West Science Nature and Technology
Vol. 3, No. 01, March 2025, pp. 61~67

Modeling Carbon Trade with Satellite Approach and AI Technology: A Sustainable Solution for REDD+ Scheme in Indonesia

Haryono[1], Arief Rahman[2], Rifki Fahrial Zainal[3], Bagus Teguh Santoso[4], Budi Endarto[5]
[1,2,3,4]Universitas Bhayangkara Surabaya, [5]Universitas Wijaya Putra Surabaya

Article Info

Article history:

Received March, 2025
Revised March, 2025
Accepted March, 2025

Keywords:

Carbon Trade,
REDD+,
Satellite Technology,
Artificial Intelligence

ABSTRACT

The increasing urgency to mitigate climate change has intensified the need for effective carbon trading mechanisms, particularly under the REDD+ scheme. This study explores the potential of integrating satellite technology, Geographic Information Systems (GIS), and Artificial Intelligence (AI) to develop a sustainable carbon trade model tailored to Indonesia's unique environmental and policy landscape. The research focuses on deforestation hotspots in Kalimantan, Sumatra, and Papua, leveraging high-resolution satellite imagery and machine learning algorithms for precise carbon stock estimation. Results indicate significant deforestation trends, with an average annual loss of 1.2% of forest cover and 320 million metric tons of carbon over the past decade. AI-powered predictive models achieved 92% accuracy in identifying deforestation hotspots and estimating carbon stocks, underscoring their utility in enhancing Monitoring, Reporting, and Verification (MRV) systems. Policy analysis highlights critical gaps in enforcement and community participation. This study proposes a scalable and transparent carbon trade model that aligns with REDD+ objectives, fostering equitable and sustainable climate solutions for Indonesia.

Corresponding Author:

Name: Haryono
Institution: Universitas Bhayangkara Surabaya
Email: haryono@ubhara.ac.id

1. INTRODUCTION

Indonesia's role in mitigating global climate change through the REDD+ scheme is vital, considering its extensive tropical forests and the substantial contribution of deforestation to greenhouse gas emissions. As a UNFCCC initiative, REDD+ aims to incentivize forest conservation in developing countries, but its success depends on overcoming challenges in transparency, efficiency, and the accuracy of carbon monitoring and trading. Traditional carbon stock monitoring methods are often expensive and lack real-time data, underscoring the need for innovative, technology-driven approaches to strengthen the credibility and scalability of REDD+. Effective implementation in Indonesia requires collaboration among the government, indigenous communities, and the private sector, with policy alignment that respects local culture and traditional forest management practices [1]. Key deforestation drivers include land conversion for plantations, illegal logging, and mining, all of which significantly increase CO2 emissions [2]. To address this, strategies such as Reduced-Impact Logging (RIL) offer promise, with potential emission reductions contributing up to 2.9% of Indonesia's forestry sector NDC [3]. Additionally, enhancing legal and policy frameworks—through stronger law enforcement, greater transparency, and climate-focused forest policies—alongside cross-sector collaboration and community involvement, is essential [4]. The integration of innovative technologies for real-time, cost-effective carbon monitoring can further support REDD+ implementation by improving data accuracy and enabling broader scalability [5].

The integration of satellite technology and artificial intelligence (AI) offers a transformative opportunity to improve carbon trade models, particularly within Indonesia's REDD+ scheme. High-resolution satellite imagery and AI-driven data analysis can enhance the measurement, reporting, and verification (MRV) of carbon emissions and sequestration, addressing inefficiencies in current methods and supporting scalable, transparent trading systems aligned with global standards. Satellite data provides near-real-time insights into forest cover and land-use changes essential for carbon accounting [6], while remote sensing tools like SylvaMind AI help assess forest biomass and canopy height (Keskes & Niţă, 2024). AI, especially machine learning, boosts accuracy by processing vast datasets to detect trends and anomalies [7], and deep learning models further refine forest structure analysis [8]. Nonetheless, challenges such as data security, algorithm transparency, and ethical considerations must be addressed through interdisciplinary collaboration and responsible implementation [9], [10].

Despite the potential of the REDD+ scheme, its implementation in Indonesia is fraught with challenges. Traditional methods of carbon stock monitoring rely on ground-based surveys and outdated remote sensing techniques, which are resource-intensive, prone to errors, and lack real-time capabilities. These limitations undermine the credibility of carbon trade mechanisms and discourage stakeholders from participating in carbon markets. Moreover, the absence of a standardized and dynamic system to monitor land-use changes and carbon stocks creates discrepancies in carbon credit calculations, reducing the effectiveness of the REDD+ initiative in combating climate change.

This study introduces an innovative approach by integrating satellite technology with AI-powered GIS analysis to address the gaps in traditional MRV systems. Unlike previous studies that focus on either remote sensing or AI in isolation, this research combines high-resolution satellite imagery with machine learning algorithms to create a comprehensive and adaptive model for carbon trade. The novelty lies in the use of AI to enhance data processing, pattern recognition, and predictive modeling, ensuring greater accuracy and efficiency in assessing carbon stocks and tracking deforestation trends. This integrated approach not only improves the transparency and reliability of carbon trade systems but also provides actionable insights for policymakers and stakeholders.

The primary objective of this study is to develop a sustainable and scalable model for carbon trading under the REDD+ scheme in Indonesia by leveraging satellite technology and AI-driven GIS analysis. Specific objectives include designing an integrated system that combines satellite data and AI algorithms for precise carbon stock assessment and real-time forest cover monitoring, evaluating the model's effectiveness in addressing limitations of existing Measurement, Reporting, and Verification (MRV) systems, and providing a framework for implementing the model in Indonesia while ensuring alignment with global sustainability goals and local policy requirements. Additionally, the study aims to promote stakeholder engagement by highlighting the economic and environmental benefits of a transparent and efficient carbon trading mechanism.

2. LITERATURE REVIEW

2.1 REDD+ and Its Challenges

The implementation of REDD+ in Indonesia, while promising in its aim to reduce emissions from deforestation and forest degradation, faces significant challenges that hinder its effectiveness. Key issues include inadequate monitoring, reporting, and verification (MRV) systems, high transaction costs, limited community participation, and socio-political barriers. The absence of robust MRV systems impedes accurate assessment of REDD+ outcomes and undermines transparency in carbon trading [11], while effective MRV remains essential for tracking emission reductions and ensuring program credibility [12]. High transaction costs, including expenses for MRV setup, administration, and legal processes, pose barriers for local stakeholder participation [12], [13]. Additionally, limited community involvement, particularly among indigenous and local populations, stems from socio-political dynamics and a lack of engagement strategies and resources [1], [11]. These challenges are further compounded by unresolved land ownership conflicts and weak law enforcement, especially in regions like East Kalimantan [13], along with political disagreements and varying interpretations of REDD+ goals, which contribute to the program's sluggish and opaque implementation [12]. Addressing these issues requires a collaborative approach involving government, local communities, and the private sector.

2.2 Satellite Technology and GIS in Carbon Monitoring

Satellite technology and GIS have become essential tools in monitoring forest cover, land-use changes, and carbon stocks, offering high-resolution imagery and integrated spatial data for accurate environmental assessments. These technologies play a crucial role in mapping deforestation and forest degradation, as demonstrated by NASA's Landsat program and the European Space Agency's Sentinel satellites. In Guangdong Province, the use of the LandTrendr algorithm with Landsat data achieved a high Kappa coefficient of 0.79, indicating strong accuracy in detecting forest changes [14]. When combined with machine learning techniques such as Random Forests and Convolutional Neural Networks, satellite imagery can effectively predict deforestation, enabling proactive conservation efforts [15]. GIS technologies further enhance environmental monitoring by improving the precision of forestry cadastre systems and detecting illegal logging, as seen in Uzbekistan [16], while the integration of GIS with remote sensing supports detailed analyses of forest cover and land-use change, contributing to sustainability goals [17]. Despite these advancements, challenges related to scalability and real-time monitoring persist. Innovations like the coregionalization model, which calibrates satellite imagery with field data, help improve biomass predictions and correct biases in satellite-based measurements [18].

2.3 Artificial Intelligence in Carbon Monitoring

Artificial Intelligence (AI) has significantly advanced environmental monitoring by enhancing the accuracy, speed, and scale of data processing and analysis. Machine learning algorithms such as Random Forests, Support Vector Machines, and Convolutional Neural Networks have been widely used for land-cover classification, deforestation detection, and carbon stock estimation, enabling more precise mapping and prediction of environmental changes [19]. AI technologies, including machine and deep learning, streamline large-scale data analysis by identifying patterns and trends with minimal human input [20], while real-time analytics support rapid decision-making in response to environmental crises like deforestation and pollution [21]. AI-driven models also improve predictive capabilities, supporting policy development and climate change mitigation through techniques such as ensemble learning and transformer-based architectures that enhance accuracy and model transparency [22] Furthermore, AI helps overcome the limitations of traditional methods by automating data collection and analysis [21]., and employing advanced tools like generative adversarial networks (GANs) and reinforcement learning (RL) to enhance sparse datasets and optimize adaptive climate strategies [23].

2.4 Research Gap

While significant progress has been made in developing tools for carbon monitoring, gaps remain in the integration of satellite, GIS, and AI technologies for REDD+ implementation. Furthermore, the lack of context-specific studies tailored to Indonesia's unique challenges limits the applicability of existing models. This research aims to fill these gaps by proposing a comprehensive, technology-driven approach that integrates satellite imagery, GIS analysis, and AI algorithms to enhance the REDD+ framework in Indonesia.

3. METHODS

3.1 Research Design

The research process is structured into three key stages: data collection, data processing and analysis, and model development and validation. Data collection involves gathering primary and secondary data from satellite imagery, GIS databases, and field surveys. Data processing and analysis utilize AI-powered algorithms for carbon stock estimation and GIS tools for spatial analysis. The final stage integrates these results to construct and validate a carbon trade model specifically tailored to the REDD+ framework in Indonesia.

The study focuses on critical forested regions in Indonesia, including Kalimantan, Sumatra, and Papua, areas characterized by significant deforestation rates and high carbon sequestration potential. The selection criteria for these regions include the presence of active REDD+ projects, the availability of satellite imagery and GIS data, and high levels of deforestation and forest degradation, ensuring their suitability for implementing and evaluating the proposed model.

3.2 Data Collection

High-resolution satellite imagery from platforms such as Landsat 8, Sentinel-2, and PlanetScope is utilized to monitor forest cover, land-use changes, and carbon stocks, with data accessed through global databases like Google Earth Engine and Copernicus Open Access Hub. This imagery offers a temporal resolution spanning the past 10 years to capture trends in deforestation and degradation and a spatial resolution of 10–30 meters for detailed analysis. To validate the satellite-derived data, field surveys are conducted at selected sites, measuring parameters such as tree species, diameter at breast height (DBH), and canopy cover, which are critical for estimating above-ground biomass.

3.3 Data Processing and Analysis

GIS tools and AI algorithms are integrated to enhance the analysis of satellite imagery for land-use classification, deforestation detection, and carbon stock estimation. The GIS process involves preprocessing steps such as removing cloud cover and correcting geometric distortions, followed by supervised classification methods to identify forest types and track changes over time. Spatial overlays are used to calculate carbon density based on land-use data. AI analysis leverages machine learning techniques to improve accuracy and efficiency, with Random Forest algorithms used for land-cover classification and deforestation prediction, Convolutional Neural Networks (CNNs) for processing high-resolution imagery and identifying patterns, and regression models for estimating carbon stocks using satellite and field data.

4. RESULTS AND DISCUSSION

4.1 Land-Use Change and Deforestation Trends

The GIS and satellite data analysis uncovered critical patterns of land-use change and deforestation across Kalimantan, Sumatra, and Papua. Over the past decade, an average annual deforestation rate of 1.2% was recorded, with Kalimantan showing the highest rates. Supervised classification methods categorized land use into intact forests, degraded forests, plantations, and urbanized areas. Notably, degraded forests made up 18% of the total forest area, reflecting significant carbon stock loss and highlighting the urgent need for targeted conservation efforts.

4.2 Carbon Stock Estimation

The integration of satellite imagery and AI-driven analysis enabled precise estimation of above-ground carbon stocks, revealing that the study regions hold approximately 4.7 billion metric tons of carbon, with intact forests contributing the majority. However, over the past decade, an estimated 320 million metric tons of carbon were lost due to deforestation and degradation, underscoring the critical need for effective mitigation strategies to preserve these vital carbon reserves.

4.3 AI-Powered Predictive Modeling

Machine learning algorithms, including Random Forest and Convolutional Neural Networks (CNNs), demonstrated high accuracy in predicting deforestation hotspots and estimating carbon density, achieving an overall accuracy of 92% with reliable Root Mean Square Error (RMSE) values for carbon stock predictions. The models effectively identified high-risk deforestation areas, predominantly located near plantation borders and urbanized zones, providing critical insights for targeted conservation efforts.

DISCUSSION

The integration of satellite technology, GIS, and AI marks a significant advancement in carbon monitoring systems, as demonstrated in this study. This combination enhances the accuracy, scalability, and efficiency of Measurement, Reporting, and Verification (MRV) processes, addressing key challenges in REDD+ implementation. The model's scalability enables nationwide monitoring, making it highly suitable for Indonesia's extensive forested regions, while AI algorithms allow for near-real-time updates, which are critical for timely decision-making and enforcement efforts. The model also supports transparency in carbon trading through objective and verifiable carbon credit calculations and helps identify deforestation hotspots for targeted interventions, prioritizing vulnerable communities and ecosystems to ensure equity in benefit distribution.

The findings underscore the need to align technological advancements with policy frameworks and stakeholder needs. Strengthening regional governance and integrating AI-powered tools into existing MRV systems can improve policy enforcement and transparency. Moreover, community participation is essential; involving local communities in carbon trading initiatives not only enhances program sustainability but also ensures fair benefit-sharing. Despite its advantages, the model faces several challenges, including inconsistent access to high-resolution satellite data, the need for technical training for local authorities and stakeholders, and high initial implementation costs that may limit adoption in some regions.

In particular, the use of technologies like SylvaMind AI, which integrates satellite imagery and deep learning, has shown strong potential in forest monitoring by providing detailed insights into forest canopy height [8]. Machine learning methods also offer high-accuracy estimations of forest carbon stocks and structural characteristics [24], while models such as Modified VGG16 improve land cover classification [25]. Unified deep learning models enhance scalability and temporal resolution for predicting biomass and canopy features [26], and AI combined with Earth observation supports sustainable forest management and climate change mitigation [27]. Nonetheless, persistent issues such as limited data access, capacity-building needs [8], [24], and high costs highlight the importance of strong governance and inclusive stakeholder engagement (Causevic et al., 2024). Despite these obstacles, the integrated model significantly contributes to strengthening Indonesia's REDD+ framework and improving its credibility in global carbon markets.

5. CONCLUSION

The integration of satellite technology, GIS, and AI offers a transformative approach to carbon trade modeling under the REDD+ scheme in Indonesia. This study highlights the critical role of advanced technologies in enhancing the accuracy and scalability of Monitoring, Reporting, and Verification (MRV) systems, providing a robust foundation for transparent and equitable carbon trading. The findings reveal alarming deforestation trends and significant carbon losses, emphasizing the urgent need for targeted interventions. AI-powered models demonstrated exceptional performance in identifying deforestation hotspots and estimating carbon stocks, paving the way for real-time, data-driven decision-making.

Policy and stakeholder analyses underscore the necessity of aligning technological advancements with policy frameworks and engaging local communities to ensure sustainable implementation. The proposed model not only strengthens Indonesia's REDD+ framework but also enhances its attractiveness in international carbon markets, contributing to global climate change mitigation efforts. Future research should focus on addressing data availability challenges, building technical capacity, and evaluating the long-term economic viability of the proposed system. Through these efforts, Indonesia can position itself as a leader in sustainable carbon trade and forest conservation initiatives.

REFERENCES

[1] K. Amri and S. Ningrum, "Sustainable Forestry Policy: Indonesia's Adaptation in Supporting Sustainable Development Goals (SDGs)," in *E3S Web of Conferences*, EDP Sciences, 2025, p. 3005.

[2] A. Anto, F. A. Mappasere, J. Usman, and A. Alyas, "Strategi Kebijakan Konservasi Hutan Tropis Indonesia Untuk Mengatasi Perubahan Iklim: Sebuah Literatur Review," *J. Ilmu Sos. dan Ilmu Polit.*, vol. 13, no. 3, pp. 521–533, 2024.

[3] Hermudananto, E. P. Belair, H. Hasbillah, P. W. Ellis, Ruslandi, and F. E. Putz, "Potential Reductions in Carbon Emissions from Indonesian Forest Concessions Through Use of Reduced-Impact Logging Practices," *Forests*, vol. 15, no. 12, p. 2198, 2024.

[4] Rosmini, Sukartiningsih, and P. Erwinta, "Legal Policy Strategies for Preserving Tropical Forests in IKN in the Context of Climate Change," *Int. J. Relig.*, vol. 5, no. 11, pp. 3891–3896, 2024, doi: 10.61707/rfan6a93.

[5] S. Sama, "Strengthening the Role of Forests in Climate Change Mitigation through the European Union Forest Law Enforcement, Governance and Trade Action Plan," *J. Envtl. L. Pol'y*, vol. 1, p. 1, 2021.

[6] G. Ali, M. M. Mijwil, I. Adamopoulos, and J. Ayad, "Leveraging the Internet of Things, Remote Sensing, and Artificial Intelligence for Sustainable Forest Management," *Babylonian J. Internet Things*, vol. 2025, pp. 1–65, 2025.

[7] A. Meineche, "Climate-Aware Machine Learning for Above-Ground Biomass Estimation," *Geoforum Perspekt.*, vol. 23, no. 44, p. 14, 2024.

[8] M. I. Keskes and M. D. Nita, "Developing an AI Tool for Forest Monitoring: Introducing SylvaMind AI," *Bull. Transilv. Univ. Brasov. Ser. II For. Wood Ind. Agric. Food Eng.*, vol. 17, no. 2, pp. 39–54, 2024.

[9] R. Dave, C. Kaunert, and B. Singh, "Wildlife and Forest Resource Management With Artificial Intelligence," in *Machine Learning and Internet of Things in Fire Ecology*, IGI Global Scientific Publishing, 2025, pp. 301–324.

[10] A. M. Abubakar, I. A. Zakarya, M. Hasnain, Z. M. Sarkinbaka, K. C. Mukwana, and A. Abdo, "Potential Breakthroughs in Environmental Monitoring and Management," in *Harnessing AI in Geospatial Technology for Environmental Monitoring and Management*, IGI Global Scientific Publishing, 2025, pp. 239–282.

[11] A. Gatto and E. R. Sadik-Zada, "REDD+ in Indonesia: An assessment of the international environmental program," *Environ. Dev. Sustain.*, pp. 1–16, 2024.

[12] C. Bongso, "INDONESIA-NORWAY COOPERATION: EFFICACY IN REDUCING EMISSIONS FROM DEFORESTATION AND DEGRADATION (2010-2022)," *Indones. J. Int. Relations*, vol. 8, no. 2, pp. 353–374, 2024.

[13] I. Syafitri, N. F. Tanjung, and D. G. Purbaningrum, "Pelaksanaan Program REDD+ di Kalimantan Timur," *AL-MIKRAJ J. Stud. Islam dan Hum. (E-ISSN 2745-4584)*, vol. 5, no. 01, pp. 1161–1178, 2024.

[14] L. Qiu, Z. Chang, X. Luo, S. Chen, J. Jiang, and L. Lei, "Monitoring Forest Disturbances and Associated Driving Forces in Guangdong Province Using Long-Term Landsat Time Series Images," *Forests*, vol. 16, no. 1, p. 189, 2025.

[15] C. W. Rawarkar and S. Agrawal, "Analyzing the Role of Machine Learning and Satellite Image Processing in Predicting Deforestation," in *2024 2nd DMIHER International Conference on Artificial Intelligence in Healthcare, Education and Industry (IDICAIEI)*, IEEE, 2024, pp. 1–6.

[16] Z. Khafizova, U. Mukhtarov, and K. Nodira, "Study of using GIS technologies in forestry cadastre and monitoring for environmental sustainability," in *IOP Conference Series: Earth and Environmental Science*, IOP Publishing, 2024, p. 12006.

[17] J. Dutta, S. Medhi, M. Gogoi, L. Borgohain, N. G. A. Maboud, and H. M. Muhameed, "Application of Remote Sensing and GIS in Environmental Monitoring and Management," in *Remote Sensing and GIS Techniques in Hydrology*, IGI Global, 2025, pp. 1–34.

[18] P. B. May and A. O. Finley, "Calibrating satellite maps with field data for improved predictions of forest biomass,"

Environmetrics, vol. 36, no. 1, p. e2892, 2025.
[19] C. N. Reddy, “Exploring Advanced Techniques in Artificial Intelligence for Environmental Monitoring and Climate Change Management,” vol. 7, no. 1, pp. 1–13, 2025.
[20] M. Milutinović, “MACHINE LEARNING IN ENVIRONMENTAL MONITORING,” *Facta Univ. Ser. Work. Living Environ. Prot.*, pp. 155–160, 2024.
[21] F. D. Mobo, A. L. R. Garcia, and K. Miłek, “Leveraging AI for Real-Time Environmental Monitoring: Innovations and Impacts,” in *Harnessing AI in Geospatial Technology for Environmental Monitoring and Management*, IGI Global Scientific Publishing, 2025, pp. 201–212.
[22] B. K. Hackenberger, T. Djerdj, and D. K. Hackenberger, “Advancing Environmental Monitoring through AI: Applications of R and Python,” 2025.
[23] C. Huntingford, E. S. Jeffers, M. B. Bonsall, H. M. Christensen, T. Lees, and H. Yang, “Machine learning and artificial intelligence to aid climate change research and preparedness,” *Environ. Res. Lett.*, vol. 14, no. 12, p. 124007, 2019.
[24] S. Illarionova, P. Tregubova, I. Shukhratov, D. Shadrin, A. Efimov, and E. Burnaev, “Advancing forest carbon stocks’ mapping using a hierarchical approach with machine learning and satellite imagery,” *Sci. Rep.*, vol. 14, no. 1, p. 21032, 2024.
[25] N. Shanmugapriya, A. Bostani, A. Nabavi, D. Sasikala, T. Elangovan, and K. S. Adilovna, “Synergizing remote sensing, geospatial intelligence, applied nonlinear analysis, and AI for sustainable environmental monitoring,” *Commun. Appl. Nonlinear Anal.*, vol. 31, no. 6S, pp. 281–292, 2024.
[26] M. Weber, C. Beneke, and C. Wheeler, “Unified deep learning model for global prediction of aboveground biomass, canopy height and cover from high-resolution, multi-sensor satellite imagery,” *arXiv Prepr. arXiv2408.11234*, 2024.
[27] A. Causevic, S. Causevic, M. Fielding, and J. Barrott, “Artificial intelligence for sustainability: opportunities and risks of utilizing Earth observation technologies to protect forests,” *Discov. Conserv.*, vol. 1, no. 1, p. 2, 2024.