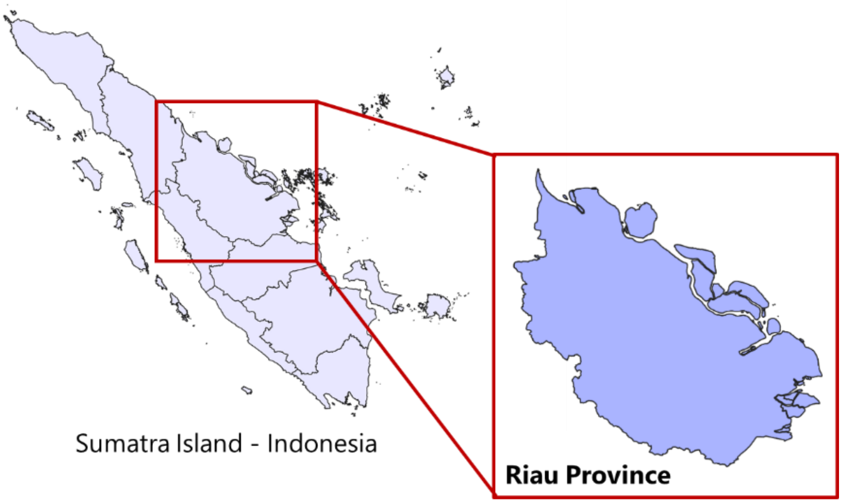


Figure 1. Study area.

2.2 Data Sources

This study uses a combination of remote sensing-derived spectral indices, land classification data, and official administrative boundary datasets, as detailed in Table 1, to assess carbon stock changes at a 50 x 50 meter scale. The selected variables are designed to capture vegetation dynamics, land cover transformations, and hydrological features relevant to the environments.

Table 1. Data source.

Variable	Formula	Data Source	Description
Individual Bands	Blue (B2), Green (B3), Red (B4), NIR (B8), SWIR 1 (B11), SWIR 2 (B12)	European Space Agency (ESA) Sentinel-2	Spatial resolution ranges from 10 to 20 meters, with a revisit time of approximately 5 days.
Forest Discrimination Index (FDI)	$FDI = NIR_{B8} - (Red_{B4} + Green_{B3})$		
Mangrove Discrimination Index (MDI)	$MDI = \frac{NIR_{B8} - SWIR2_{B12}}{SWIR2_{B12}}$		
Modified Normalized Difference Water Index (MNDWI)	$MNDWI = \frac{Green_{B3} - SWIR1_{B11}}{Green_{B3} + SWIR1_{B11}}$		
Normalized Difference Built-up Index (NDBI)	$NDBI = \frac{SWIR1_{B11} - NIR_{B8}}{SWIR1_{B11} + NIR_{B8}}$		
Normalized Difference Vegetation Index (NDVI)	$NDVI = \frac{NIR_{B8} - Red_{B4}}{NIR_{B8} + Red_{B4}}$		
Wetland Forest Index (WFI)	$WFI = \frac{NIR_{B8} - Red_{B4}}{SWIR2_{B12}}$		
Land Use Land Cover (LULC)	-	Indonesian Ministry of Environment and Forestry	It consists of 22 land use and land cover (LULC) classes (see Table 2), based on reference years 2015 and 2020
Administrative Bounds	-	BPS Statistics Indonesia	Administrative boundaries of provinces, districts, sub-districts, and villages in Riau

Satellite imagery from Sentinel-2 serves as the primary source of spectral data, providing medium-resolution observations across various wavelengths, including visible, near-infrared (NIR), and shortwave infrared (SWIR) bands. These bands are used individually and as foundational inputs for deriving key environmental indices. A suite of spectral indices is applied to enhance the classification and interpretation of land cover and vegetation types. The Forest Discrimination Index (FDI) and Mangrove Discrimination Index (MDI) are specifically designed to detect and differentiate forest and mangrove ecosystems, respectively, both significant for carbon sequestration. The Modified Normalized Difference Water Index (MNDWI) enables the delineation of surface water bodies, which is crucial in peatland hydrological analysis. To assess anthropogenic changes, the Normalized Difference Built-up Index (NDBI) is used to identify built-up or urbanized areas, while the Normalized Difference Vegetation Index (NDVI) provides a standardized measure of vegetation vigor and canopy density, widely employed for monitoring biomass. The Wetland Forest Index (WFI) is additionally utilized to highlight forested wetland areas commonly associated with tropical peatland environments.

Complementing these remotely sensed variables, Land Use and Land Cover (LULC) data provided by the Indonesian Ministry of Environment and Forestry is used. This dataset categorizes the landscape into 22 distinct land cover classes based on validated national standards for the reference years 2015 and 2020, enabling a comprehensive assessment of land cover change dynamics such as deforestation or land conversion, which directly affect local carbon stocks. Administrative boundary data from BPS-Statistics Indonesia further provides geospatial delineations at the province, district, and village levels, serving as an essential layer for spatial aggregation, policy relevance, and aligning analytical outputs with official administrative units, particularly for site-specific interventions and monitoring frameworks.

2.3 Methodology

This study employs a three-phase geospatial and AI-driven MRV framework to enable accurate carbon pricing optimization for Indonesia's energy transition. The framework integrates Earth observation data, machine learning, GIS analytics, and Generative AI, as detailed in Figure 2.

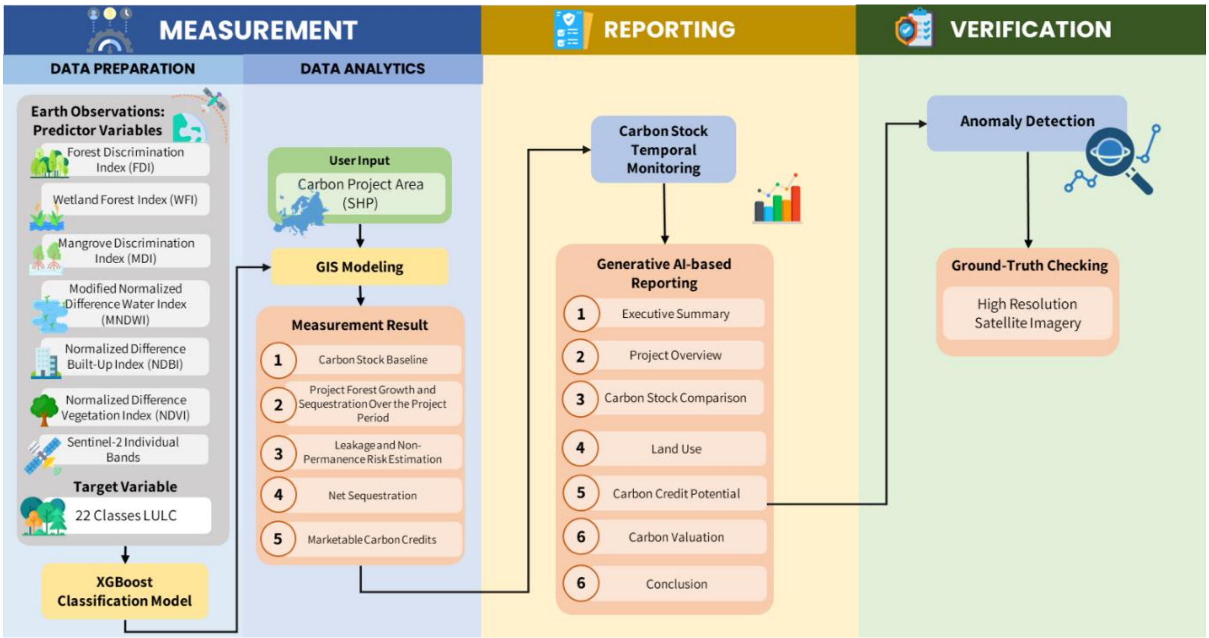


Figure 2. Research framework MRV.

The process begins with the Measurement phase, where Earth observation data from satellite imagery is transformed into meaningful predictor variables, including a range of vegetation and land cover indices. The FDI is used to differentiate forested areas from other land cover types, while the WFI is specifically designed to identify and map forest ecosystems in wetlands. The MDI is a specialized index for classifying mangrove forests in coastal regions. Several spectral indices are applied, such as the NDVI, a widely adopted index for assessing vegetation health and density based on the difference in near-infrared and red light reflectance, and the MNDWI, which is employed to delineate water bodies from soil and vegetation. The framework also integrates individual bands from Sentinel-2 satellite imagery to ensure high-resolution spatial input. These multidimensional datasets are processed through an Extreme Gradient Boosting (XGBoost) classification model trained to classify LULC into 22 distinct classes, laying the foundation for identifying and quantifying carbon-relevant ecosystems across a defined project area. Building on this classification, user-provided geospatial boundaries, typically in the form of shapefiles, are used to initiate spatial analysis through GIS modeling. This process integrates and analyzes various spatial data layers by overlaying remote sensing data with administrative boundaries to delineate specific project areas. GIS tools enable the spatial aggregation of carbon stock data from individual pixels to larger administrative units, making the data policy-relevant and easier for stakeholders to interpret. This serves as a crucial step in transforming raw data into actionable insights for site-specific interventions and monitoring frameworks, ensuring that analytical outputs such as carbon stock estimates and sequestration potential are spatially referenced and aligned with official geographical units.

The resulting analytics produce key carbon measurement outputs, including baseline carbon stock estimates, projections of forest growth and carbon sequestration potential over time, assessments of leakage and permanence risks, and the calculation of net carbon sequestration. From these, the system can estimate the volume of marketable carbon credits, forming a critical basis for pricing strategies. The next phase, Reporting, leverages the output from carbon stock monitoring and translates it into structured, decision-ready documentation through a generative AI system. This component of the framework automates the production of essential carbon project reports, including project overview, carbon stock comparison, land use, carbon credit potential, and carbon valuation. These outputs are temporally informed and tailored to support both regulatory compliance and market transparency, offering a scalable and efficient method for turning data into policy-relevant narratives. In the final phase, Verification, the framework employs anomaly detection algorithms to scan for irregularities or inconsistencies within the monitored carbon stock data. When anomalies are identified, they undergo a ground-truth verification process using high-resolution satellite imagery, ensuring that reported changes in carbon stocks reflect actual environmental conditions on the ground and adding a vital layer of credibility to the system.

2.3.1. Data Collection and Preprocessing

This study employed a set of remote sensing indicators derived from multispectral satellite imagery to assess vegetation characteristics, land cover types, and hydrological features across the study area. The primary dataset consisted of Sentinel-2 surface reflectance imagery processed through Google Earth Engine, a cloud-based geospatial analysis platform that supports large-scale environmental monitoring and spatial data processing. Prior to extracting remote sensing indicators, several preprocessing steps were conducted to ensure data quality and temporal consistency. Cloud masking was applied using the Sentinel-2 QA60 band and the s2cloudless algorithm to systematically identify and remove pixels contaminated by clouds and cirrus, a crucial step for maintaining the accuracy of surface reflectance data in cloud-prone tropical environments. Image compositing was then performed by aggregating cloud-free scenes over a specified time window, typically a dry-season period to minimize seasonal variability, using a median reducer to create a single, representative image mosaic. This process effectively reduces noise and fills gaps left by masked clouds, ensuring a complete and temporally consistent dataset. All bands were resampled to a uniform 10-meter spatial resolution using bilinear interpolation to maintain spatial consistency across indices involving different spectral bands. Study area masking was applied using the administrative boundaries of Teluk Meranti Village, sourced from BPS-Statistics Indonesia, to spatially subset the imagery. Spectral normalization was then conducted to ensure comparability of reflectance values across time and space. Each computed index (e.g., NDVI, MNDWI, and FDI) was generated from the harmonized image composites and exported for further machine learning modeling.

2.3.2. XGBoost Classifier Model Development

In this study, the development of the XGBoost classifier model is integral to accurately classifying LULC types across diverse landscapes, providing a foundation for estimating carbon stocks and informing carbon pricing strategies. XGBoost is a scalable, ensemble-based machine learning algorithm recognized for its high performance in classification tasks, including remote sensing applications. It constructs an ensemble of decision trees, with each subsequent tree correcting the errors of its predecessors, optimizing the model through gradient descent and regularization techniques. This approach enhances both accuracy and computational efficiency, making it suitable for processing large-scale geospatial datasets (Matyukira, 2023). The efficacy of XGBoost in LULC classification has been demonstrated in various studies; for example, Abdi (2020) highlighted its superior performance over traditional classifiers such as Random Forest and Support Vector Machines in urban land cover classification tasks, while Minati et al. (2023) applied XGBoost to unmanned aerial vehicle imagery for mangrove cover detection, achieving high accuracy and demonstrating the model's applicability in diverse ecological contexts.

2.3.3. Measurement Calculation

The carbon measurement methodology constitutes a foundational step for estimating carbon stock levels and assessing the marketable carbon credit potential of the project area. This process integrates classified LULC with empirically derived carbon stock coefficients sourced from Indonesia's Forest Reference Emission Level (FREL) documentation. Carbon stock estimation encompasses four principal components:

- Above-Ground Biomass (AGB), which refers to all living vegetation above the soil, such as tree trunks, branches, and leaves;
- Below-Ground Biomass (BGB), which accounts for the living root systems of plants;
- Dead Organic Matter (DOM), which includes all non-living woody debris, litter, and fallen trees; and
- Soil Organic Carbon (SOC), which is the carbon stored in the soil, particularly in the rich organic soils of peatland (Please see Table 2).

The AGB, BGB, and DOM values are adopted from Indonesia's official FREL submission to the UNFCCC, where ecosystem-specific constants are defined for various land cover types, including primary forests, peat swamp forests, mangroves, shrubs, and agricultural land.

All calculations are performed on a 50 × 50 m pixel grid, corresponding to an area of 0.25 hectares per pixel. Each pixel classified into one of the 22 LULC categories is assigned the respective carbon stock values for each component, and the total carbon stock per pixel is obtained by summing AGB, BGB, DOM, and SOC as in Equation 1. This total is then aggregated across the entire project area to establish a baseline carbon stock as the reference point for further analysis.

$$\text{Carbon Stock} = \text{AGB}+\text{BGB}+\text{DOM}+\text{SOC} \qquad (1)$$

To evaluate carbon sequestration potential over time, the projected increase in forest biomass is estimated using Equation 2, which captures temporal changes in carbon stock. This step captures net carbon uptake associated with forest regeneration, restoration, or improved management practices over the defined project implementation period.

$$\text{Project Sequestration (tCO}_2\text{e/year)}=\frac{Carbon\ Stock_{year\ n}-Carbon\ Stock_{baseline}}{\mathrm{Pr}\,oject\ Duration} \qquad (2)$$

To account for risks associated with leakage (i.e., emissions displaced to areas outside the project boundary) and non-permanence (e.g., re-release of carbon due to fire or land-use reversal), a conservative buffer of 10% is applied to the projected sequestration using Equation 3. Net sequestration is then obtained by subtracting this risk-adjusted amount from the total projected sequestration, as shown in Equation 4. Finally, to determine the marketable carbon credits, the net sequestration is multiplied by a fixed pricing factor of IDR 96,000 per ton of CO_2e, reflecting prevailing or benchmarked voluntary market prices in Indonesia (Equation 5).

$$RiskAdjustment(tCO2e) = 0.1 \times ProjectedSequestration \qquad (3)$$

$$NetSequestration(tCO2e/year) = ProjectedSequestration - RiskAdjustment \qquad (4)$$

$$Marketable\ Carbon\ Credits\left(\frac{IDR}{year}\right) = Net\ Sequestration \times 96{,}000 \qquad (5)$$

Table 2. Carbon stock calculation reference.

Code	Class	Description	Carbon stock (Mg/ha)				
			Above	Below	Dead	Soil	Total
2001	Primary Dryland Forest	Natural tropical forest on non-wetlands, including lowland to montane types, with minimal human disturbance.	338,35	98,81	61,36	172,5	671,02
2002	Secondary Dryland Forest	Like above, but with visible signs of logging (e.g., roads, patches).	213,28	64,22	71,16	172,5	521,16
2004	Primary Mangrove Forest	Natural tropical forest in wet/swamp areas (e.g., peat, marsh) with minimal disturbance.	236,17	73,45	13,7	172,5	495,82
20041	Secondary Mangrove Forest	Swamp forest showing signs of logging activities.	118,02	13,57	14,4	172,5	318,49
2005	Primary Swamp Forest	Coastal wetland forest (muddy, brackish) dominated by mangroves/Nipa, undisturbed.	311,75	78,24	64,25	298	752,24
20051	Secondary Swamp Forest	Like above, but with evidence of logging activity.	179,55	7,58	47,68	298	532,81
2006	Plantation Forest	Homogeneous tree plantations for industry, reforestation, or community use.	75.78	24.63	0	172.5	272.91
2007	Wet Shrub (Dry)	Heavily logged dryland areas under natural regrowth, not yet stable.	19.34	4.56	0	111	134.9
20071	Wet Shrub (Wet)	Heavily logged wetland areas under natural regrowth, not yet stable.	19.34	4.56	0	298	321.9
20091	Pure Dry Agriculture	Grassland with scattered natural trees, found in dry/wet habitats, common in eastern Indonesia.	14.08	2.82	0	111	127.9
20092	Mixed Dry Agriculture	Dryland farming areas like moor, gardens, and shifting cultivation.	64.64	12.93	0	111	188.57
20093	Paddy Field	Wetland rice fields with dyke patterns; includes rain-fed and irrigated fields.	10	2.36	0	66	78.36
20094	Fishpond/ Aquaculture	Areas used for fish/shrimp/salt farming.	0	0	0	119	119
20122	Transmigration Areas	Settlements with nearby gardens or agroforestry systems.	14.08	2.82	0	23.3	40.2
2010	Estate Crop	Planted areas for perennial or tree-based agricultural commodities.	48.1	15.63	0	66	129.73

Code	Class	Description	Carbon stock (Mg/ha)				
			Above	Below	Dead	Soil	Total
2012	Settlement	Built-up areas: urban, rural, or industrial.	2.17	0.63	0	23.3	26.1
20121	Port and Harbour	Large visible port or harbor infrastructure.	0	0	0	23.3	23.3
2014	Bare Ground	Exposed land with no vegetation, such as sandbanks, craters, or post-fire areas.	2.4	0.57	0	111	113.97
20141	Mining Areas	Open-pit mines and associated tailing areas.	0	0	0	23.3	23.3
5003	Open Water	Natural water bodies like oceans, rivers, lakes, and ponds.	0	0	0	119	119
50011	Open Swamps	Wetlands with sparse vegetation.	0	0	0	298	298
3000	Savanna and Grasses	Cloud, shadow, or data gaps >4 cm² at 1:100,000 scale.	4.06	0.96	0	111	116.02

2.3.4. Generative AI-based Automatic Reporting

A generative AI-driven framework is incorporated to automate the generation of analytical reports, leveraging the capabilities of Large Language Models (LLMs). LLMs are advanced deep learning models trained on extensive text corpora, enabling them to comprehend and generate human-like language (Naveed et al, 2023). Their proficiency in understanding context and producing coherent narratives makes them suitable for tasks such as summarization, question answering, and report generation (Zhao, 2025). Generative AI is used to present automatic reports in a user-friendly and interpretable format, bridging the gap between technical data analysis and accessible decision-making insights. This approach is particularly effective in translating complex geospatial and environmental indicators into concise, context-aware narratives that support stakeholder engagement, policy design, and spatial planning.

From a technical perspective, the integration of LLMs into the system is achieved through an Application Programming Interface (API), which connects the data processing backend to the language generation model. Once the spatial and statistical analyses are completed, the processed outputs, including key variables and summary statistics, are transmitted via structured prompts to the LLM. The API ensures secure and efficient data transfer, while prompt engineering is applied to guide the LLM in generating relevant and targeted content based on predefined reporting logic. The resulting AI-generated report is structured to include several key components tailored to environmental and carbon-related analysis:

- Executive Summary, providing an overview of findings;
- Project Overview, describing the study area, objectives, and methodologies;
- Carbon Stock Comparison, evaluating spatial and temporal differences in biomass carbon;
- Land Use, summarizing land cover classifications and change detection;
- Carbon Credit Potential, estimating possible carbon offset values;
- Carbon Valuation, translating potential credits into economic value; and
- Conclusion, presenting synthesized insights and policy-relevant implications.

2.3.5. Validation Using High-Resolution Satellite Imagery

Validation was conducted to detect potential anomalies and ensure the reliability of spatial outputs. This step was particularly important for identifying misclassifications or unusual patterns in vegetation, water bodies, and built-up areas that may have resulted from spectral confusion or cloud-related noise in the medium-resolution data. For this purpose, high-resolution satellite imagery from Google Satellite was used. With a spatial resolution significantly finer than that of Sentinel-2, these images allowed for detailed cross-referencing of land features on the ground. The availability of high-resolution basemaps via Google Earth provided a visually rich and up-to-date reference to assess the correspondence of classified results with actual land cover characteristics. This qualitative validation method ensures that automated remote sensing-based classifications are grounded in observable spatial reality, supporting more accurate downstream analysis and policy recommendations.

2.3.6. Dashboard Development

To enhance the usability and accessibility of the research outputs, a web-based dashboard was developed as an integral tool to support the full implementation of the MRV framework. This dashboard is designed to empower stakeholders (e.g., policymakers, environmental planners, and community-level actors) to independently carry out carbon assessment processes anytime and anywhere without relying on specialized technical expertise. It was built using a combination of Node.js for the backend and React for the frontend, ensuring both scalability and responsiveness across platforms. This architecture enables seamless data processing, user interaction, and real-time visualization. Within the dashboard, users are provided with an intuitive interface to select their area of interest for carbon stock identification, after which the system automatically performs geospatial measurements based on pre-integrated remote sensing indices. Users can then download an auto-generated report in PDF format, which includes components such as an executive summary, land use classification, carbon stock estimates, carbon credit potential, and valuation insights.

3. Results and Discussions

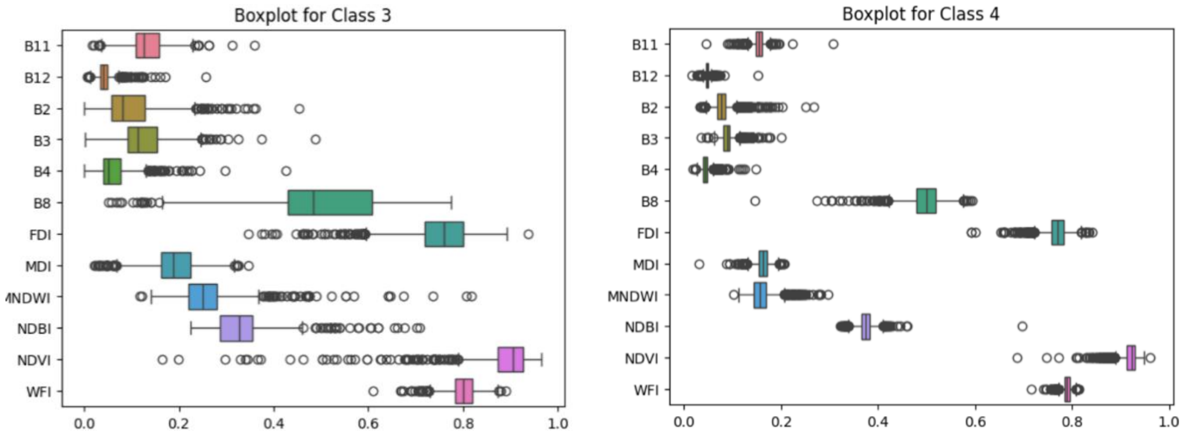
3.1 Remote Sensing-Based MRV Model for Carbon Stock Quantification

3.1.1 Land Use Land Cover Modelling

The LULC modeling process begins with identifying the characteristics of Sentinel-2 satellite image bands across 22 LULC classes. For example, as shown in Figure 3, which presents a boxplot comparison of spectral bands for Class 3 (Primary Mangrove Forest) and Class 4 (Secondary Mangrove Forest), each band displays a distinct distribution pattern, demonstrating that remote sensing data from Sentinel-2 imagery can effectively capture the spectral differences between land cover classes.

To classify the 22 LULC classes, a Gradient Boosting Classifier was developed and trained on normalized Sentinel-2 data using 5-fold cross-validation with 300 estimators. Performance evaluation was conducted on four key metrics: accuracy, precision (macro-averaged), recall (macro-averaged), and F1-score (macro-averaged). During each fold, both training and testing scores were recorded to observe model consistency and generalization ability across different data splits. The results (Table 3), presented per fold, illustrate how the model performed during each iteration of cross-validation, while the mean and standard deviation for each metric across all folds were calculated to provide a more robust assessment of performance.

For quantitative accuracy, the XGBoost model achieved an overall accuracy of 0.700, with a precision of 0.725, a recall of 0.723, and an F1-score of 0.719 across 5-fold cross-validation. While these scores are promising, future studies will incorporate ground-truth data from field measurements to further validate the model’s performance and ensure greater precision, particularly in distinguishing between similar land cover classes, thereby strengthening the system’s credibility for use in carbon market transactions.



(a) (b)

Figure 3. Bands Comparison of Class 3 Primary Mangrove Forest (a) and Class 4 Secondary Mangrove Forest (b).

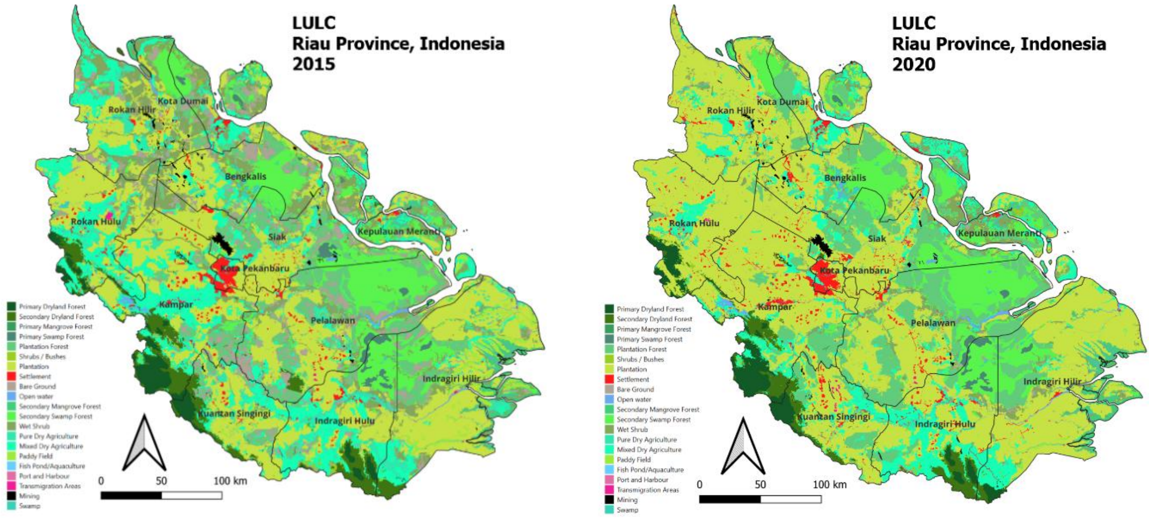
Table 3. Modelling results.

Evaluation	Result
Accuracy	0.700
Precision	0.725
Recall	0.723
F1-Score	0.719

3.1.2 Carbon Stock Calculation

The observed LULC changes between 2015 and 2022 in Riau Province, as shown in Figure 4, particularly in the western regions such as Rokan Hulu, Kampar, Kuantan Singingi, and Indragiri Hulu, are closely linked to ongoing environmental and socio-economic dynamics. These areas have experienced significant deforestation and land conversion, primarily driven by the expansion of oil palm and timber plantations. Between 1990 and 2020, Riau lost approximately 4.63 million hectares of forest, with oil palm plantations expanding six-fold to cover about 3.52 million hectares by 2020. The transformation of land cover has been especially pronounced on peatlands, which are crucial carbon sinks. The proportion of oil palm plantations established on peatlands increased from 9% in 1990 to 29% in 2020, highlighting a shift toward more carbon-rich areas. This shift has significant implications for carbon emissions and climate change, as peatland conversion releases substantial amounts of stored carbon into the atmosphere (Juniyanti and Situmorang, 2023; Numata et al., 2022). Moreover, the expansion of plantations has been associated with increased fire frequency, particularly in areas transitioning from secondary peat swamp forests to plantations. Fires are often used as a land-clearing method, exacerbating carbon emissions and contributing to regional haze problems (Adrianto et al, 2019). These land use changes are further influenced by policy and governance challenges, with policy failures, lack of enforcement capacity, and the involvement of both companies and smallholders in land management identified as underlying causes of deforestation and land cover change in Riau (Juniyanti and Situmorang, 2023).

The carbon stock assessment for Riau Province was conducted for the years 2015 and 2020 using LULC data at a spatial resolution of 250 m^2. The calculation incorporated four primary carbon pools: AGB, BGB, Dead Organic Matter, and Soil Organic Carbon, with estimations based on constants provided in Table 2 and applied using Formula 1 to standardize carbon stock calculations across different land cover types. The results, depicted in Figure 4(a) and Figure 4(b), show that the highest carbon stocks are predominantly located in the Pelalawan, Indragiri Hulu, Indragiri Hilir, western Kuantan Singingi, Kampar, and Rokan Hulu regencies, with significant carbon reserves also present in parts of Dumai and Bengkalis. These areas are characterized by extensive peatland forests known for their substantial carbon sequestration capabilities. Between 2015 and 2020, changes in carbon stock were observed, reflecting land use dynamics such as deforestation, peatland degradation, and conversion to agricultural land. However, as shown in Figure 5 and Figure 6, conservation initiatives like the Restorasi Ekosistem Riau (RER) project have played a pivotal role in mitigating carbon loss. Established in 2013, RER focuses on restoring and protecting peat swamp forests in the Kampar Peninsula and Padang Island, successfully conserving over 150,000 hectares of peatland estimated to store approximately 2.14 billion tonnes of carbon, with 97% residing below ground in saturated peat soils.



(a) (b)

Figure 4. Riau Land use land cover in 2015 (a) and 2020 (b)

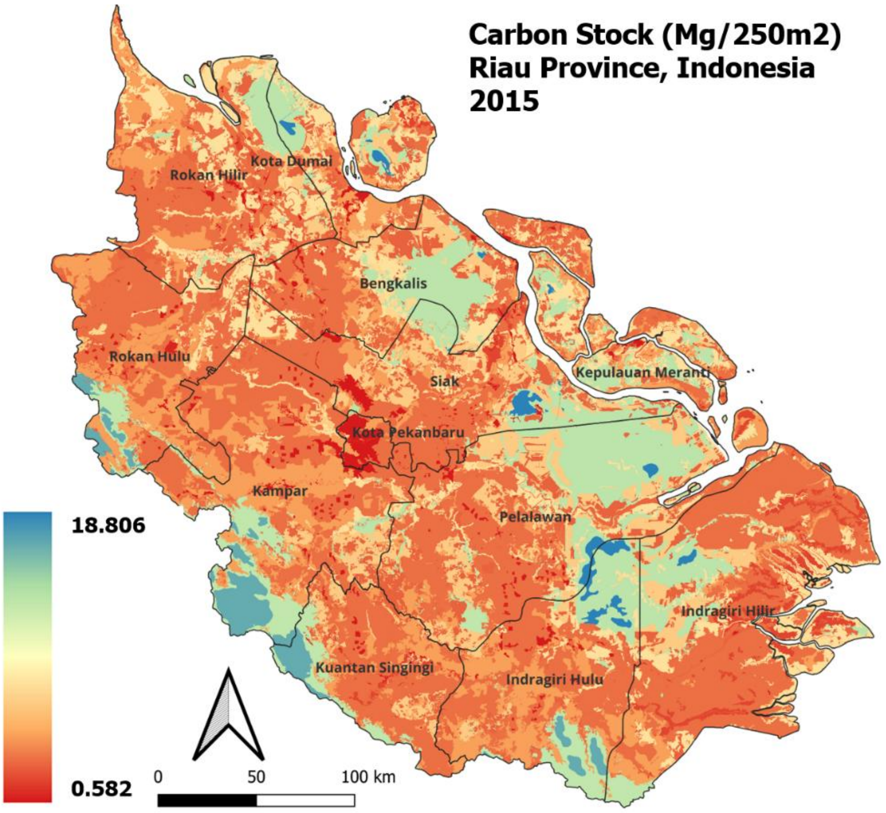


Figure 5. Carbon stock measurement of Riau Province in 2015

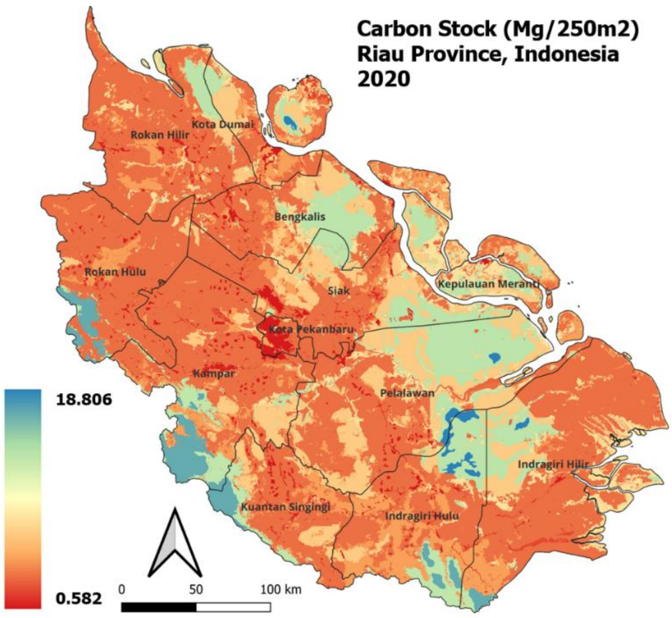


Figure 6. Carbon stock measurement of Riau Province in 2020

Figure 7 illustrates the changes in carbon stock across Riau Province's regencies and cities between 2015 and 2020. The data show a general decline in carbon stock in most regions, notably in Bengkalis, Indragiri Hulu, Kampar, Dumai City, Rokan Hilir, Rokan Hulu, and Siak, with Rokan Hilir experiencing the most significant reduction. The substantial decrease in Rokan Hilir's carbon stock is closely linked to extensive land-use changes, particularly the conversion of forests and peatlands into oil palm plantations. Between 2009 and 2011, the district saw an increase of approximately 177,138 hectares in oil palm plantation areas, leading to net CO_2 emissions of about 7.1 million tons annually, significantly diminishing the region's carbon storage capacity (Sampebatu et al, 2016). Conversely, Kepulauan Meranti and Pelalawan regencies demonstrated an increase in carbon stock during the same period, largely attributed to the implementation of the Riau Ecosystem Restoration (RER) project, which focuses on restoring and protecting peat swamp forests in these areas. RER's efforts have been instrumental in enhancing carbon sequestration and mitigating emissions from peatland degradation. In contrast, Indragiri Hilir and Kuantan Singingi regencies exhibited relatively stable carbon stock levels between 2015 and 2020, indicating minimal land-use changes and effective conservation practices in these regions.

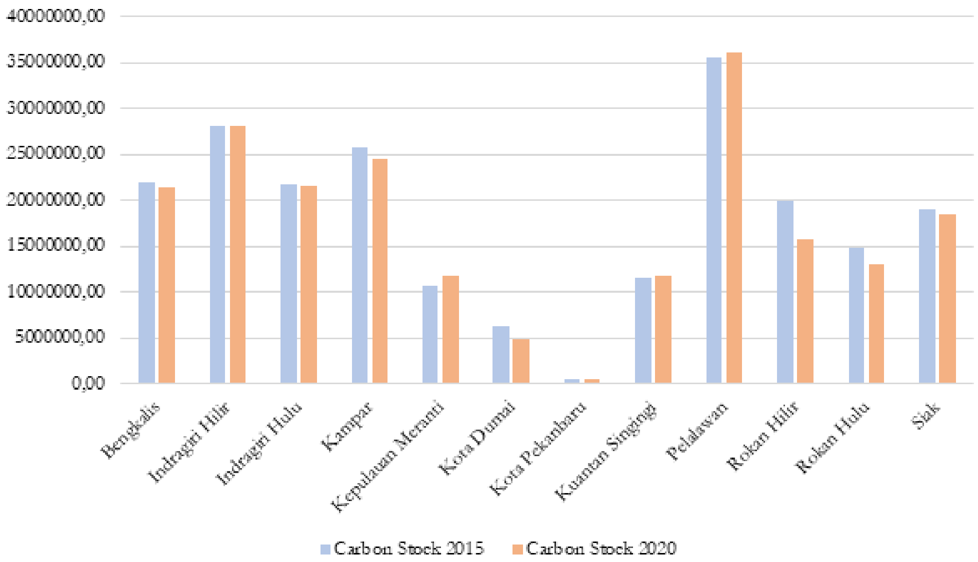


Figure 7. Carbon stock change 2015-2020 (Mg).

3.1.3 Carbon Credit Potential

Figure 8 illustrates the annual net carbon sequestration across Riau Province's regencies and cities between 2015 and 2020, highlighting regions with significant potential for carbon credit initiatives. Notably, Pelalawan and Kepulauan Meranti regencies exhibit the highest net carbon sequestration rates, a positive trend largely attributed to the implementation of the RER project, which focuses on the restoration and protection of peat swamp forests in these areas.

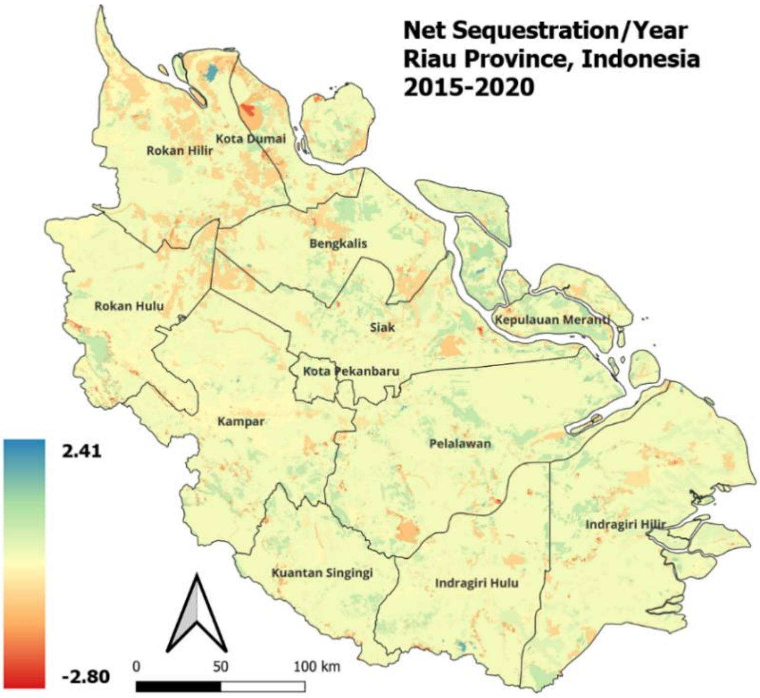


Figure 8. Net sequestration per year.

3.1.4 Carbon Valuation

Figure 9 presents the estimated economic value of carbon stock across regencies and cities in Riau Province, calculated using the prevailing carbon price in Indonesia as of January 2025, set at IDR 96,000 per ton for units. This valuation translates the carbon sequestration potential of each region into monetary terms, highlighting areas with significant opportunities for carbon credit initiatives. The analysis shows that Pelalawan Regency holds the highest carbon stock value, approaching Rp40 billion, largely attributed to the presence of extensive peatland forests and the implementation of the RER project, which focuses on restoring and protecting peat swamp forests in the area. Following Pelalawan, Indragiri Hilir, Bengkalis, and Kepulauan Meranti regencies exhibit significant carbon stock values ranging between IDR 24 billion and IDR 31 billion, characterized by vast peatland ecosystems known for their high carbon sequestration capacities. In contrast, urban areas such as Pekanbaru City and Dumai City show the lowest carbon stock values, estimated between IDR 1.2 billion and IDR 8.9 billion, primarily due to urban development and limited forested areas, resulting in reduced carbon sequestration potential. Figure 9 also identifies key areas with substantial carbon storage that can be optimized for carbon credit schemes, with monetization of carbon stock through such initiatives providing financial incentives for conservation while contributing to Indonesia's commitment to reducing greenhouse gas emissions as outlined in its Enhanced NDCs.

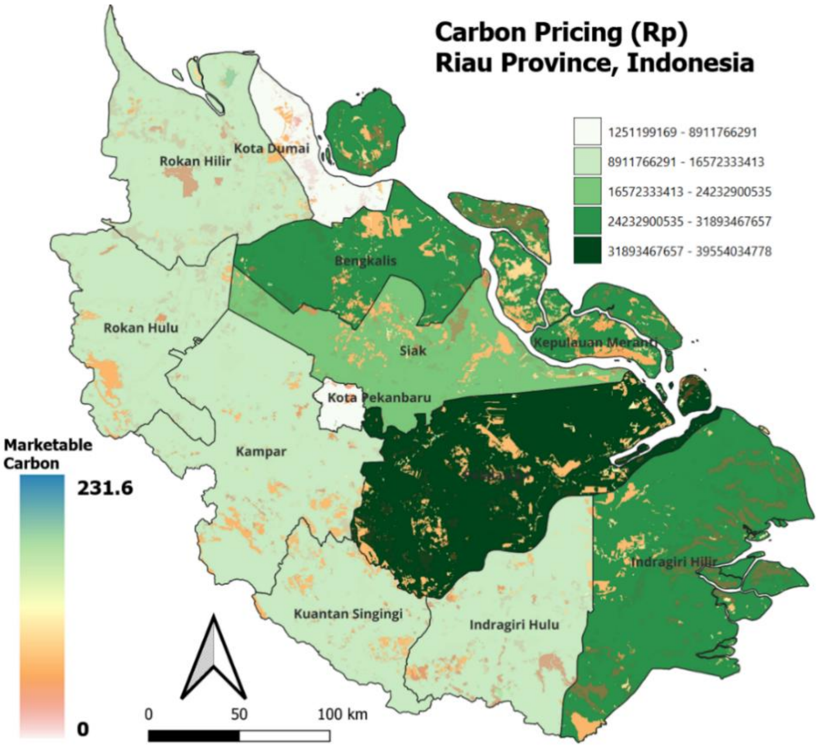


Figure 9. Estimated economic value of carbon stock across regencies and cities in Riau Province.

3.2. Generative AI-Powered Automated Reporting System

3.2.1. Prompt Engineering and Contextual Narrative Generation

In developing an automated reporting system utilizing Generative AI, the process of prompt engineering is pivotal in transforming raw geospatial data into coherent, contextually relevant narratives. This approach enables users to generate detailed analytical reports by specifying particular regions of interest, thereby facilitating region-specific environmental diagnostics. To create reports that present a comprehensive analysis based on remote sensing-derived carbon stock estimations, prompt engineering is applied systematically to each section of the report. This structured design ensures that each component reflects spatial specificity, data relevance, and interpretative depth, ultimately guiding actionable insights for climate and land-use governance. Below is the structured outline of the Carbon Stock Comparative Analysis Report, along with prompt formulations designed to elicit intelligent, content-rich outputs from the generative model.

a. **Executive Summary**
This section provides a concise summary of the key findings from the carbon stock analysis, highlighting significant temporal changes in carbon storage, identifying top-performing and declining regions in terms of sequestration, and introducing the broader implications of the findings.
Prompt:

> "Summarize the key findings of the carbon stock analysis conducted for [selected region by user], highlighting the most significant changes between 2015 and 2020. Indicate the regions with the highest sequestration potential and those experiencing notable losses, and explain the environmental relevance in a non-technical yet scientific tone."

b. **Project Overview**
This section outlines the objective and scope of the carbon stock monitoring effort, the geospatial and temporal dimensions considered, and the rationale for using remote sensing methods to estimate carbon dynamics.
Prompt:

> “Provide a scientific overview of the carbon monitoring project for [selected region by user], including the region’s topographic and climatic characteristics, the temporal scope (2015–2020), and the rationale for using remote sensing and geospatial analysis to estimate carbon stock and land use dynamics.”

c. **Carbon Stock Comparison**

This section compares carbon stock across two temporal snapshots (e.g., 2015 and 2020), showing how the region’s carbon sink capacity has changed and quantifying gains or losses across key biomass components.

Prompt:

> “Using the [analyzed data], compare the estimated carbon stock in [selected region by user] between 2015 and 2020. Calculate the absolute and percentage changes for above-ground biomass, below-ground biomass, dead organic matter, and soil organic carbon. Provide a scientific explanation of the likely drivers behind these observed changes.”

d. **Land Use**

This section investigates how LULC changes influenced carbon stock variability, interpreting transitions such as deforestation, afforestation, or urban expansion in the context of carbon sequestration.

Prompt:

> “Analyze how land use and land cover changes (LULC) between 2015 and 2020 in [selected region by user] have influenced carbon stock. Identify major transitions (e.g., forest to agriculture or shrubland to settlement) and explain their corresponding impact on carbon sequestration capacity.”

e. **Carbon Credit Potential (Total Carbon Stock)**

This section estimates the total volume of carbon stored in the region and evaluates its eligibility and value in the carbon credit market, with the analysis aligned to carbon accounting standards (e.g., IPCC guidelines).

Prompt:

> “Based on [analysed data], calculate the total carbon stock in [selected region by user] for the year 2020, based on biomass and soil estimates. Break down the contributions of above-ground, below-ground, dead biomass, and soil carbon. Estimate the carbon credit potential and describe its implications for climate finance and carbon market participation.”

f. **Carbon Pricing (Carbon Valuation)**

The environmental value of carbon sequestration is translated into monetary terms using the prevailing national or regional carbon pricing standard (e.g., IDR 96,000 per ton in Indonesia as of January 2025).

Prompt:

> “Using the estimated carbon stock for [selected region by user] in 2020, calculate its monetary value based on the carbon price of IDR 96,000 per ton. Present the total carbon valuation in Rupiah and interpret its relevance for ecosystem services and green economy potential in the region.”

g. **Conclusion**

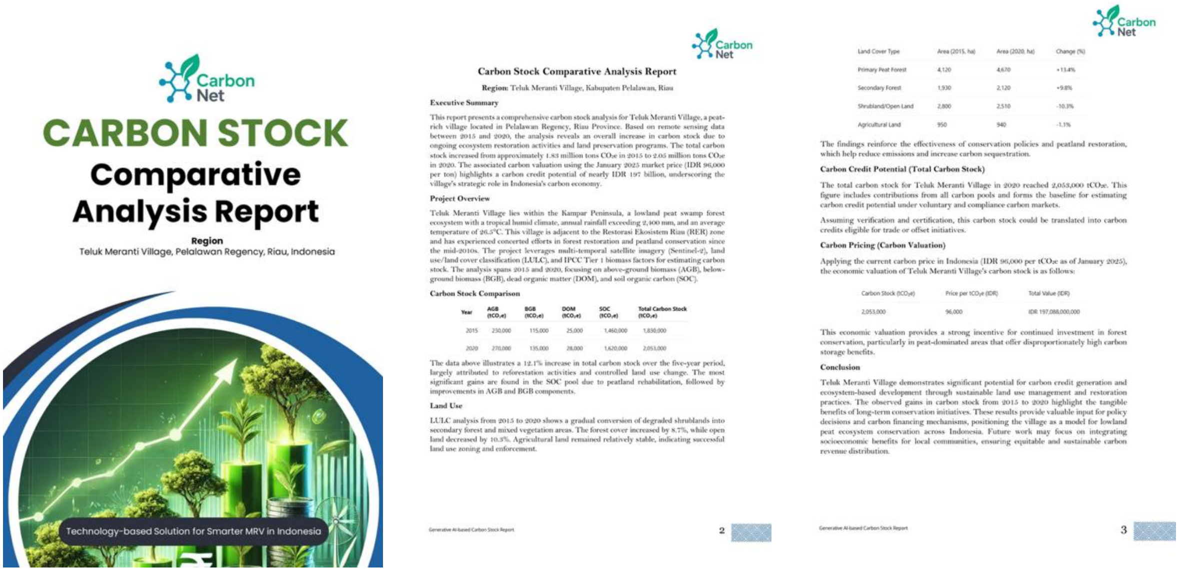
This final section synthesizes the findings and discusses implications for stakeholders, including policy recommendations to enhance carbon sequestration, conserve biomass-rich ecosystems, and leverage carbon finance mechanisms.

Prompt:

> “Summarize the main findings of the carbon stock analysis in [selected region by user], focusing on changes over time, land use impact, total valuation, and carbon credit potential. Provide recommendations for policymakers, land managers, and conservation stakeholders based on the analytical results.”

3.2.2. Use Case Demonstration and Policy-Relevant Insights

This use case illustrates how granular carbon stock assessment at the village level can support environmental and economic policy design. Desa Teluk Meranti, located in a critical peat ecosystem, was selected by the user through an interactive spatial interface. Based on this selection, the system automatically retrieved and processed synthetic remote sensing data for land use classification, carbon pool estimation, and valuation analysis over a five-year period. The resulting report, AI-generated based on the user's region of interest, demonstrates the potential for automated and scalable carbon accounting, especially in under-monitored areas. The integration of Tier 1 IPCC carbon factors and national carbon pricing enables the translation of technical biomass estimates into financially relevant insights, with the generated PDF report for Desa Teluk Meranti shown in Figure 10.



CARBON STOCK
Comparative Analysis Report
Region
Teluk Meranti Village, Pelalawan Regency, Riau, Indonesia

Technology-based Solution for Smarter MRV in Indonesia

Carbon Stock Comparative Analysis Report

Region: Teluk Meranti Village, Kabupaten Pelalawan, Riau

Executive Summary

This report presents a comprehensive carbon stock analysis for Teluk Meranti Village, a peat-rich village located in Pelalawan Regency, Riau Province. Based on remote sensing data between 2015 and 2020, the analysis reveals an overall increase in carbon stock due to ongoing ecosystem restoration activities and land preservation programs. The total carbon stock increased from approximately 1.83 million tons CO_2e in 2015 to 2.05 million tons CO_2e in 2020. The associated carbon valuation using the January 2025 market price (IDR 96,000 per ton) highlights a carbon credit potential of nearly IDR 197 billion, underscoring the village's strategic role in Indonesia's carbon economy.

Project Overview

Teluk Meranti Village lies within the Kampar Peninsula, a lowland peat swamp forest ecosystem with a tropical humid climate, annual rainfall exceeding 2,400 mm, and an average temperature of 26.5°C. This village is adjacent to the Restorasi Ekosistem Riau (RER) zone and has experienced concerted efforts in forest restoration and peatland conservation since the mid-2010s. The project leverages multi-temporal satellite imagery (Sentinel-2), land use/land cover classification (LULC), and IPCC Tier 1 biomass factors for estimating carbon stock. The analysis spans 2015 and 2020, focusing on above-ground biomass (AGB), below-ground biomass (BGB), dead organic matter (DOM), and soil organic carbon (SOC).

Carbon Stock Comparison

Year	AGB (tCO_2e)	BGB (tCO_2e)	DOM (tCO_2e)	SOC (tCO_2e)	Total Carbon Stock (tCO_2e)
2015	230,000	115,000	25,000	1,460,000	1,830,000
2020	270,000	135,000	28,000	1,620,000	2,053,000

The data above illustrates a 12.1% increase in total carbon stock over the five-year period, largely attributed to reforestation activities and controlled land use change. The most significant gains are found in the SOC pool due to peatland rehabilitation, followed by improvements in AGB and BGB components.

Land Use

LULC analysis from 2015 to 2020 shows a gradual conversion of degraded shrublands into secondary forest and mixed vegetation areas. The forest cover increased by 8.7%, while open land decreased by 10.3%. Agricultural land remained relatively stable, indicating successful land use zoning and enforcement.

Generative AI-based Carbon Stock Report 2

Land Cover Type	Area (2015, ha)	Area (2020, ha)	Change (%)
Primary Peat Forest	4,120	4,670	+13.4%
Secondary Forest	1,930	2,120	+9.8%
Shrubland/Open Land	2,800	2,510	-10.3%
Agricultural Land	950	940	-1.1%

The findings reinforce the effectiveness of conservation policies and peatland restoration, which help reduce emissions and increase carbon sequestration.

Carbon Credit Potential (Total Carbon Stock)

The total carbon stock for Teluk Meranti Village in 2020 reached 2,053,000 tCO_2e. This figure includes contributions from all carbon pools and forms the baseline for estimating carbon credit potential under voluntary and compliance carbon markets.

Assuming verification and certification, this carbon stock could be translated into carbon credits eligible for trade or offset initiatives.

Carbon Pricing (Carbon Valuation)

Applying the current carbon price in Indonesia (IDR 96,000 per tCO_2e as of January 2025), the economic valuation of Teluk Meranti Village's carbon stock is as follows:

Carbon Stock (tCO_2e)	Price per tCO_2e (IDR)	Total Value (IDR)
2,053,000	96,000	IDR 197,088,000,000

This economic valuation provides a strong incentive for continued investment in forest conservation, particularly in peat-dominated areas that offer disproportionately high carbon storage benefits.

Conclusion

Teluk Meranti Village demonstrates significant potential for carbon credit generation and ecosystem-based development through sustainable land use management and restoration practices. The observed gains in carbon stock from 2015 to 2020 highlight the tangible benefits of long-term conservation initiatives. These results provide valuable input for policy decisions and carbon financing mechanisms, positioning the village as a model for lowland peat ecosystem conservation across Indonesia. Future work may focus on integrating socioeconomic benefits for local communities, ensuring equitable and sustainable carbon revenue distribution.

Generative AI-based Carbon Stock Report 3

Figure 10. Generated report example.

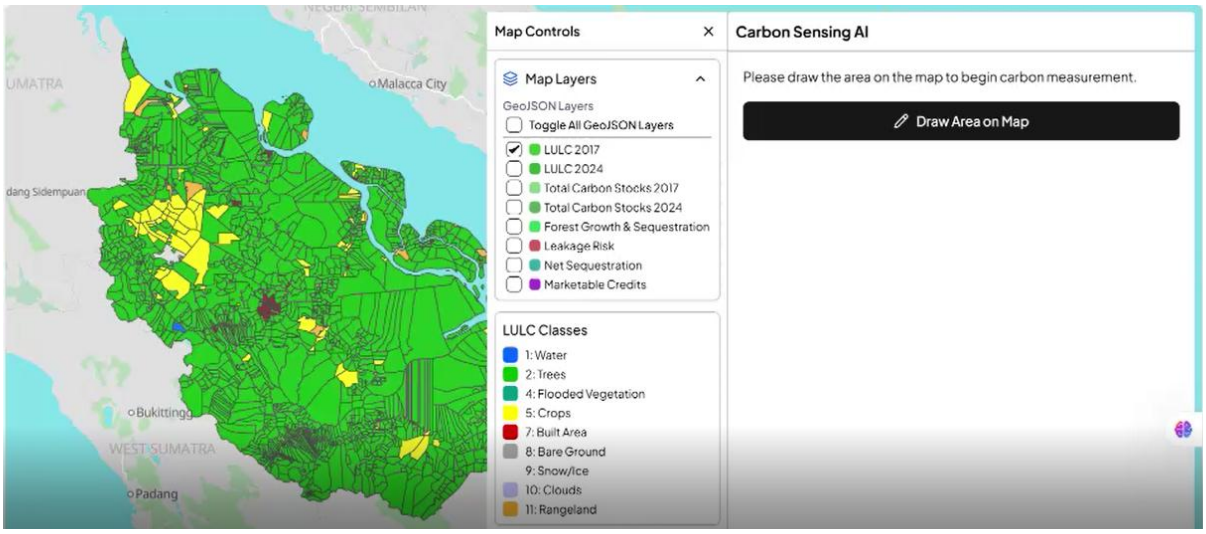
This use case highlights three major insights relevant for regional and national policy. The first case is the Monitoring the Impact of Restoration Programs. The observed increase in total carbon stock from 2015 to 2020 provides scientific validation of the peatland restoration and conservation initiatives implemented in the Kampar Peninsula, suggesting that continued support for such programs, especially under the national Peatland Restoration Agency or successor initiatives, can yield measurable climate benefits.

The second case is the Informing Carbon Market Readiness. By estimating both carbon stock and its monetary valuation (IDR 197 billion), this analysis offers a replicable template for identifying carbon credit potential at the village level, with Teluk Meranti serving as a model for jurisdictional REDD+ pilots or voluntary carbon market engagement, aligning with Indonesia's Enhanced NDC targets and Presidential Regulation No. 98/2021 on carbon pricing.

The third case is the Supporting Spatial Planning and Land-Use Regulation. The LULC change detection confirms that forest regrowth and reduced land degradation are associated with higher carbon sequestration, underscoring the importance of integrating carbon density data into spatial planning documents, permitting frameworks, and customary land-use governance, particularly in regions like Riau where land conflict and peat fires remain a concern, as high-resolution carbon data can be pivotal in reconciling development goals with environmental safeguards.

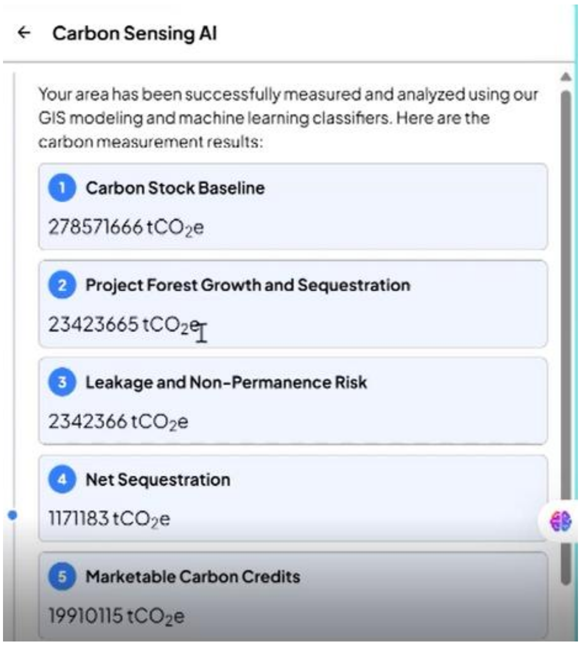
3.3. Dashboard Development and Implementation

The CarbonNet dashboard serves as an innovative and interactive spatial interface for carbon stock analysis. As shown in Figure 11, the dashboard presents users with a comprehensive GIS-based map featuring multiple selectable layers that display various aspects of carbon and land use data. The initial display shows a color-coded map of Riau Province with toggleable map controls in the left panel, including LULC data for both 2017 and 2024, Total Carbon Stock maps for both years, Leakage Risk assessment, and Net Sequestration visualization. The map clearly shows different land cover classifications through a color-coded legend indicating categories such as Urban areas (blue), Forest (green), Dense Vegetation (darker green), Crops (yellow), Palm Oil (yellow-orange), Water (blue), and Shrubland/Scrub (light green). A key functionality demonstrated in Figure 11 is the "Draw Area on Map" feature, which allows users to select specific regions of interest by drawing directly on the map interface to calculate carbon stock. After a user draws their area of interest, the dashboard automatically processes this selection using GIS modeling and machine learning classifiers, with results presented as shown in Figure 12. Figure 12 displays five critical metrics calculated for the user-defined area: Carbon Stock Baseline, Projected Forest Growth and Sequestration, Leakage and Non-Permanence Risk, Net Sequestration, and Marketable Carbon Credits.



Please draw the area on the map to begin carbon measurement.

Figure 11. Main dashboard interface with interactive mapping features.



Your area has been successfully measured and analyzed using our GIS modeling and machine learning classifiers. Here are the carbon measurement results:

1 Carbon Stock Baseline
278571666 tCO$_2$e

2 Project Forest Growth and Sequestration
23423665 tCO$_2$e

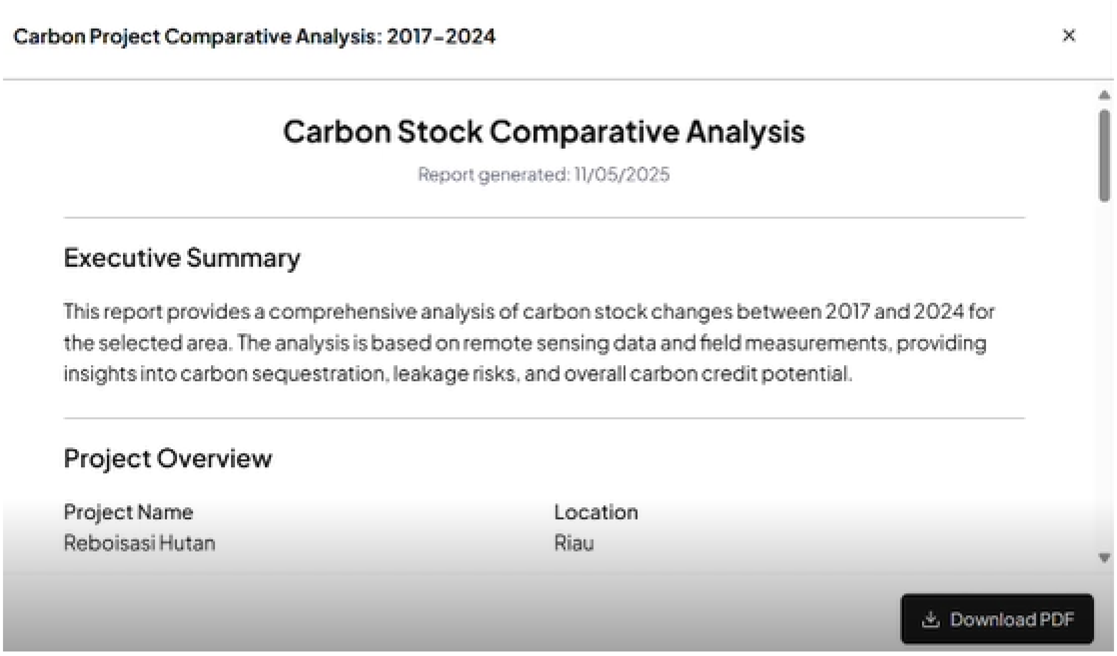
3 Leakage and Non-Permanence Risk
2342366 tCO$_2$e

4 Net Sequestration
1171183 tCO$_2$e

5 Marketable Carbon Credits
19910115 tCO$_2$e

Figure 12. Carbon measurement results.

The generated report has a comprehensive layout as displayed in Figure 13, including an Executive Summary and Project Overview, and presents a detailed analysis of carbon stock changes between 2017 and 2024 based on both remote sensing data and field measurements, with users able to download the PDF version to share findings with stakeholders or incorporate them into policy documents.



Carbon Project Comparative Analysis: 2017–2024

Carbon Stock Comparative Analysis

Report generated: 11/05/2025

Executive Summary

This report provides a comprehensive analysis of carbon stock changes between 2017 and 2024 for the selected area. The analysis is based on remote sensing data and field measurements, providing insights into carbon sequestration, leakage risks, and overall carbon credit potential.

Project Overview

Project Name	Location
Reboisasi Hutan	Riau

Figure 13. Report generated example in the dashboard.

The implementation of this sophisticated dashboard democratizes access to complex carbon stock data, making it available to various stakeholders, including policymakers, land managers, and conservation organizations, while its ability to automatically generate comprehensive reports with just a few clicks represents a significant advancement in environmental monitoring technology. By combining interactive spatial selection with automated analysis and AI-generated reporting, the Carbon Sensing AI dashboard effectively bridges the gap between technical carbon assessment and actionable policy insights for environmental management and carbon market participation in Riau Province.

The dashboard's village-level precision, as demonstrated in the Desa Teluk Meranti case study referenced in the document, supports more targeted conservation efforts and enables better monitoring of restoration programs such as those in the Kampar Peninsula. This granular approach to carbon assessment aligns with Indonesia's Enhanced NDC targets and provides valuable data for implementing Presidential Regulation No. 98/2021 on carbon pricing, with the CarbonNet AI dashboard representing a significant technological advancement in carbon MRV systems in Indonesia.

4. Conclusion

Indonesia's pursuit of NZE by 2060 necessitates a precise, equitable, and scalable approach to carbon pricing, particularly given the nation's reliance on coal and the ecological heterogeneity of its archipelago. This study introduces and validates a comprehensive AI-driven geospatial framework that addresses key challenges in MRV by integrating remote sensing, Generative AI, and interactive data visualization. The case of Riau Province demonstrates how land use dynamics, especially peatland degradation and palm oil expansion, significantly impact carbon stock, while restoration programs like the RER can yield measurable gains in carbon sequestration. The framework's automated reporting system and CarbonNet dashboard enhance transparency, local engagement, and policy relevance by generating granular, location-specific carbon stock insights and valuations.

By merging AI and geospatial analysis with Indonesia's policy instruments, this study paves the way for a dynamic, data-driven carbon pricing strategy that aligns with Indonesia's Enhanced NDCs and supports a just energy transition. The proposed system not only improves the efficiency of carbon accounting and green financing but also reinforces Indonesia's leadership in climate-smart innovation across the Global South. The methodology demonstrated in Riau Province, with its diverse peatland and forest ecosystems, provides a robust template for other regions facing similar challenges; for instance, this framework could be applied to analyze carbon dynamics in Kalimantan or Papua, which also possess vast forest and peatland areas. By adapting the LULC classification to local ecological contexts, the AI-driven MRV system can provide a scalable solution for carbon accounting across the Indonesian archipelago and other regions in the Global South.

Acknowledgments

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