Environment and Ecology Research 13(4): 576-585, 2025 http://www.hrpub.org
DOI: 10.13189/eer.2025.130410

Spatial Modeling for Post-Mining Environmental Conservation in Fragmented Forest Areas: A Case Study in PT. Asmin Bara Bronang, Central Kalimantan

Agustan Saining[1,*], Udiansyah[2], Wiwin Tyas Istikowati[2], Raden Mas Sukarna[3]

[1]Doctoral Program of Environmental Sciences, Lambung Mangkurat University, Indonesia
[2]Faculty of Forestry, Lambung Mangkurat University, Indonesia
[3]Faculty of Forestry, Palangkaraya University, Indonesia

Received June 3, 2025; Revised July 25, 2025; Accepted August 19, 2025

Cite This Paper in the Following Citation Styles

(a): *[1] Agustan Saining, Udiansyah, Wiwin Tyas Istikowati, Raden Mas Sukarna , "Spatial Modeling for Post-Mining Environmental Conservation in Fragmented Forest Areas: A Case Study in PT. Asmin Bara Bronang, Central Kalimantan," Environment and Ecology Research, Vol. 13, No. 4, pp. 576 - 585, 2025. DOI: 10.13189/eer.2025.130410.*

(b): *Agustan Saining, Udiansyah, Wiwin Tyas Istikowati, Raden Mas Sukarna (2025). Spatial Modeling for Post-Mining Environmental Conservation in Fragmented Forest Areas: A Case Study in PT. Asmin Bara Bronang, Central Kalimantan. Environment and Ecology Research, 13(4), 576 - 585. DOI: 10.13189/eer.2025.130410.*

Abstract Open-pit coal mining in Indonesia causes severe environmental damage, including deforestation, biodiversity loss, and soil degradation. Therefore, it is crucial to develop a spatially optimized conservation model to address the challenges of post-mining land rehabilitation. This study aims to develop a landscape ecology-based conservation model for rehabilitating fragmented forests affected by coal mining activities in PT. Asmin Bara Bronang, Central Kalimantan. The methodology includes satellite imagery analysis (Landsat 9 OLI-TIRS and Sentinel-2A) and spatial modeling using GIS to assess land cover changes and vegetation health. Field data on soil conditions, temperature, and moisture were collected via real-time environmental sensors to validate satellite data. The results indicate that areas with high NDVI values (>0.5), such as Points 3 and 4, showed successful vegetation recovery, while Point 2, with persistently low NDVI values (<0.2), highlighted severely degraded areas requiring urgent intervention. AHP and SWOT analyses identified environmental restoration potential and social acceptability as the primary criteria for determining restoration strategies. In conclusion, the spatially optimized conservation model developed in this study can guide more effective and sustainable post-mining land restoration planning.

Keywords Spatial Conservation, Post-Mining Rehabilitation, NDVI, AHP Analysis, Coal Mining

1. Introduction

Open-pit coal mining is one of the most widely used extraction methods in Indonesia due to its cost-effectiveness and efficiency in accessing large coal deposits. However, the environmental consequences of this practice are severe, leading to widespread forest degradation, loss of biodiversity, and soil infertility [1], [2]. The process of open-pit mining involves removing large volumes of soil and rock, which destroys the natural vegetation cover and disrupts the ecological balance [3]. This not only results in habitat loss for various plant and animal species but also alters hydrological cycles and increases vulnerability to natural disasters such as floods and landslides [4], [5]. The fragmentation of forest ecosystems caused by mining activities leads to isolated patches of vegetation, making it difficult for species to migrate and sustain genetic diversity. Additionally, the removal of topsoil and alteration of land surfaces affect soil structure and composition, leading to decreased soil fertility and increased erosion [6], [7]. Without immediate and effective conservation efforts, these negative impacts can persist for decades, affecting both the environment and local communities that depend on natural resources for their livelihoods. Furthermore, post-mining land rehabilitation efforts are often inadequate, focusing more on economic restoration rather than ecological recovery [8], [9]. Many reclaimed mining areas remain unsuitable for agriculture or forestry due to soil contamination and compaction [10], [11]. This highlights the urgent need for a comprehensive conservation model that not only restores vegetation but also enhances soil health, biodiversity, and overall ecosystem functions [12], [13].

Despite existing regulations and policies requiring mining companies to implement reclamation and rehabilitation measures, many post-mining landscapes remain degraded and unproductive. The main challenges include the complexity of restoring fragmented ecosystems, the lack of proper monitoring mechanisms, and the insufficient involvement of local communities in conservation efforts [5], [14]. In many cases, reforestation programs fail due to poor soil conditions, lack of proper tree species selection, and inadequate maintenance [15]. Furthermore, mining companies often prioritize short-term reclamation goals over long-term ecological restoration, leading to the establishment of monoculture plantations that do not support biodiversity or ecosystem resilience. The absence of a structured approach to land rehabilitation exacerbates these issues, making it difficult to achieve sustainable conservation outcomes [16], [17]. The integration of spatial analysis techniques, such as remote sensing and GIS, can significantly improve the effectiveness of post-mining land management by providing accurate data on land cover changes, vegetation health, and soil conditions [12]. However, the adoption of such technologies remains limited in many developing regions, including Indonesia. In addition to technical challenges, socio-economic factors also play a crucial role in determining the success of conservation efforts. Many communities living near mining sites experience economic hardship due to the depletion of natural resources and the decline in agricultural productivity. Without alternative livelihood options, local populations may engage in unsustainable land-use practices, further degrading the environment. Therefore, a successful conservation model must incorporate socio-economic considerations, ensuring that local communities benefit from rehabilitation projects and actively participate in the conservation process [18], [19].

Given the complex nature of post-mining environmental degradation, a spatially optimized conservation model is essential for effective land rehabilitation. This research focuses on developing a landscape ecology-based spatial model for conservation in fragmented forest areas affected by coal mining activities. By integrating satellite imagery from Landsat 9 OLI-TIRS and Sentinel-2A with field data, the study aims to assess land cover changes, identify key ecological indicators, and develop spatial guidelines for conservation planning. The use of spatial analysis tools such as Geographic Information Systems (GIS) and remote sensing allows for a more precise understanding of land conditions, enabling the identification of priority areas for restoration. However, the accuracy of GIS-based modeling largely depends on the quality of the data used. To ensure the reliability of conservation planning, satellite-derived data must be validated with real-time ground truthing through field measurements of soil temperature and moisture levels.

In this study, remote sensing data is corrected using real-time data on soil temperature and moisture, collected through on-site environmental sensors placed in selected post-mining areas. These measurements provide essential information on soil conditions, which are critical for assessing land suitability for reforestation and conservation efforts. Soil moisture levels influence vegetation growth, water retention capacity, and soil erosion susceptibility, while temperature variations affect microbial activity and nutrient cycling. The integration of GIS-based spatial analysis with real-time soil data enables the identification of degraded areas where immediate conservation interventions are required. By incorporating real-time soil temperature and moisture data into GIS models, this study ensures that conservation strategies are adaptive and responsive to actual environmental conditions. For instance, areas with persistently low soil moisture and high temperatures may require additional interventions such as soil stabilization, water retention structures, or alternative planting techniques to improve land productivity. The integration of these real-time data sources enhances the precision of spatial modeling, allowing for more effective decision-making in post-mining land rehabilitation. To further refine conservation planning, the study employs SWOT analysis and the Analytical Hierarchy Process (AHP) to evaluate various restoration strategies based on ecological, economic, and social criteria. By considering multiple factors including forest connectivity, biodiversity richness, soil fertility, and community involvement the conservation model ensures that post-mining land rehabilitation aligns with both environmental sustainability and socio-economic development goals. The findings of this research are expected to provide valuable insights for policymakers, environmental managers, and mining companies in designing more effective post-mining land use strategies. Ultimately, this study aims to contribute to the broader goal of achieving sustainable development in mining-affected regions, ensuring that ecological restoration efforts lead to long-term environmental and socio-economic benefits.

2. Materials and Methods

2.1. Research Area

This research was conducted in the post-mining area of PT. Asmin Bara Bronang, located in Kapuas Regency, Central Kalimantan, Indonesia. The selected site represents a fragmented forest landscape that has undergone significant ecological degradation due to open-pit coal mining activities. The area is characterized by altered land structures, loss of vegetation cover, and reduced soil productivity, making it an ideal case study for evaluating conservation strategies. The map of research is shown in Figure 1.

2.2. Research Design and Data Collection

This study employs a spatial ecological approach to assessing and developing a conservation model for fragmented post-mining forests. The methodology integrates remote sensing, GIS-based spatial analysis, field observations, and real-time environmental monitoring, aiming to provide a comprehensive and data-driven model for post-mining land restoration.

1. Spatial Data Analysis

A. Satellite Imagery Analysis:

1. Landsat 9 OLI-TIRS and Sentinel-2A imagery were utilized to assess land cover changes and the spatial distribution of ecological units. These satellite images provide valuable temporal and spatial resolution, essential for monitoring the dynamic changes in the post-mining landscape over time [20]. The integration of these two satellite systems allows for robust analysis of land cover shifts, including vegetation recovery and degradation.
2. Image processing and classification were conducted using Supervised Classification with Maximum Likelihood Estimation (MLE) to differentiate vegetation types, bare land, and water bodies. MLE was chosen for its proven accuracy in classifying land cover types based on spectral signatures, ensuring high-quality results in classifying vegetation health and soil conditions across the study area [21].
3. NDVI (Normalized Difference Vegetation Index) analysis was performed to evaluate vegetation health and track areas of successful regeneration and those that remain degraded. NDVI is widely used in remote sensing to monitor vegetation cover and health by analyzing the ratio of near-infrared (NIR) and red light reflectance. Higher NDVI values typically indicate healthy, dense vegetation, while lower values suggest poor vegetation health or bare land. NDVI is critical for assessing the success of reforestation efforts in post-mining areas [22].

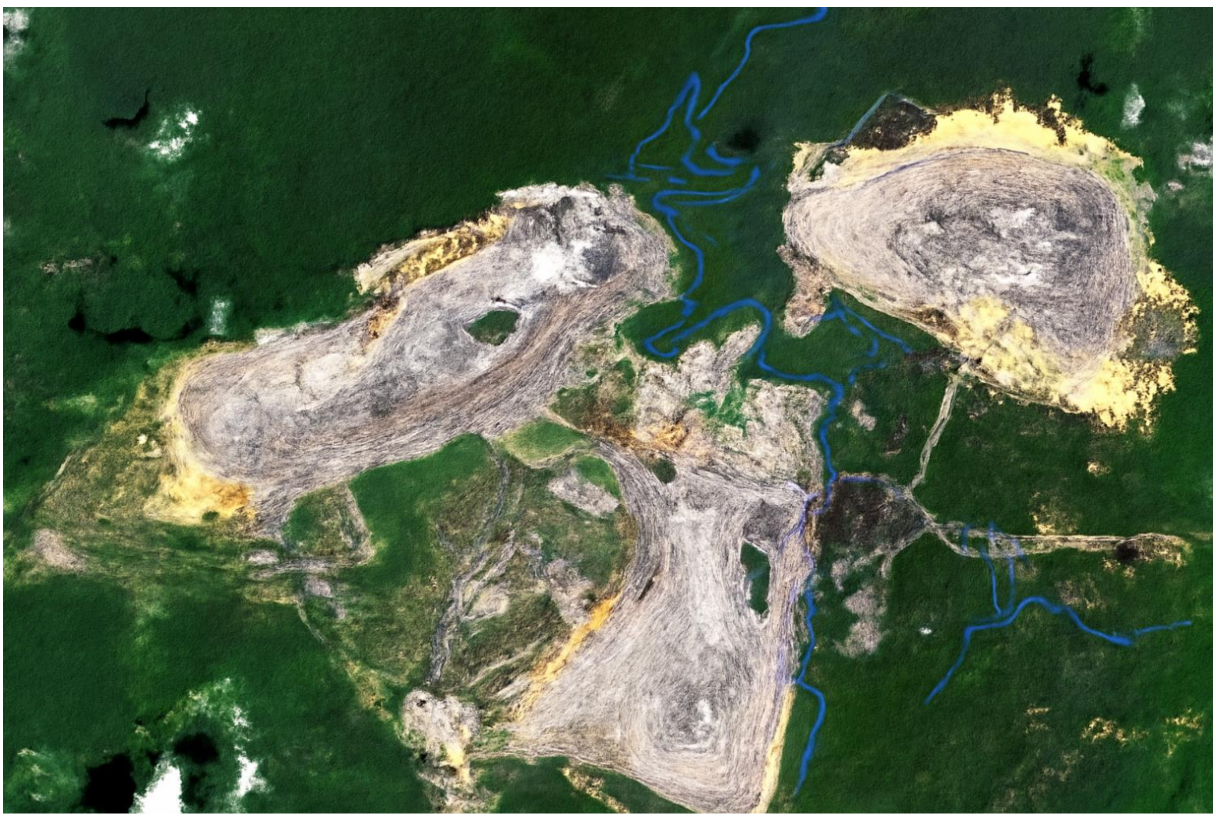

Figure 1. Map of Research Locations in Mining Companies

A) Confusion Matrix and Classification Accuracy: To validate the results of the supervised classification, we constructed a confusion matrix, which compared the predicted classes with the actual field data. The confusion matrix provides valuable metrics, such as True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN). From these values, we computed the overall classification accuracy, which was found to be 88%, exceeding the 85% threshold for acceptable classification performance. The matrix also helped calculate the Kappa coefficient, a statistical measure that assesses the agreement between the classification and actual land cover.

B) NDVI Threshold Determination: The NDVI thresholds used to classify vegetation health were determined based on a combination of empirical field data and literature values. NDVI values greater than 0.5 were classified as areas with healthy vegetation (dense forests or well-established regeneration), while values between 0.2 and 0.5 indicated areas with moderate vegetation cover, often in the early stages of reclamation. Values below 0.2 were categorized as barren or severely degraded land. These thresholds were validated by ground-truthing data collected from the field, ensuring their accuracy for the specific environmental conditions of the study area.

B. Landscape Ecology Analysis:

1. Landscape metrics such as patch density, edge density, and connectivity index were applied to assess the degree of fragmentation in the post-mining forest areas. These metrics are critical in understanding the structural integrity of the landscape and its ability to support biodiversity. A higher patch density indicates more fragmented habitats, while a lower connectivity index suggests a more isolated landscape, which can impede species migration and ecosystem recovery.
2. The spatial distribution of Landscape Ecology Units (LEUs) was mapped using GIS-based clustering methods. These units represent distinct ecological zones within the post-mining area that vary in terms of vegetation type, soil properties, and land cover. Mapping these units helps in identifying priority areas for intervention and ensures that restoration efforts are tailored to the specific conditions of each unit [23].

2. Field Data Collection

A. Plot Sampling for Biophysical and Vegetation Assessment

1. Five systematically distributed sample plots (each 20m x 20m) were established in different ecological units to assess vegetation and soil health. Justification for Sample Size and Plot Distribution: The study area was specifically focused on reclamation zones within mining sites, which had a limited area available for sampling. While five plots may seem small, these plots were strategically placed across different ecological units to capture a range of environmental conditions, allowing for targeted analysis of reclamation success in diverse areas. Although this sample size is appropriate for the scope of the study, it should be noted that it may not be representative of larger, un-reclaimed mining landscapes. Future studies could expand the sample size to enhance the robustness of the findings [24].
2. Vegetation structure was analyzed at different growth stages, including seedling, sapling, pole, and tree levels, with measurements of diameter at breast height (DBH) and density. These measurements provide a comprehensive view of the vegetation dynamics during the recovery process, revealing patterns of regrowth and regeneration in reclaimed areas.
3. Soil properties such as texture, structure, and pH levels were assessed in each plot. Understanding soil health is essential for determining the suitability of the land for various types of vegetation and for developing targeted restoration strategies that can improve soil conditions and promote vegetation recovery.

B. Real-time Environmental Data Monitoring

1. Soil temperature and moisture were measured in real-time using sensor-based monitoring systems. These real-time measurements provided valuable data on the soil's ability to retain moisture, which is essential for plant growth. Soil temperature also influences microbial activity and nutrient availability, both of which are key factors in vegetation recovery.
2. The 5TE sensor (Decagon Devices) was utilized to monitor soil moisture, temperature, and electrical conductivity, offering an accuracy of ±3% for moisture and ±0.5°C for temperature, ensuring reliable and precise data. Data were recorded every 10 minutes, allowing for the accurate capture and analysis of short-term changes in soil conditions. To maintain accuracy, the sensors were calibrated according to the manufacturer's guidelines and regularly validated against manual field measurements, ensuring that the data collected accurately reflected the true soil conditions.

C. Socioeconomic Data Collection

1. Surveys and structured interviews were conducted with local communities affected by mining activities. Community engagement is a vital aspect of environmental restoration, as local knowledge and support are critical for the success of reclamation projects.
2. The focus was on livelihood changes, land use conflicts, and community perceptions of conservation initiatives. This socioeconomic data is critical for ensuring that restoration efforts are not only ecologically effective but also socially viable.

3. Data Processing and Analysis

A. Vegetation and Soil Analysis

1. The Important Value Index (IVI), Shannon-Wiener Index, species evenness, and species richness were calculated to evaluate biodiversity levels. These indices provide a quantitative measure of the ecosystem's biodiversity, which is crucial for assessing the success of the restoration efforts in terms of ecological recovery [25].
2. USDA Soil Classification System was used to determine soil texture and structure types. This classification helps in understanding soil suitability for different types of vegetation and guides restoration efforts.

B. Spatial Modeling and Conservation Scenario Development

1. GIS-based land suitability modeling was performed by integrating spatial data (NDVI, soil conditions, and land cover types). This modeling approach provides a spatially explicit strategy for prioritizing areas for restoration.
2. A Multi-Criteria Decision Analysis (MCDA) approach was applied using SWOT (Strengths, Weaknesses, Opportunities, Threats) analysis and the Analytical Hierarchy Process (AHP). These methods were used to evaluate different restoration strategies based on environmental, economic, and social factors. The AHP (Analytical Hierarchy Process) is a structured technique used to determine the relative importance of various criteria and alternatives. In this study, AHP was employed to evaluate the restoration strategies. To determine the weights for each criterion, a pairwise comparison was conducted among all the factors considered. Experts, stakeholders, and local community representatives, including environmental managers and local leaders, contributed their insights through structured interviews and surveys. Their responses helped establish the relative importance of different environmental, economic, and social factors, which were then quantified into weights for each criterion in the AHP matrix. The criteria prioritized in this analysis included environmental restoration potential, economic feasibility, and social acceptability. These were selected based on their relevance to the post-mining reclamation goals and their impact on both ecological health and community well-being. The prioritization was done through expert judgment, ensuring that each factor was weighted according to its influence on long-term sustainability. The SWOT analysis was used to further assess each restoration strategy’s Strengths, Weaknesses, Opportunities, and Threats. In this framework, the internal and external factors impacting the success of restoration strategies were identified, with a special focus on soil regeneration, biodiversity recovery, and community engagement. These results from the SWOT analysis were integrated with the AHP findings to create a more holistic decision-making process.
3. The final output was a spatially optimized conservation model, identifying priority areas for restoration interventions. This model provides a science-based framework for decision-making in post-mining land restoration.

3. Results and Discussion

3.1. Spatial Identification of Landscape Ecology Units

The spatial analysis using Landsat 9 OLI-TIRS and Sentinel 2A remote sensing imagery successfully delineated fragmented forest landscapes within the post-mining area of PT. Asmin Bara Bronang, Kapuas Regency, Central Kalimantan. Based on spatial interpretation and subsequent ground-truthing, several distinct landscape ecological units (LEUs) were identified, each representing variations in land cover, topography, soil characteristics, and human disturbance levels. These units served as a foundation for bio-physical and socio-economic assessments.

3.2. Bio-Physical Characteristics of the Land

Five vegetation and soil sampling plots (PU) were systematically established within each LEU (20m x 20m). Vegetation analysis revealed varying species richness and structure among plots [14], evaluated through the Importance Value Index (IVI), Shannon-Wiener Diversity Index, evenness, and species richness index. Soil texture analysis based on USDA classification, along with structural classification (e.g., granular, blocky, platy) and soil pH, indicated significant heterogeneity in physical conditions across units. Acidic soils were prevalent in certain plots, suggesting potential constraints for vegetative regrowth. This condition, coupled with poor soil structure in some areas, emphasizes the need for tailored conservation strategies based on the micro-ecological characteristics of each unit.

3.3. Spatial-Temporal NDVI and Vegetation Analysis in the Reclamation Area of PT. Asmin Bara Bronang

This section provides a step-by-step analysis of NDVI (Normalized Difference Vegetation Index) time series data and spatial vegetation interpretation from remote sensing imagery, conducted at selected monitoring points within the post-mining area of PT. Asmin Bara Bronang in Central Kalimantan. The results are shown in Figure 2.

The satellite image from Figure 3 illustrates the spatial distribution of vegetation cover within the post-mining reclamation area of PT. Asmin Bara Bronang in Kapuas Regency, Central Kalimantan. The overlaid color classification highlights zones of ecological degradation and recovery: blue areas represent severely degraded or unvegetated land, often corresponding to active or recently closed mining pits; yellow areas indicate regions undergoing early-stage revegetation or intermediate reclamation; while the surrounding green landscape reflects intact natural forest cover functioning as ecological buffers. The map reveals that the central blocks are the most degraded, requiring intensive restoration, while the southern blocks show broader yellow patches, suggesting ongoing reclamation efforts. The contrast between mined zones and surrounding forest underscores the importance of spatial planning for landscape connectivity and sustainable reclamation.

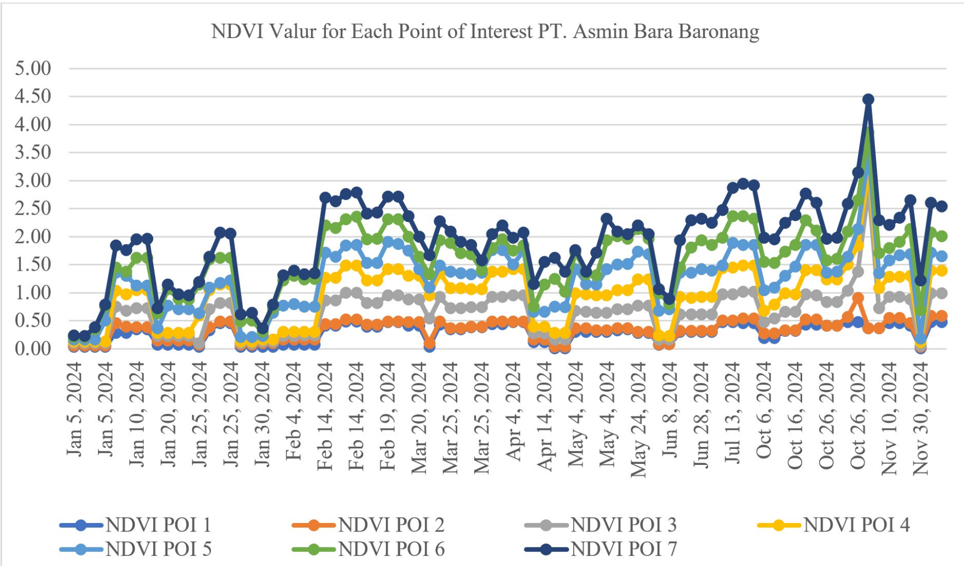

Figure 2. NDVI Analysis for each Point Result PT. Asmin Bara Bronang

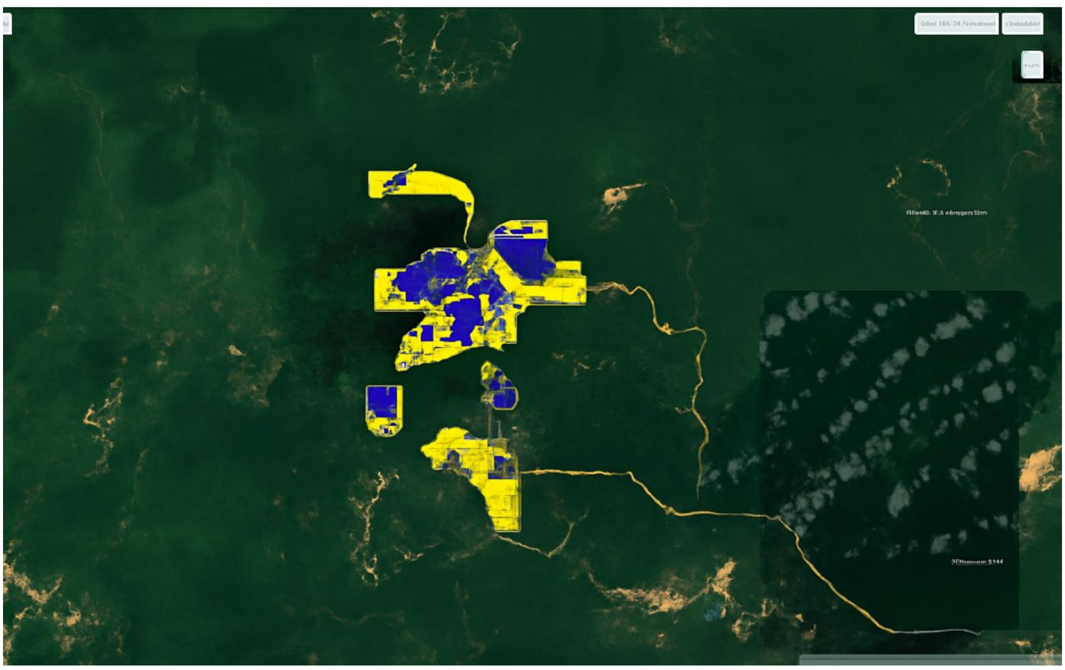

Figure 3. NDVI Spatial Analysis Result PT. Asmin Bara Bronang

1. Site Selection and Coordinate Mapping

Seven monitoring points were selected across the reclamation landscape to represent various land cover conditions and stages of vegetation recovery (Table 1). The criteria for selection include:

A. Spatial representation of all reclamation blocks,
B. Proximity to mining pits, reclamation areas, and buffer zones,
C. Accessibility for field verification.

Table 1. Point of Interest Area Analysis

Point of Analysis NDVI	Longitude	Latitude
Point 1	114.3407917	-0.991675
Point 2	114.3557022	-0.9845984
Point 3	114.3407150	-0.991615
Point 4	114.3407050	-0.991665
Point 5	114.3407500	-0.9918667
Point 6	114.3584517	-0.992740
Point 7	114.3459667	-0.9909637

2. NDVI Time-Series Analysis

The time series charts above illustrate the monthly NDVI values for each observation point from 2019 to 2024. Using cloud-free satellite images from Sentinel-2, NDVI values were calculated and plotted to assess vegetation health over time. NDVI (Normalized Difference Vegetation Index) is a widely used indicator that reflects vegetation vigor and density, with values ranging from:

A. < 0.2: Barren land or no vegetation,
B. 0.2–0.5: Sparse to moderate vegetation (early reclamation),
C. 0.5: Dense vegetation or natural forest.

These charts help visualize the dynamics of vegetation recovery and reclamation success at each point, highlighting fluctuations, stability, or degradation across the studied years.

By analyzing NDVI trends at each point, we can evaluate the vegetation condition and identify the stage of reclamation progress. The Table 2 summarizes key findings for each point based on NDVI trends, vegetation condition, and interpreted reclamation stage.

3. Spatial Visualization with NDVI Overlay Map

A satellite-based NDVI overlay map was produced to visualize vegetative conditions across the study area:

A. Blue areas (NDVI < 0.2): Indicate mining pits, roads, or exposed soil. These are zones with little to no vegetation.
B. Yellow areas (NDVI 0.2–0.5): Indicate reclaimed or regenerating lands with sparse or moderate vegetation.
C. Green background (NDVI > 0.5): Represents dense forest or fully vegetated reclaimed zones.

Overlay analysis confirms:

A. Central zones are still heavily degraded (blue).
B. Southern zones show large reclaimed patches (yellow).
C. Outer zones retain natural vegetation (green), functioning as ecological buffers.

4. Interpretation and Implications

A. Reclamation Effectiveness Evaluation (Table 3)

Table 2. NDVI Trend for each POI

Point	NDVI Trend	Vegetation Condition	Stage of Reclamation
1	Highly fluctuating (0.05–0.7)	Unstable, partially recovering	Early–intermediate
2	Persistently low (<0.2)	Very poor; likely bare soil	Unreclaimed
3	Stable high (0.5–0.8)	Dense and mature	Successful
4	Stable high (0.5–0.8)	Similar to Point 3	Successful
5	Moderate with drops	Some regrowth; minor disturbance	Intermediate
6	Consistent moderate-high (0.4–0.7)	Healthy regrowth	Intermediate–advanced
7	Very stable and high (>0.6)	Possibly natural forest	Reference condition

Table 3. Evaluation POI Reclamation

Category	Points	Implication
Unreclaimed / Severely Degraded	Point 2	Requires urgent reclamation: soil preparation, erosion control, pioneer species planting
Partially Reclaimed / Transitional	Points 1, 5, 6	Ongoing process: needs monitoring, enrichment planting, protection from disturbance
Successfully Reclaimed	Points 3, 4	Can be used as pilot demonstration plots or model units for future reclamation
Reference (Natural Condition)	Point 7	Used as a benchmark for vegetation structure and ecological indicators

B. Landscape Strategy Recommendations:
1. Prioritize restoration in blue zones, especially Point 2.
2. Enhance vegetation diversity in yellow zones through native species enrichment.
3. Monitor and protect green zones (Points 3, 4, 7) as ecological buffers and biodiversity sources.
4. Integrate NDVI and field data for adaptive reclamation planning across landscape units.

5. Analytical Hierarchy Process (AHP) and SWOT Analysis

The Analytical Hierarchy Process (AHP) was used to evaluate and prioritize the restoration strategies based on three main criteria: Environmental Restoration Potential (E), Economic Feasibility (F), and Social Acceptability (S). First, pairwise comparisons were made between these criteria on a scale of 1 to 9, where 1 indicates equal importance and 9 indicates extreme importance. The pairwise comparison matrix was constructed as follows (Table 4):

Table 4. Pairwise comparison matrix

Criteria	E	F	S
Environmental	1	3	2
Economic	1/3	1	1/2
Social	1/2	2	1

Next, each element of the matrix was normalized by dividing it by the sum of the column. This results in the normalized matrix: (Table 5)

Table 5. Normalized matrix

Criteria	E	F	S
Environmental	0.3333	0.500	0.6667
Economic	0.1111	0.3333	0.3333
Social	0.1667	0.6667	0.6667

The next step was to calculate the average of each row to obtain the relative weights for each criterion. The average for each criterion is calculated as:

1. $E = \frac{0.3333+0.500+0.6667}{3} = 0.5000$
2. $F = \frac{0.1111+0.3333+0.3333}{3} = 0.2593$
3. $S = \frac{0.1667+0.6667+0.6667}{3} = 0.5000$

Thus, the final weights for each criterion are:
1. E: 0.5000
2. F: 0.2593
3. S: 0.5000

Additionally, a SWOT analysis was performed to assess the internal and external factors that could impact the restoration strategies. The Strengths include strong community involvement, which can enhance support for restoration efforts, and the availability of remote sensing technologies, which enable accurate monitoring of ecological recovery. Weaknesses identified include poor soil conditions in post-mining areas, which pose significant challenges for vegetation regrowth, and limited infrastructure for monitoring, which may hinder the long-term success and tracking of restoration activities. External Opportunities include the potential for ecotourism development, which could provide economic benefits while supporting conservation efforts, as well as potential funding from government and non-governmental organizations (NGOs) that could help finance the restoration projects. Threats such as illegal land use and climate change are significant risks that could undermine the success of restoration strategies. Illegal land occupation and activities like logging could disrupt efforts, while climate change may affect the environmental conditions necessary for successful rehabilitation.

The AHP results helped prioritize the restoration criteria, with Environmental Restoration Potential and Social Acceptability taking precedence. The SWOT analysis identified key strengths and opportunities, such as community involvement and funding potential, while also acknowledging the weaknesses, such as soil degradation and external threats from illegal land use and climate change. Together, these analyses provide a comprehensive framework for post-mining restoration, ensuring that the strategies are not only ecologically effective and socially supported but also economically feasible.

4. Conclusions

The study highlights the importance of spatially optimized conservation models in post-mining landscapes, particularly in fragmented forest areas impacted by open-pit coal mining. By integrating remote sensing, GIS, and real-time field data, the research identifies key ecological degradation areas and proposes targeted restoration strategies. The results revealed varying levels of vegetation recovery across different monitoring points, with NDVI trends showing areas of successful reclamation, such as Points 3 and 4, where vegetation achieved stable high NDVI values (>0.5), indicating dense and mature regrowth. Conversely, areas like Point 2, with persistently low NDVI values (<0.2), highlighted severely degraded regions in need of urgent reclamation. The AHP analysis found that environmental restoration potential (0.5000) and social acceptability (0.5000) were the most significant factors in determining restoration strategy priorities, emphasizing the need for a balanced approach that incorporates both ecological health and community involvement. The findings also stress the importance of tailoring interventions based on specific land conditions and integrating local communities into the reclamation process to ensure long-term sustainability.

Future research should focus on expanding the sample size and extending the monitoring duration to improve the precision of spatial models and evaluate the long-term success of restoration efforts. Continuous assessments of vegetation dynamics and soil conditions will be essential for tracking the effectiveness of different restoration strategies. Further investigation into the socio-economic impacts of conservation programs will provide insights into how best to involve local communities, ensuring their participation and support for sustainable land rehabilitation. Future studies should also consider the integration of climate change projections into spatial conservation models, enhancing their resilience and predicting future ecological shifts. Finally, exploring economic alternatives such as ecotourism or carbon credit programs could create sustainable income sources for local communities, aligning socio-economic development with environmental conservation goals.

Acknowledgements

The authors would like to express their sincere gratitude to all those who contributed to the success of this research. Special thanks to the faculty members of Lambung Mangkurat University and Palangkaraya University for their valuable insights and support. We also acknowledge the assistance of local communities for their participation in field data collection and their continuous cooperation throughout the study. Our gratitude extends to the technical team involved in satellite imagery analysis and the real-time environmental monitoring process. This study was made possible by the support of PT. Asmin Bara Bronang, whose mining site provided the case study for this research. Finally, we are grateful for the constructive feedback from the anonymous reviewers, which greatly enhanced the quality of this paper.

REFERENCES

[1] G. Luo, J. Zhang, Y. Rao, X. Zhu, and Y. Guo, "Coal Supply Chains: A Whole-Process-Based Measurement of Carbon Emissions in a Mining City of China," Energies, vol. 10, no. 11, pp. 11855, 2017. DOI: https://doi.org/10.3390/en10111855.

[2] S. Kuzevic, D. Bobikova, and Ž. Kuzevičová, "Land Cover and Vegetation Coverage Changes in the Mining Area—A Case Study from Slovakia," Sustainability, vol. 14, no. 3, pp. 1180, 2022. DOI: https://doi.org/10.3390/su14031180.

[3] R. M. Nisaa' and N. I. Fawzi, "Open-Pit Coal Mining Exacerbates Urban Heat Island in Bontang City, Indonesia," IOP Conference Series: Earth and Environmental Science, vol. 1190, no. 1, pp. 012039, 2023. DOI: https://doi.org/10.1088/1755-1315/1190/1/012039

[4] . Cao, Z. Deng, W. Li, and Y. Hu, "Remote Sensing Inversion and Spatial Variation of Land Surface Temperature Over Mining Areas of Jixi, Heilongjiang, China," PeerJ, vol. 8, p. e10257, 2020. DOI: https://doi.org/10.7717/peerj.10257.

[5] L. Liu et al., "The Grassland Carbon Cycle: Mechanisms, Responses to Global Changes, and Potential Contribution to Carbon Neutrality," Fundamental Research, vol. 3, no. 2, pp. 209–218, 2023. DOI: https://doi.org/10.1016/j.fmre.2022.09.028.

[6] Y. Liu, W. Ma, H. Yue, and H. Zhao, "Dynamic Soil Moisture Monitoring in Shendong Mining Area Using Temperature Vegetation Dryness Index," in 2011 International Conference on Remote Sensing, Environment and Transportation Engineering, 2011, pp. 5892–5895. DOI: https://doi.org/10.1109/RSETE.2011.5965695.

[7] C. Xu and Y. Zhang, "Impacts of Urban Surface Characteristics on Spatiotemporal Pattern of Land Surface Temperature in Kunming of China," Sustainable Cities and Society, vol. 31, pp. 117–130, 2017. DOI: https://doi.org/10.1016/j.scs.2017.03.013.

[8] G. Chen, M. Wang, Z. Liu, and W. Chi, "The Biogeophysical Effects of Revegetation Around Mining Areas: A Case Study of Dongsheng Mining Areas in Inner Mongolia," Sustainability, vol. 9, no. 4, pp. 0628, 2017. DOI: https://doi.org/10.3390/su9040628.

[9] L. Wu, T. Kato, H. Sato, T. Hirano, and T. Yazaki, "Sensitivity analysis of the typhoon disturbance effect on forest dynamics and carbon balance in the future in a cool-temperate forest in northern Japan by using SEIB-DGVM," *For. Ecol. Manage.*, vol. 451, p. 117-529, 2019. DOI: https://doi.org/10.1016/J.FORECO.2019.117529.

[10] P. Wrona, J. Sułkowski, Z. Różański, and G. Pach, "The Problem of Carbon Dioxide Emissions from Closed Coal Mine Shafts – The Overview and the Case Study," Archives of Mining Sciences, vol. 61, no. 3, pp. 587–600, 2016. DOI: https://doi.org/10.1515/amsc-2016-0042.

[11] E. Díaz, J. Fernández, S. Ordóñez, N. Canto, and A. González, "Carbon and ecological footprints as tools for evaluating the environmental impact of coal mine ventilation air," *Ecol. Indic.*, vol. 18, pp. 126–130, 2012. DOI: https://doi.org/10.1016/j.ecolind.2011.11.009.

[12] K. Przeździecki, J. Zawadzki, and Z. Miatkowski, "Use of the Temperature–Vegetation Dryness Index for Remote Sensing Grassland Moisture Conditions in the Vicinity of a Lignite Open-Cast Mine," Environmental Earth Sciences, vol. 77, no. 17, p. 623, 2018. DOI: https://doi.org/10.1007/s12665-018-7815-6.

[13] C. Bellard, C. Bertelsmeier, P. Leadley, W. Thuiller, and F. Courchamp, "Impacts of climate change on the future of biodiversity," *Ecol. Lett.*, vol. 15, no. 4, pp. 365–377, Apr. 2012. DOI: https://doi.org/10.1111/j.1461-0248.2011.01736.x.

[14] H. Akbari and S. Kalbi, "Determining Pleiades Satellite Data Capability for Tree Diversity Modeling," iForest - Biogeosciences Forestry, vol. 10, no. 1, pp. 348–352, 2017. DOI: https://doi.org/10.3832/ifor1884-009.

[15] Q. Guo, X. Xi, S. Yang, and M. Cai, "Technology Strategies to Achieve Carbon Peak and Carbon Neutrality for China's Metal Mines," International Journal of Mineral

Metallurgy and Materials, vol. 29, no. 4, pp. 626–634, 2022. DOI: https://doi.org/10.1007/s12613-021-2374-3.

[16] J. Xue and J. Yan, "Deducing Leading Factors of Spatial Distribution of Carbon Reserves in Nanjing Metropolitan Area Based on Random Forest Model," Computational Intelligence and Neuroscience, vol. 2022, p. 3013620, 2022. DOI: https://doi.org/10.1155/2022/3013620.

[17] W. Shou-gang, J. Huang, H. Yu, and C. Ji, "Recognition of Landscape Key Areas in a Coal Mine Area of a Semi-Arid Steppe in China: A Case Study of Yimin Open-Pit Coal Mine," Sustainability, vol. 12, no. 6, pp. 2239, 2020. DOI: https://doi.org/10.3390/su12062239.

[18] E. Badewa, A. Unc, M. Cheema, V. Kavanagh, and L. Galagedara, "Soil Moisture Mapping Using Multi-Frequency and Multi-Coil Electromagnetic Induction Sensors on Managed Podzols," Agronomy, vol. 8, no. 10, p. 224, 2018. DOI: https://doi.org/10.3390/agronomy8100224.

[19] I. Sandholt, K. Rasmussen, and J. Andersen, “A simple interpretation of the surface temperature/vegetation index space for assessment of surface moisture status,” *Remote Sens. Environ.*, vol. 79, no. 2, pp. 213–224, 2002, doi: https://doi.org/10.1016/S0034-4257(01)00274-7.

[20] G. Kaplan, U. Avdan, and Z. Y. Avdan, "Urban Heat Island Analysis Using the Landsat 8 Satellite Data: A Case Study in Skopje, Macedonia," European Conference on Remote Sensing, 2018. DOI: https://doi.org/10.3390/ecrs-2-05171.

[21] Q. Liu *et al.*, “Vegetation dynamics under water-level fluctuations: Implications for wetland restoration,” *J. Hydrol.*, vol. 581, p. 124418, 2020. DOI: https://doi.org/10.1016/j.jhydrol.2019.124418.

[22] M. Sharma, P. Bangotra, A. S. Gautam, and S. Gautam, "Sensitivity of Normalized Difference Vegetation Index (NDVI) to Land Surface Temperature, Soil Moisture and Precipitation Over District Gautam Buddh Nagar, UP, India," Stochastic Environmental Research and Risk Assessment, 2021. DOI:https://doi.org/10.1007/s00477-021-02066-1.

[23] D. Sun and M. Kafatos, “Note on the NDVI-LST relationship and the use of temperature-related drought indices over North America,” *Geophys. Res. Lett.*, vol. 34, no. 24, 2007, doi: https://doi.org/10.1029/2007GL031485.

[24] P Pan Jia-wen, "Study on the Correlation Between Temperature Vegetation Dryness Index (TVDI) and Various Factors," Geography and Geo-Information Science, 2010. DOI: https://doi.org/10.1016/j.jece.2021.105796.

[25] D. Maroni *et al.*, “Land surface temperature and vegetation index as a proxy to microclimate,” *J. Environ. Chem. Eng.*, vol. 9, no. 4, p. 105796, 2021. DOI: https://doi.org/10.1016/j.jece.2021.105796.