

Monetizing Carbon Emissions: Advanced Strategies for Optimizing Carbon Economic Value Using Machine Learning and Geospatial Analysis

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Abstract

The transition to cleaner energy sources requires supportive financial policies and regulations. Carbon pricing is one mechanism that encourages emission reduction while creating economic opportunities through the carbon market. With vast tropical forests, peatlands, and mangroves, Indonesia has significant potential for terrestrial carbon storage. However, the use of carbon revenue to finance the energy transition remains underexplored. Our study aims to: (i) measure the potential Carbon Economic Value (CEV) in East Java with greater spatial detail using geospatial and remote sensing approaches, (ii) model future CEV using machine learning to generate accurate projections adaptable to land cover and policy shifts, and (iii) examine the relationship between carbon economic potential and poverty reduction. The novelty of our study lies in the first application of Ying et al.'s framework in Indonesia, extended with Labor Force Participation Rate (LFPR) and Human Development Index (HDI), and combined with Long Short-Term Memory (LSTM)-based forecasting. Projections show that CEV may reach IDR 13.8 trillion in 2025 before declining to IDR 7.6 trillion in 2026, signaling risks from land degradation and reduced sequestration capacity. Poverty in 2024 ranges from 3.06% in Batu City to 20.83% in Sampang, underscoring disparities across regions. Equitable CEV distribution should be prioritized, but policies must also integrate indicators such as the LFPR and HDI. Results indicate that CEV could reduce poverty from 9.56% to 5.75%, while three clusters of regions provide a basis for more targeted, sustainable policy design.

Keywords:

carbon economic potential, clustering analysis, geospatial analysis, machine learning, poverty reduction.

1. Introduction

Climate change has emerged as an urgent global challenge, compelling nations worldwide to adopt effective mitigation strategies. SDG 13, “*Take urgent action to combat climate change and its impacts*,” aims to reduce global greenhouse gas emissions, enhance climate resilience and adaptive capacity, and strengthen coordination and cooperation on climate-related issues (Nathaniel & Adeleye, 2021). A pivotal strategy in addressing this challenge involves accelerating the transition to clean energy. However, this energy transition extends beyond technological aspects, necessitating innovative fiscal policies and financing mechanisms, including carbon pricing schemes. Empirical studies show

that carbon pricing can successfully incentivize incremental emissions reductions (Tvinnereim & Mehling, 2018).

One mitigation approach implemented in numerous countries is the carbon market mechanism. These schemes have emerged as part of the global green finance architecture, enabling countries and private actors to claim emission reductions through forest conservation or land rehabilitation in exchange for financial compensation. However, West et al. (2023) has raised concerns about the credibility of such claims, particularly in voluntary forest conservation projects, many of which overstate their actual climate benefits due to unrealistic baseline assumptions. These mechanisms now involve many stakeholders, including investors, multilateral institutions, and the private sector. The recent global increase in the value of voluntary carbon markets reflects the interest in and need for results-based incentive mechanisms to support net-zero emission targets. Several countries have demonstrated the successful implementation of a carbon market. For instance, Sweden reduced its greenhouse gas emissions by 27 percent between 1990 and 2018, with most reductions occurring since the early 2000s (Jonsson et al., 2020), and New Zealand achieved a 42 percent reduction in forestry sector emissions through a comprehensive emissions trading system.

As a nation endowed with abundant and diverse natural resources, Indonesia possesses significant potential for carbon monetization. Indonesia has the largest tropical forest area globally, encompassing approximately 120 million hectares, nearly half of the nation's total land area (Kementerian Lingkungan Hidup dan Kehutanan, 2024). Indonesia also has the largest mangrove cover in the world, storing an estimated 3.14 petagrams of carbon (PgC), about 33 percent of all carbon stored in coastal ecosystems globally (Arifanti et al., 2024). Furthermore, Indonesia's extensive peatlands, spread across major islands such as Sumatra, Kalimantan, and Papua, represent substantial carbon reserves, capable of storing up to 55–60 billion tons of carbon (Page et al., 2011). These vast natural carbon reserves position Indonesia strategically to derive economic benefits through results-based payment schemes, voluntary carbon markets, and international compensation mechanisms such as REDD+.

Despite the rapid global development of carbon market mechanisms, their implementation in Indonesia remains relatively nascent and faces various challenges. A primary challenge is the limited availability of data and information necessary for accurately assessing the economic value of Indonesia's carbon reserves. Additionally, the low level of understanding among stakeholders regarding the economic potential of carbon results in suboptimal utilization of these schemes. Given the extensive tropical forests, mangroves, and peatlands, Indonesia holds substantial economic carbon value potential if managed appropriately. Therefore, efforts are required to estimate and predict the magnitude of Indonesia's economic carbon value as an initial step in constructing evidence-based policy frameworks and carbon utilization strategies that support the transition toward a green economy.

With its vast and diverse territory, East Java possesses significant natural resources capable of supporting the development of a carbon economy. Mangrove ecosystems along the eastern and southern coasts, community forests in the central and southern regions, and dryland agriculture and agroforestry practices across various districts constitute vital assets that function as carbon emission sinks. Conversely, East Java also confronts complex socioeconomic challenges, such as high poverty rates in rural and coastal areas, development disparities, and pressure on natural resources due to economic activities. This situation necessitates new approaches to bridge community economic needs with environmental conservation efforts. Carbon management forms part of climate change mitigation strategies and has evolved into an innovative fiscal instrument to support the energy transition and sustainable regional development (Zhang et al., 2024). Consequently, it is imperative to further examine the potential economic value of carbon in this province as a basis for formulating inclusive and sustainable green development policies.

Previous studies examining Carbon Economic Value (CEV) have predominantly focused on global and national scales, which establish critical foundations for climate mitigation and green economy policies. Arifanti et al. (2024) demonstrated the substantial carbon storage capacity of Indonesian mangrove ecosystems and their monetization potential within global carbon markets. At the global scale, Ying et

al. (2023) developed a comprehensive framework for measuring CEV using Net Primary Productivity (NPP) and remote sensing technologies to assess terrestrial carbon sink income enhancement potential across China. Building on predictive methodologies, Xu et al. (2022) employed Long Short-Term Memory (LSTM) models to forecast forest carbon sink capacity in China, establishing the necessity for robust predictive frameworks in carbon valuation systems. At the national level, studies such as Masolele et al. (2021) and Pelletier et al. (2019) integrated geospatial and machine learning approaches to estimate carbon stocks and land-use change, though these applications have largely focused on tropical deforestation monitoring rather than economic valuation. The geographic focus of existing research has created a significant knowledge gap in subnational CEV quantification and forecasting, particularly within Indonesia's East Java province. Despite these advances, research explicitly quantifying and forecasting CEV at the subnational scale, particularly in East Java, remains limited. This gap underscores the novelty of our study, which applies Ying et al.'s (2023) framework for the first time in Indonesia, extends it with socio-economic variables, and introduces machine learning forecasting to provide policy-relevant insights.

We integrate geospatial data, remote sensing technology, and machine learning to accurately identify carbon economic potential. These approaches extensively use satellite data such as Landsat, Sentinel, and MODIS to map land cover, track land-use changes, and estimate carbon reserves in vegetation and soil (Ban et al., 2015; Hansen et al., 2013). Ying et al. (2023) developed a formula to calculate ideal carbon sink revenue using NPP from MODIS satellites. Additionally, satellite data from platforms such as WorldView and TerraSAR-X have enhanced mapping resolution, particularly in identifying peatlands and tropical forests with high carbon potential. To improve predictive accuracy and support evidence-based policymaking, geospatial data is also integrated with machine learning approaches, such as random forest and support vector machine, in modeling carbon stocks, detecting deforestation, and projecting emission reduction potentials (Masolele et al., 2021; Pelletier et al., 2019). This integration facilitates more efficient, adaptive, and scalable estimation processes, rendering it highly relevant for supporting regional carbon economy development.

Therefore, this study aims to contribute to green economy development through three objectives. First, to measure CEV in East Java with greater precision and spatial detail using geospatial and remote sensing approaches. Second, to forecast CEV for forthcoming years with the support of machine learning methods to generate data-driven projections responsive to land cover changes and policy shifts. Third, to examine the relationship between CEV and social welfare by integrating indicators such as poverty, Labor Force Participation Rate (LFPR), and Human Development Index (HDI). The novelty of this study lies in applying, for the first time, the framework developed by Ying et al. (2023) in the Indonesian context, with a focus on East Java Province. The contribution goes further by extending the framework through the integration of socio-economic indicators beyond poverty, namely LFPR and HDI, and by employing an LSTM algorithm to produce forward-looking projections of CEV. These contributions distinguish the study from earlier works and provide both methodological advancement and practical policy insights.

2. Methods and Materials

2.1 Data collection

Our study utilizes data obtained from Statistics Indonesia (*Badan Pusat Statistik*, BPS), Bank of Indonesia, the World Bank, as well as geospatial data sourced from Google Earth Engine (GEE) and Global Mangrove Watch. The dataset spans ten years, from 2015 to 2024. Geospatial data acquired from GEE were processed using zonal statistics applied to a 1 km × 1 km grid resolution. The collected data were analyzed using Python and R programming languages to address the research objectives. Table 1 presents a comprehensive list of all datasets employed in this study.

2.2 Carbon Economic Value Estimation Approach

The CEV is estimated based on NPP. Ying et al (2023) utilized NPP to estimate the ideal per capita income derived from the carbon economy. In their approach, NPP values were divided by the population within a region and multiplied by the carbon prices observed across various carbon markets. NPP is employed in this context because it represents the net amount of carbon vegetation absorbs through photosynthesis after accounting for plant respiration. Thus, it reflects an ecosystem’s capacity to sequester carbon emissions. Consequently, NPP serves as a foundation for evaluating a region’s ecological contribution to climate change mitigation and translating it into economic value through carbon pricing mechanisms.

Table 1. Descriptions and sources of dataset.

Data	Source
Net Primary Productivity (NPP)	Terra Net Primary Production Gap-Filled Yearly Global 500m, Google Earth Engine Dataset
Mangrove Land Cover	Global Mangrove Watch
Land Use and Land Cover	Dynamic World V1, Google Earth Engine Dataset
Carbon Prices	Carbon Pricing Dashboard, World Bank
Population per Grid	LandScan Global Population Data 1 km, Google Earth Engine Dataset
Rupiah Exchange Rate	Bank Indonesia
Population Below the Poverty Line	BPS-Statistics Indonesia
Gross Regional Domestic Product (GRDP)	BPS-Statistics Indonesia
Labor Force Participation Rate (LFPR)	BPS-Statistics Indonesia
Human Development Index (HDI)	BPS-Statistics Indonesia

Prior to calculating the CEV, spatial filtering was applied to identify areas with high carbon sequestration potential. This selection was based on Land Use and Land Cover classifications from the Dynamic World V1 dataset, focusing on areas labeled as trees, grass, and flooded vegetation. In addition, we incorporated mangrove areas identified by the Global Mangrove Watch dataset. Thus, four land cover categories were used for CEV computation.

We estimated values using a spatial grid with a 1 km × 1 km resolution. NPP values derived from remote sensing were extracted for each grid cell. These NPP values, expressed in kg·C/m², were scaled by a factor of 0.0001. Since carbon prices are typically expressed in metric tons of CO₂, units must be converted from kg·C/m² to metric tons of CO₂ to align with standard carbon trading conventions. The conversion follows Equation (1), where NPP_i is the NPP value in area i (scaled by 0.0001), and $Area_i$ represents the surface area of region i in square meters. The resulting value is divided by 1,000 to convert from kilograms to tons. To convert from tons of carbon (C) to tons of carbon dioxide (CO₂), we use a factor of 3.67, which reflects the molecular weight ratio of CO₂ (44) to carbon (12) (IPCC, 2008).

$$CO_2 \text{ Absorbed}_i = NPP_i \times Area_i \times \frac{1}{1000} \times \frac{44}{12} \quad (1)$$

We then multiply the potential CO₂ absorbed by the average carbon price observed in Asia’s Emissions Trading Systems (ETS). We use only ETS schemes from Asia to ensure geographic and policy relevance to Indonesia’s socioeconomic and environmental context. This approach aims to produce a more realistic representation of Indonesia’s carbon economy potential, particularly in East Java Province. Fourteen ETS schemes are used as benchmarks: Tokyo CaT, Beijing Pilot ETS, China National ETS, Shanghai Pilot ETS, Shenzhen Pilot ETS, Guangdong Pilot ETS, Korea ETS, Chongqing Pilot ETS, Hubei Pilot ETS, Tianjin Pilot ETS, Fujian Pilot ETS, Kazakhstan ETS, Saitama ETS, and Indonesia ETS. Table 2 presents the average carbon prices and the exchange rate used for conversion into local currency (IDR).

The resulting values of CO₂ absorption potential are subsequently multiplied by the annual average carbon price (in USD) and the corresponding annual exchange rate of the IDR to USD. The exchange rates used were calculated as the yearly average for each respective year, ensuring temporal consistency in valuation. Accordingly, we calculate the CEV for a given region and period, as shown in Equation (2).

$$CEV_{it} = CO_2Absorbed_{it} \times Carbon Price_t \times Exchange Rate_t \quad (2)$$

We apply Equation (2) to each 1 km × 1 km grid cell in the study area, enabling a spatially explicit estimation of the Carbon Economic Value at high resolution. The resulting CEV values are then spatially aggregated to higher administrative levels, specifically sub-districts and districts, to provide regional representations of carbon value. These aggregated values form the basis for further analysis conducted in this study.

Table 2. Average carbon prices from Asian ETS and Rupiah exchange rate used.

Year	Average Carbon Price (USD/ton CO ₂)	Rupiah Exchange Rate (IDR/USD)
2024	8.63	15,847
2023	9.78	15,255
2022	6.56	14,871
2021	4.83	14,312
2020	6.81	14,572
2019	5.76	14,146
2018	6.11	14,246
2017	6.60	13,384
2016	6.62	13,307
2015	11.17	13,392

2.3 Carbon Economic Value Prediction for 2025 and 2026

Numerous studies have attempted to forecast both the carbon economic value and carbon pricing. For instance, Ying et al. (2023) employed a simple linear regression model to predict per capita income from carbon sinks, whereas Xu et al. (2022) utilized an LSTM network to estimate forest carbon sink capacity in China. This study adopts a similar LSTM-based approach, albeit slightly modified, using a multistep LSTM model. This model directly forecasts the carbon economic value for two subsequent years rather than using an iterative step-by-step approach. Such a modification mitigates error propagation commonly observed in traditional recursive forecasting models. By training the multistep LSTM model to predict the next two years concurrently, this approach enhances efficiency and improves stability, particularly for short- to medium-term policy planning scenarios.

The input architecture of an LSTM model comprises three dimensions (Brownlee, 2018). The first dimension corresponds to the number of samples processed per training iteration (batch size). The second denotes the number of time steps used for prediction (Lim & Zohren, 2021). The third represents the number of features per time step (Widiputra et al., 2021). For this study, we utilized data from 2015 to 2024 at the sub-district level. Through experimentation, we selected a time step length of four, meaning the model used data from the previous four years to predict the subsequent two years. For instance, to predict values for 2023 and 2024, the model incorporated data from 2019 through 2022. We used three input features: absorbed CO₂ potential, average carbon price, and exchange rate. After transformation, the resulting LSTM input dimension was (2473, 4, 3).

We split the dataset into training and validation subsets, with 80 percent allocated to training and 20 percent to testing. Accordingly, the training dataset had dimensions of (1978, 4, 3), while the validation dataset had dimensions of (495, 4, 3). The training data were used for hyperparameter tuning. For each hyperparameter configuration, model performance was evaluated on the validation set using standard

metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2).

A conventional neural network (NN) model was also employed to provide a benchmark. The purpose was to evaluate the comparative performance of the LSTM model against a simpler architecture that lacks long-term memory capability. The conventional NN model serves as a baseline, allowing for an objective comparison in the context of multistep carbon value forecasting. Both models were evaluated using identical metrics (RMSE, MAE, and R^2) to ensure consistent and unbiased performance assessment. The results from this comparative evaluation were then used to identify the optimal model for forecasting the carbon economic value for 2025 and 2026.

2.4 Regional Clustering Methodology

We expect the CEV to serve as a strategic resource for addressing various development challenges at the district and municipal levels. A regional clustering analysis was conducted to group districts and cities in East Java based on similarities in their socioeconomic characteristics to guide effective utilization strategies. The clustering outcomes enable the formulation of more targeted and context-specific policies for each cluster.

The Silhouette method was employed to determine the optimal number of clusters. This method assesses the cohesion within a cluster and the separation from other clusters, producing a Silhouette score ranging from -1 to 1, where higher values indicate better-defined clustering structures. Due to its ability to balance intra-cluster similarity and inter-cluster dissimilarity, this approach is widely recognized and applied in cluster validation (Kassambara, 2017).

The clustering analysis incorporated four key variables: CEV, poverty rate, HDI, and LFPR. Including these variables supports a holistic approach to optimizing the role of CEV within sustainable development policy, integrating both social conditions and local economic capacities. The clustering process was conducted at the district and municipal levels using the K-Means algorithm.

3. Results and Discussions

3.1 Spatial and Temporal Distribution Characteristics of Carbon Economic Value Potential in East Java

Descriptive analysis, as shown in Figure 1, clearly demonstrates that the total carbon economic value from 2015 to 2024 exhibits a fluctuating trend, with a marked upward tendency in the later years of the period. During the initial phase (2015–2017), the aggregate economic value exhibited an upward trend, rising from IDR 7.69 trillion to IDR 9.24 trillion. Subsequently, the value experienced a gradual decline, reaching IDR 7.52 trillion by 2019, likely driven by increasing or decreasing carbon prices and a weakening exchange rate. A significant rebound occurred in 2020, reaching IDR 10.06 trillion, suggesting a recovery or shift in economic and environmental conditions. However, 2021 recorded the lowest value of the decade at IDR 6.87 trillion, firmly attributed to a sharp decline in carbon prices.

We observed a steep increase in 2022, with Malang district registering the highest total value gain of IDR 252 billion. This upward momentum continued into 2023, peaking at IDR 14.84 trillion, as Banyuwangi district experienced the most significant increase in total value at IDR 845 billion. A substantial rise in carbon prices and a stronger exchange rate primarily drove these increases. By 2024, the economic value declined again to IDR 12.48 trillion, indicating a possible correction or stabilization following the previous surge. The increase in carbon economic value is significantly influenced by the rise in carbon prices, with a correlation coefficient ($r = 0.947$), and the appreciation of the USD against the IDR, demonstrating a strong correlation ($r = 0.519$).

Spatial analysis of carbon economic potential in East Java from 2022 to 2024 reveals significant geographical variation, strongly correlating with carbon sequestration capacity. Figure 2 illustrates the

average spatial distribution of carbon economic value on a 1 km × 1 km grid in East Java during 2022–2024. The map reveals a predominant pattern in the southern region, where the maximum carbon economic value at the grid level reached IDR 826.10 million in Bantur subdistrict, Malang district. This outcome is attributed to the area’s high NPP. Specifically, the grid holds the highest NPP value in East Java at 1.74 kg C/m²/year, as reported by the MODIS Terra Net Primary Production Gap-Filled Yearly Global 500m dataset.

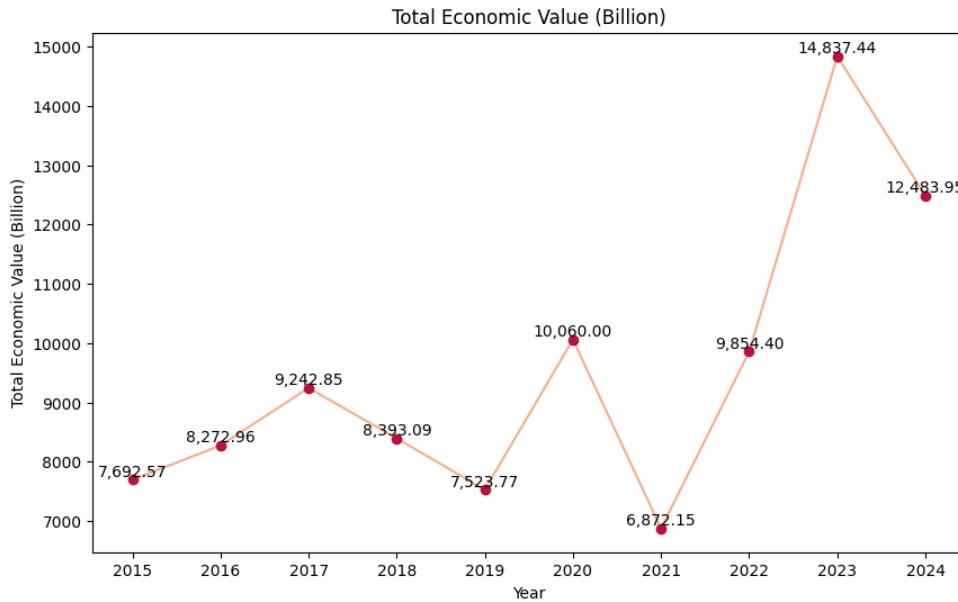


Figure 1. Annual total economic value trend.

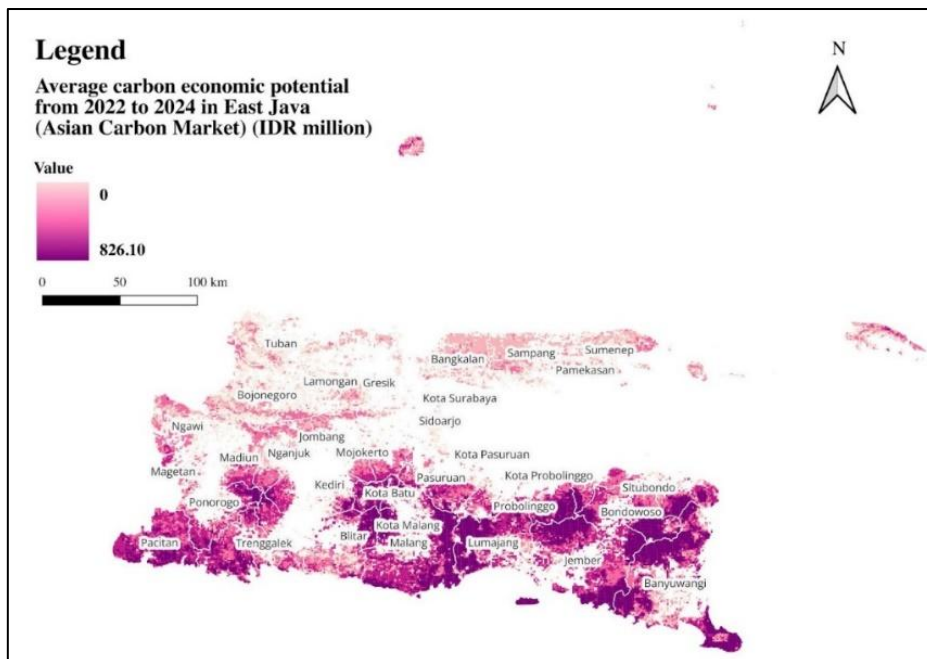


Figure 2. Average carbon economic potential 2022-2024 per grid 1x1 km in East Java.

In contrast, the northern regions of East Java exhibit significantly lower values. This spatial distribution aligns with quantitative data on carbon sequestration capacity presented in Table 3. The five regions with the highest carbon sequestration levels are in southern East Java. Malang district ranks as the most significant carbon sink, absorbing approximately 11.72 million tons of CO₂ through its natural ecosystems, followed by Banyuwangi and Jember.

Table 3. Total carbon sequestration for the top five districts in 2024.

Districts	Carbon sequestration (Thousand Tons CO ₂)				Total Natural Resources
	Tree	Flooded Vegetation	Grass	Mangrove	
Malang	11,688.60	24.13	7.60	0.26	11,720.59
Banyuwangi	10,903.21	24.57	61.57	89.17	11,078.52
Jember	10,325.94	46.77	4.02	0.00	10,376.73
Lumajang	6,148.44	42.43	18.70	0.00	6,209.57
Pacitan	5,934.82	0.00	0.00	0.00	5,934.82

The effectiveness of carbon sequestration across East Java varies considerably depending on the dominant types of natural resources in each region. Table 4 reveals that tree cover is the most effective ecosystem type for carbon sequestration in most parts of the province. Other ecosystems, such as flooded vegetation, grassland, and mangroves, also contribute to carbon capture, though their effectiveness and spatial extent differ.

This variability explains why their contributions to the total carbon economic value are generally lower than those of tree cover. Notably, mangroves show high effectiveness in selected areas such as Banyuwangi and Malang, with Surabaya City being the only region where mangroves represent the most effective carbon sink among the natural resource categories. However, due to limited area coverage, the overall contribution of mangroves to carbon sequestration remains relatively small. The diversity in carbon sequestration effectiveness underscores the importance of comprehensive land management strategies. A balanced composition of natural resources can enhance the carbon economic potential of a region. Hence, strategic land-use planning for this composition is essential to maximize carbon economic potential. Regions with high carbon economic value potential can serve as models for developing climate change mitigation policies based on carbon economics and inform future incentive allocation schemes under carbon trading mechanisms.

3.2 Carbon Economic Value Potential in 2025 and 2026

Based on the results of hyperparameter tuning, the best-performing model was an LSTM neural network comprising two layers: the first with 128 units and the second with 64 units. The batch size used was 32, with a total of 200 training epochs. We applied the Adam optimizer during training. The same hyperparameter configuration was adopted for the NN model, with the distinction that the NN used dense layers instead of LSTM layers.

Table 5 presents the modeling results. Both LSTM and NN demonstrated higher accuracy when predicting one year ahead compared to two years, which aligns with findings from previous studies (Wahyuddin et al., 2025). The closer the prediction horizon, the better the model performance. Thus, shorter-term predictions tend to be more reliable. While the LSTM model achieves satisfactory accuracy for one-year-ahead projections, its performance decreases for two-year horizons, largely due to the limited time span of available data (2015–2024). This highlights the need for caution when interpreting long-term forecasts.

In terms of statistical performance metrics such as RMSE, MAE, and R², the NN model yielded the highest accuracy, with R² reaching 0.99 and MAE at 2.276. However, when used to predict CEV for 2025 and 2026, the NN model produced several negative predictions, which are logically implausible since carbon economic value should be zero or positive. This issue may stem from multiple factors, including the limited amount of historical data used during model training, which may hinder the model's ability to capture long-term patterns, and the absence of explicit architectural constraints within the NN to prevent negative output values (Goodfellow et al., 2016). In contrast, the LSTM model did not produce any negative predictions. We attribute this stability to LSTM's internal memory

mechanisms, which enhance its ability to retain long-term dependencies and generate more consistent time series predictions (Hochreiter & Schmidhuber, 1997). Therefore, we selected the LSTM model for the final prediction phase of this study.

Table 4. Carbon sequestration effectiveness based on natural resource characteristics in 2024.

Districts	Carbon sequestration (Thousand Tons CO ₂ per km ²)			
	Tree Cover Effectiveness	Flooded Vegetation Effectiveness	Grassland Effectiveness	Mangrove Effectiveness
Pacitan	4.35	0.00	0.00	0.00
Ponorogo	4.19	0.00	0.00	0.00
Trenggalek	4.19	0.00	0.00	0.00
Tulungagung	3.81	3.38	0.00	0.00
Blitar	4.27	0.00	4.68	0.00
Kediri	4.10	0.00	3.68	0.00
Malang	4.73	2.94	3.71	3.63
Lumajang	4.65	3.44	4.56	0.00
Jember	4.58	3.50	3.92	0.00
Banyuwangi	4.67	3.03	3.16	3.79
Bondowoso	4.52	0.00	4.32	0.00
Situbondo	4.27	0.00	0.00	2.99
Probolinggo	4.38	2.38	4.67	0.00
Pasuruan	3.80	1.13	3.11	1.66
Sidoarjo	1.11	0.38	0.00	1.55
Mojokerto	3.24	0.00	2.53	0.00
Jombang	3.07	2.64	3.18	0.00
Nganjuk	3.12	2.24	3.87	0.00
Madiun	3.49	0.00	0.00	0.00
Magetan	3.51	0.00	2.97	0.00
Ngawi	3.02	0.00	2.77	0.00
Bojonegoro	2.57	2.25	2.47	0.00
Tuban	2.23	2.26	2.31	0.00
Lamongan	2.34	1.77	0.00	0.00
Gresik	2.71	0.40	2.76	1.68
Bangkalan	2.32	1.47	2.33	1.84
Sampang	2.31	1.06	2.47	1.73
Pamekasan	2.36	0.00	0.00	1.98
Sumenep	2.65	2.00	2.70	1.88
Kediri City	3.61	0.00	0.00	0.00
Malang City	4.12	0.00	0.00	0.00
Probolinggo City	0.00	2.58	0.00	0.00
Pasuruan City	0.00	1.03	0.00	0.00
Surabaya City	1.05	0.92	0.00	1.58
Batu City	4.47	0.00	0.00	0.00

Table 5. Evaluation results of carbon economic value modeling for 2025 and 2026.

Model	Prediction Horizon	RMSE	MAE	R ²	% of Negative Predictions
LSTM	1 year ahead	8.36	2.41	0.95	0%
	2 years ahead	11.95	3.23	0.90	0%
	Overall	10.31	2.82	0.92	0%
NN	1 year ahead	3.33	2.20	0.99	36.18%
	2 years ahead	3.74	2.35	0.99	15.17%
	Overall	3.54	2.28	0.99	25.68%

Based on the LSTM predictions, the total CEV in East Java for 2025 is projected to reach IDR 13.8 trillion, reflecting a 10.6 percent increase from 2024. The highest CEV values are concentrated in the southern region, particularly in Malang, Banyuwangi, and Jember, each with CEV values exceeding IDR 1 trillion, as illustrated in Figure 3. Nevertheless, these three districts are expected to experience a 20 percent decrease compared to their 2024 levels. The steepest decline is projected for Pacitan, dropping by 37 percent from IDR 811 billion to IDR 503 billion. Trenggalek also registers a significant decrease of 23 percent, from IDR 594 billion to IDR 455 billion.

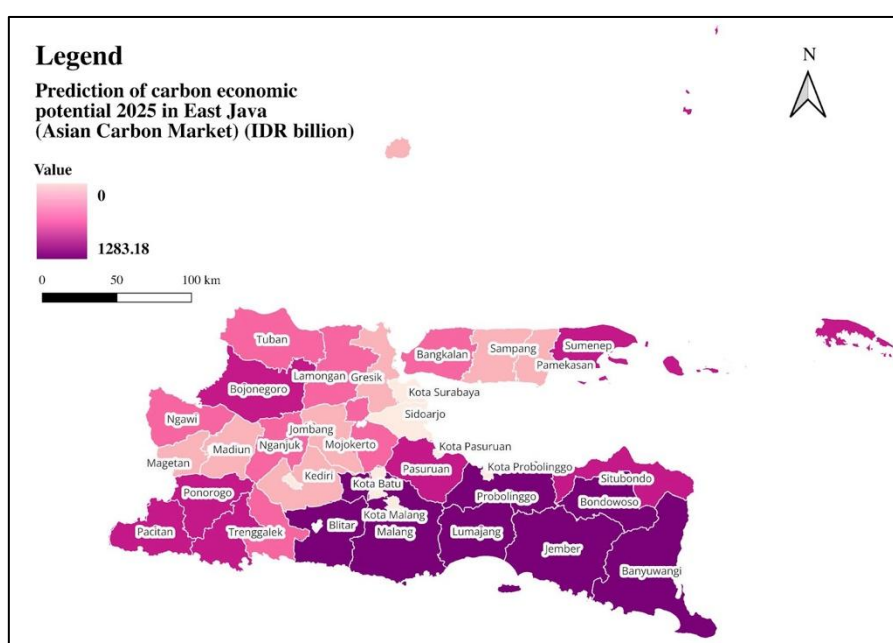


Figure 3. Carbon economic potential forecast for 2025.

For regions projected to experience declining CEV, policy responses may include reinforcing the ecosystem’s carbon absorption capacity through expanded green land cover and forest rehabilitation. Conversely, substantial increases are anticipated in Surabaya and Sidoarjo, with CEV rising from IDR 3 billion to IDR 120 billion and from IDR 4 billion to IDR 121 billion, respectively. These sharp increases suggest strong potential for carbon-based economic development in urban and coastal zones. Accordingly, local governments in these areas could begin designing carbon value utilization policies to support low-emission development programs, including investments in green infrastructure, energy efficiency improvements, and integration of CEV into fiscal and spatial planning frameworks.

In contrast, the 2026 CEV projection presents an interesting anomaly: the total CEV is expected to decline significantly to approximately IDR 7.6 trillion, a value comparable to 2019. Two plausible explanations may account for this downturn. First, the model’s predictive performance is lower for longer horizons, as indicated in Table 5, where two-year-ahead predictions show reduced accuracy. Therefore, policymakers should update forecasts near the end of 2025 using the latest data to obtain a more accurate projection for 2026.

Second, the predicted decline could result from environmental degradation or a reduction in the carbon sequestration capacity of green land, potentially due to extensive land-use changes, including infrastructure development, industrial expansion, or forest conversion into intensive agricultural land. These processes can reduce NPP, the key basis for CEV estimation. Local governments must enhance ecosystem protection and restoration policies to mitigate such risks, especially in areas with high carbon sequestration contributions, such as southern East Java. Policy instruments may include stricter land-use conversion permits, incentives for sustainable businesses, and enhanced monitoring of land cover changes. Additionally, local governments should prioritize policy integration between spatial planning and climate strategies to ensure that physical development does not compromise the ecosystem’s long-term capacity to sustain carbon economic value.

3.3 The Importance of Carbon Economic Value for Social Welfare

The utilization of the carbon economy not only contributes to global climate change mitigation efforts but also offers new opportunities to enhance community welfare at the local level. This mechanism holds potential as an alternative fiscal instrument that can be harnessed to fund poverty alleviation programs, particularly in regions with significant carbon ecosystem potential but still facing socioeconomic pressures.

The marked poverty disparity in East Java, where the provincial poverty rate reached 9.56 percent as of September 2024, exceeding the national average of 8.57 percent, indicates the urgent need for targeted interventions leveraging the economic potential of carbon. Regions experiencing extreme poverty, such as Sampang District, recorded rates exceeding 20 percent and require integrated strategies addressing poverty reduction and environmental conservation.

This dual approach could also help narrow the development gap with more prosperous areas such as Surabaya, Sidoarjo, and Batu, where poverty rates have fallen below 5 percent. Governments can promote inclusive growth by aligning carbon economy initiatives with local socioeconomic needs while ensuring ecological sustainability. The spatial distribution of poverty levels across districts and municipalities in East Java is illustrated in Figure 4, providing further insight into regional disparities and potential areas of intervention.

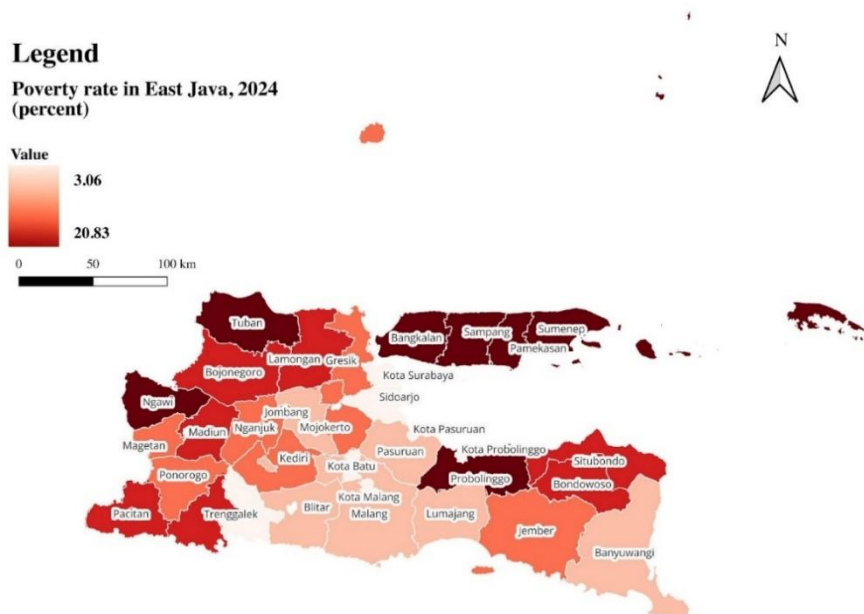


Figure 4. Distribution of poverty rate in East Java, 2024.

The CEV presents an opportunity to serve as an alternative source of sustainable financing for poverty alleviation programs, thereby reducing reliance on the national budget. To date, schemes such as Direct Cash Assistance, distributed through the Ministry of Villages, have only partially met the needs of impoverished communities, with the national allocation not exceeding IDR 78 trillion annually.

Carbon monetization through the CEV framework offers a new revenue stream for local governments, enabling results-based income generation that can be directly allocated to households below the poverty line. CEV reflects the maximum potential value of carbon monetization revenue that a region could realize. Using a district- or city-level poverty line approach, we estimate the number of poor individuals the CEV can lift out of poverty by dividing the total CEV by the annual minimum consumption requirement per person (i.e., Poverty Line × 12 months). This mechanism aligns with sustainable development objectives by linking environmental preservation efforts with direct socioeconomic benefits, offering a complementary pathway to traditional fiscal interventions for poverty reduction.

Based on Figure 5, we observe that the potential distribution of CEV to the poor population across districts and cities in East Java Province would be uneven. This observation highlights the importance of ensuring that CEV allocation is implemented more equitably and proportionally by the East Java Provincial Government. Optimal utilization of CEV can reduce the provincial poverty rate from 9.56 percent to 5.75 percent. The figure also shows that 10 districts or cities possess CEV potential that exceeds the needs of their poor residents. If effectively leveraged, the available CEV could eliminate poverty in those regions and be redistributed to support other, more impoverished areas.



Figure 5. Comparison of the number of poor people and the number of poverty alleviation potentials by district/city.

Out of 38 districts and cities in East Java, we found that 25 regions demonstrate sufficient CEV potential to contribute significantly to poverty reduction, although not all to the same extent as the top 10. However, three cities show zero CEV potential, as satellite imagery used in this analysis did not identify any green zones within their boundaries. Table 6 presents the list of 25 districts and cities, along with the number of poor residents, the estimated number of individuals whom the districts can lift out of poverty, and the percentage of potential poverty alleviation.

Policy formulation must be grounded in data to ensure equitable and impactful CEV distribution. Decision-making should incorporate key statistical indicators such as the poverty rate, LFPR, and HDI. These variables provide a comprehensive overview of the most effective interventions, whether through direct CEV distribution, skills development, or employment generation programs. By adopting this

data-driven approach, policymakers can strengthen poverty eradication efforts and ensure that CEV utilization is fair and equitably distributed across all regions of East Java.

To support the data-driven policy framework, we conducted a cluster analysis to group districts and cities in East Java based on similarities in their socioeconomic characteristics. The results of this clustering process facilitate the formulation of more targeted and context-specific policies tailored to each group of regions. To determine the optimal number of clusters, we employed the Silhouette Method, which has been proven effective in identifying the most suitable number of clusters based on the internal structure of the dataset (Rousseeuw, 1987). Based on this method, three distinct clusters were identified as the most effective configuration, as illustrated in Figure 6.

Furthermore, we developed a geospatial visualization of these clusters to depict their spatial distribution across East Java's 38 districts and cities, providing policymakers with a clear view of regional groupings and their geographical context (see Figure 7). In addition, the classification of clusters by cluster number, cluster name, and the associated districts/municipalities is presented in Table 7. Our clustering results, which are based on Carbon Economic Value (CEV), Labor Force Participation Rate (LFPR), Human Development Index (HDI), and poverty rate, can be compared with the findings of Ramadhan et al. (2024). Their study clustered East Java's districts and municipalities using HDI and the Gini Ratio as key indicators, resulting in four distinct clusters: (i) Cluster 0 with relatively low HDI and moderate Gini Ratio; (ii) Cluster 1 with high HDI and high Gini Ratio; (iii) Cluster 2 with relatively low HDI and low Gini Ratio; and (iv) Cluster 3 with relatively high HDI and moderate Gini Ratio.

Table 6. Potential poverty alleviation.

Districts /City	Poor population (thousand)	Potentially Alleviated (thousand)	Alleviation Percentage
Tulungagung	66.42	51.50	77.54%
Blitar	95.91	90.75	94.62%
Kediri	159.27	50.27	31.56%
Probolinggo	197.11	86.56	43.91%
Pasuruan	144.84	61.30	42.32%
Sidoarjo	109.39	0.68	0.62%
Mojokerto	108.72	25.59	23.54%
Jombang	110.57	25.03	22.64%
Nganjuk	108.37	33.30	30.73%
Madiun	73.15	44.27	60.52%
Magetan	59.51	16.88	28.36%
Ngawi	116.47	40.59	34.85%
Bojonegoro	147.33	37.89	25.71%
Tuban	171.24	14.89	8.70%
Lamongan	146.98	9.45	6.43%
Gresik	142.39	12.08	8.48%
Bangkalan	190.94	28.53	14.94%
Sampang	214.32	22.93	10.70%
Pamekasan	123.46	5.02	4.07%
Sumenep	196.42	46.78	23.82%
Kediri City	19.24	0.41	2.13%
Malang City	34.84	1.05	3.01%
Probolinggo City	15.24	0.08	0.52%
Pasuruan City	13.07	0.09	0.69%
Surabaya City	116.62	0.49	0.42%

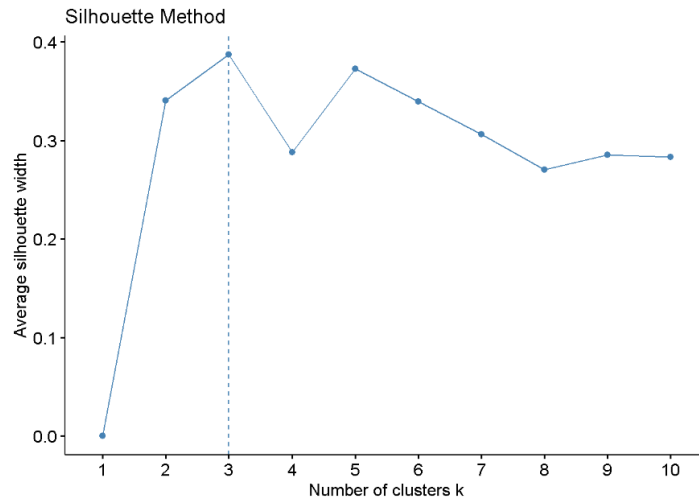


Figure 6. Silhouette method for optimum k-cluster

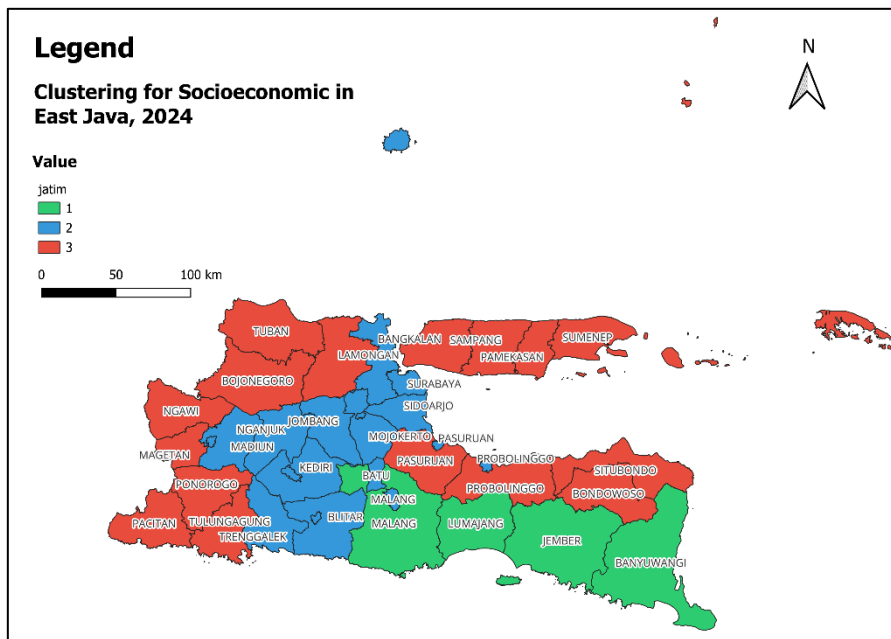


Figure 7. Clustering for socioeconomic in East Java, 2024

Table 7. Districts/Municipalities by Cluster Number and Cluster Name.

Cluster No	Cluster Name	Districts/Municipalities
1	High Green Potential Cluster	Malang, Lumajang, Jember, Banyuwangi
2	High Human Capital Potential Cluster	Tulungagung, Blitar, Kediri, Sidoarjo, Mojokerto, Jombang, Nganjuk, Madiun, Gresik, Kediri City, Blitar City, Malang City, Probolinggo City, Pasuruan City, Mojokerto City, Madiun City, Surabaya, Batu City
3	High Vulnerability Cluster	Pacitan, Ponorogo, Trenggalek, Bondowoso, Situbondo, Probolinggo, Pasuruan, Magetan, Ngawi, Bojonegoro, Tuban, Lamongan, Bangkalan, Sampang, Pamekasan, Sumenep

Despite differences in the variables employed, there is a meaningful correlation between their classification and ours. For example, most districts classified in our High Vulnerability Cluster overlap with Cluster 0 in their study, while our High Human Capital Potential Cluster aligns with their Clusters

1 and 3. This convergence suggests that the socioeconomic vulnerabilities and strengths identified in our analysis are consistent with broader welfare and inequality patterns observed by Ramadhan et al. (2024).

The High Green Potential Cluster encompasses districts in the southern coastal and eastern parts of East Java, including Malang, Lumajang, Jember, and Banyuwangi. Based on Table 8, this cluster demonstrates the highest average CEV, IDR 1,347.02 billion. Regarding socioeconomic characteristics, this cluster exhibits a moderate average HDI of 72.27 and a relatively high average LFPR of 73.22 percent. However, the average poverty rate remains relatively elevated at 8.30 percent.

Given the high average CEV potential, local governments within this cluster are well-positioned to harness carbon economy revenues to strengthen inclusive, environmentally based development strategies. Such utilization may include ecosystem-based community empowerment programs, such as agroforestry development, ecotourism, and social forestry, which simultaneously foster local employment and preserve ecological functions. Additionally, CEV funds could support integrated poverty alleviation initiatives linked to environmental conservation, such as subsidies for environmentally friendly agricultural and forestry technologies or investments in green infrastructure, e.g., coastal conservation zones with blue carbon potential. Through this strategy, the High Green Potential Cluster can serve as a model for sustainable development that harmonizes social welfare and environmental preservation.

Table 8. Clustering result of districts/municipality.

Cluster Name	Average Carbon Economic Value (Billion IDR)	Average Labor Force Participation Rate	Average Human Development Index	Average Poverty Rate (%)
High Green Potential Cluster	1,347.02	73.22	72.27	8.30
High Human Capital Potential Cluster	106.95	71.30	79.06	6.93
High Vulnerability Cluster	323.17	76.44	71.85	13.37

The High Human Capital Potential Cluster comprises central East Java regions and includes diverse districts and municipalities with distinct socioeconomic attributes. The most notable feature of this cluster is its relatively low average LFPR, averaging 71.30 percent, the lowest among all clusters. Nevertheless, this region performs well in terms of welfare outcomes, with the lowest average poverty rate at 6.93 percent. Furthermore, it records the highest average HDI among the three clusters, at 79.06, reflecting the strong quality of human capital, particularly in education, health, and living standards.

Despite these advantages, the cluster reports the lowest average CEV, with an average value of only IDR 106.95 billion. Therefore, using CEV as a fiscal instrument in this cluster should not prioritize social assistance or subsidy schemes, as in more vulnerable areas, but instead focus on stimulating the creation of high-quality, sustainable jobs. Local governments may allocate CEV funding toward labor-intensive green sectors, such as local-scale renewable energy, waste management, and circular economy innovations. These initiatives promote employment and align with the broader low-carbon development agenda. This approach allows the High Human Capital Potential Cluster to optimize its already superior human resources while enhancing its contribution to the green transition agenda.

The High Vulnerability Cluster includes regions facing the most complex socioeconomic challenges of the three clusters. The average CEV for this cluster is IDR 323.17 billion, lower than Cluster 1 but higher than Cluster 2. However, the most pressing issue in this cluster is the high average poverty rate, averaging 13.37 percent, the highest among all clusters. All districts in Madura Island, a region historically associated with elevated poverty levels, fall into this cluster. For instance, Sampang District has consistently recorded poverty rates above the provincial average.

This cluster also has the highest average LFPR at 76.44 percent. However, the average HDI is only 71.85, the lowest among the clusters, indicating poor human capital quality. The high average LFPR and low average HDI suggest a predominance of low-productivity informal employment. Accordingly, CEV utilization in this cluster should focus on inclusive and productive social development programs, such as labor-intensive public works, vocational training based on local potential, and community-based economic empowerment. Interregional CEV redistribution schemes from areas with higher potential may also be considered to accelerate development and reduce regional disparities. These efforts would help ensure more equitable growth across East Java.

4. Conclusions

Indonesia's transition toward a green economy faces two intertwined challenges: the need to safeguard carbon-rich ecosystems and the persistent disparities in regional socioeconomic conditions. While national-level studies on CEV are emerging, evidence at the subnational scale remains scarce, particularly in East Java, where land-use pressures and poverty disparities are pronounced. The novelty of this study lies in being the first to implement Ying et al.'s (2023) framework for CEV estimation in the Indonesian context, extending it with additional socioeconomic indicators (poverty, LFPR, and HDI), and introducing LSTM forecasting for forward-looking carbon valuation.

The findings can be summarized according to the study objectives as follows. CEV in East Java fluctuated during 2015–2024, peaking in 2023 and remaining relatively high in 2024. The main contributors are tree cover, inundated vegetation, grassland, and mangroves, with the highest sequestration potential concentrated in the southern region. These results emphasize the importance of targeted natural resource management to preserve high-value carbon areas. Projections of East Java's CEV using LSTM and Neural Network models suggest a rise to IDR 13.8 trillion in 2025, followed by a decline to IDR 7.6 trillion in 2026. These fluctuations may reflect both limitations in historical data availability and early signals of potential environmental degradation and reduced green land capacity. Regional governments should strengthen ecosystem protection and restoration policies in response, particularly in high carbon-sequestration zones like southern East Java. In parallel, poverty levels in East Java in 2024 exhibit substantial disparities, with a provincial average of 9.56 percent. Batu City records the lowest poverty rate at 3.06 percent, while Sampang District registers the highest at 20.83 percent. Central regions, southern and eastern coastal areas tend to experience lower poverty rates, whereas the western regions, northern coast, and Madura Island face significantly higher poverty levels.

Given this context, the equitable distribution of economic benefits derived from CEV across districts and municipalities should be a provincial priority to support poverty alleviation. Policymakers should not regard CEV as a stand-alone solution, and targeted strategies need to integrate socioeconomic indicators such as LFPR and HDI. These may include enforcing stricter regulations on land-use conversion, providing incentives for sustainable business practices, enhancing land cover monitoring, and integrating spatial planning with climate policy. In practice, redistribution of CEV should prioritize high-poverty regions through fiscal transfers, support for labor-intensive green projects, and integration with existing social protection programs. Such mechanisms would ensure that the economic benefits of carbon sequestration are shared equitably across East Java and contribute directly to poverty alleviation and inclusive development.

Nonetheless, it is important to clearly acknowledge the limitations of this study. First, the relatively short historical dataset (2015–2024) reduces the predictive accuracy of the LSTM model for multi-year forecasts. Second, the use of average carbon prices from 14 Asian ETS markets may not fully capture potential price volatility across different market scenarios. Future research could extend the temporal dataset, test alternative machine learning models, and conduct scenario-based sensitivity analyses of carbon price variations to enhance the robustness and policy relevance of CEV projections.

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