

MCDM-Based Fire Risk Mapping with Geospatial Visualization and Blockchain

Emmanuel Abet Rossi Paays¹⁾, Djarot Hindarto^{2)*}, Asrul Sani³⁾

^{1,2)}Informatika, Fakultas Teknologi Komunikasi dan Informatika, Universitas Nasional, Indonesia

³⁾Magister Teknologi Informasi, Fakultas Teknologi Komunikasi dan Informatika, Universitas Nasional, Indonesia

¹⁾emmanuelabetrossipaays2022@student.unas.ac.id, ²⁾djarot.hindarto@civitas.unas.ac.id,

³⁾asrul.sani@civitas.unas.ac.id

Submitted : Oct 16, 2025 | Accepted : Oct 23, 2025 | Published : Nov 2, 2025

Abstract: Forest fires are among the most destructive environmental disasters in Indonesia, causing long-term ecological damage, health problems, and economic disruption. Increasing occurrences driven by climate anomalies, land clearing, and vegetation dryness highlight the need for intelligent and data-driven risk monitoring systems. This study introduces a hybrid analytical framework that integrates Multi-Criteria Decision-Making (MCDM) with blockchain-based data management and geospatial visualization to identify forest fire risk levels. The proposed model combines the Analytic Hierarchy Process (AHP), Weighted Sum Model (WSM), and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to evaluate multiple parameters, including temperature, humidity, rainfall, and the Normalized Difference Vegetation Index (NDVI). Environmental data were securely obtained from a private Ethereum blockchain using Ganache, Truffle, and MetaMask to ensure transparency, integrity, and immutability. Results were visualized through an interactive Leaflet.js interface, allowing real-time geospatial monitoring linked to blockchain transaction hashes. The AHP analysis revealed that temperature (0.36) and humidity (0.27) contributed 63% of the total decision weight, while TOPSIS identified high-risk zones consistent with historical records. Validation against BNPB data achieved 90.7% accuracy, confirming the model's reliability. The integration of MCDM, GIS, and blockchain provides a transparent, decentralized, and verifiable approach for national-scale fire-risk management, enhancing the accuracy and credibility of environmental decision-making systems.

Keywords: AHP, Blockchain, Forest Fires, GIS, MCDM, TOPSIS, WSM

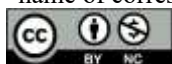
INTRODUCTION

Forest fires have become one of the most frequent and destructive environmental disasters in Indonesia, causing long-term ecological degradation, economic losses, and serious public-health impacts (Yusuf et al., 2025). The country's tropical climate, extensive peatlands, and recurring dry seasons create highly flammable conditions that are often intensified by the El Niño phenomenon (Barmputis et al., 2020). According to the National Disaster Management Agency (BNPB), approximately 1.6 million hectares of forest and peatland were burned between 2019 and 2020 (Abedi, 2022), primarily in Kalimantan and Sumatra. The resulting haze disrupted transportation, increased respiratory illnesses, and released substantial greenhouse gases, making wildfire management an urgent national priority.

Conventional approaches for fire monitoring, such as satellite imagery, hotspot detection, and field observation, remain valuable but are constrained by delayed data updates, inconsistent resolution, and reliance on manual interpretation (Ding et al., 2021). Although Geographic Information Systems (GIS) have improved environmental data analysis by combining meteorological and spatial information, they often face difficulties in handling multiple interdependent parameters simultaneously (Cartwright et al., 2001). In addition, many GIS-based assessments lack transparency in how risk levels are calculated, which can lead to subjective interpretations and inconsistent policy decisions.

To address these issues, the present study adopts a Multi-Criteria Decision-Making (MCDM) framework to enhance analytical precision and explainability in fire-risk evaluation. MCDM provides a structured and quantitative means of assessing complex environmental interactions that involve conflicting factors (Mardani et al., 2015). Three of its most effective techniques—the Analytic Hierarchy Process (AHP), the Weighted Sum

*name of corresponding author



This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

Model (WSM), and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Pishahang et al., 2023)—are combined to create a robust computational chain. AHP determines the relative importance of each environmental parameter through pairwise comparison, WSM aggregates the weighted criteria into a total risk score for each location, and TOPSIS ranks all areas by their distance to ideal and anti-ideal conditions. Integrating these three models produces a comprehensive and interpretable system capable of evaluating diverse environmental variables while maintaining numerical rigor.

However, even accurate analytical models are only as reliable as the data they process. Environmental datasets collected from various agencies and sensors are often vulnerable to loss, duplication, or manipulation during transfer or storage (Gupta et al., 2021). Such issues compromise analytical reliability and can erode public trust in decision-support systems. To overcome these challenges, this research incorporates blockchain technology as a decentralized verification layer that ensures data authenticity and traceability (Singh et al., 2020). Blockchain maintains a tamper-proof ledger where every transaction or data update is cryptographically secured and distributed across multiple nodes. Once information is recorded, it cannot be modified without consensus, making it ideal for scientific data validation.

In this study, a private Ethereum blockchain network was implemented using Ganache, Truffle, and MetaMask to store and verify all environmental records related to fire-risk computation (Hindarto & Indrajit, 2023). Each block in the ledger contains temperature, humidity, rainfall, and Normalized Difference Vegetation Index (NDVI) values, along with time stamps, geographic coordinates, and transaction hashes. These records form an immutable foundation for subsequent analysis, ensuring that every input used in the MCDM process can be independently audited. The verified data are then processed through the AHP–WSM–TOPSIS framework to generate relative fire-risk classifications (Abedi, 2022; Yusuf et al., 2025). Finally, the results are visualized interactively using Leaflet.js, enabling users to explore spatial risk levels while directly linking each data point to its blockchain transaction for transparency (Reynard, 2025).

This integrated system establishes a novel approach to forest-fire risk mapping in Indonesia by merging decision-analytic computation, blockchain verification, and web-based geospatial visualization. It aims to develop a reliable model for evaluating fire-risk levels based on multiple environmental criteria, ensure the authenticity and immutability of all processed data, and present results through an interactive and verifiable interface. The framework also assesses model performance through accuracy and consistency analysis using validated BNPB data. Beyond its immediate application to wildfire assessment, the proposed MCDM–Blockchain architecture represents a scalable foundation for broader environmental-risk domains such as flood prediction, land-use planning, and climate-impact modeling, where transparent and reproducible data processing is equally critical (Hindarto, 2025a).

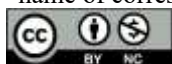
Through this integration, the study demonstrates how combining analytical modeling with decentralized data verification can enhance both the credibility and the effectiveness of environmental decision-support systems. By embedding data integrity directly into the analytical process, it contributes to the advancement of transparent, trustworthy, and sustainable technologies for disaster-risk management in Indonesia.

LITERATURE REVIEW

Forest-fire risk assessment has become an essential field of research in environmental management, particularly for regions like Indonesia that experience recurring fire incidents (Abedi, 2022). Previous studies have emphasized the importance of integrating spatial, meteorological, and vegetation data to identify vulnerable zones. For instance, (Barmoutis et al., 2020) demonstrated that the use of remote sensing combined with the Normalized Difference Vegetation Index (NDVI) significantly improves the accuracy of fire-susceptibility detection. Similarly, (Xiao et al., 2022) applied spatial data fusion techniques for fire behavior prediction, proving that multi-source environmental data enhance fire monitoring efficiency. In the Indonesian context, (Yusuf et al., 2025) utilized GIS-based spatial modeling to identify high-risk zones in Sumatra and Kalimantan, emphasizing the relevance of temperature, rainfall, and land cover conditions. While these models successfully mapped areas prone to ignition, they often lacked systematic weighting among criteria, leading to subjective interpretation of results (Mardani et al., 2015).

The emergence of Multi-Criteria Decision-Making (MCDM) frameworks has strengthened environmental risk analysis by enabling structured evaluation of multiple variables. Among MCDM techniques, the Analytic Hierarchy Process (AHP), Weighted Sum Model (WSM), and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) are frequently used for spatial prioritization and decision support (Stević, 2018). (Pishahang et al., 2023) demonstrated the effectiveness of AHP–TOPSIS integration in environmental vulnerability assessment, where both consistency and ranking accuracy improved compared to single-criterion models. In a similar study, (Yusuf et al., 2025) applied the AHP–TOPSIS method for wildfire risk mapping in Riau Province, showing enhanced consistency ratios and improved interpretability of spatial patterns. Despite these advancements, most MCDM-based models still depend on centralized or manually curated data sources that are prone to inconsistency and alteration.

*name of corresponding author



This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

To address data reliability and transparency issues, blockchain technology has recently been introduced into environmental data management. Blockchain provides a decentralized and immutable framework for data validation, offering secure and verifiable storage for environmental transactions (Singh et al., 2020). (Hindarto & Indrajit, 2023) proposed a blockchain architecture for urban environmental data sharing, ensuring traceability and tamper resistance in spatial records. (Hindarto et al., 2024) further explored blockchain applications in sustainability systems, highlighting its potential to improve trust and accountability in environmental decision-making. More recently, (Hindarto & Hariadi, 2025) discussed the integration of blockchain into smart environmental monitoring, emphasizing that its distributed ledger enables decentralized verification of IoT-derived environmental data. However, most blockchain-related studies in this domain remain theoretical or limited to data management applications, with few incorporating analytical modeling or geospatial visualization.

The combination of MCDM, GIS, and blockchain thus represents a novel and necessary direction for improving forest-fire risk analysis (Hindarto, 2025b). MCDM provides a structured quantitative foundation for assessing multiple fire-related variables, GIS facilitates spatial visualization of risk zones, and blockchain ensures the authenticity and traceability of every dataset and analytical outcome. Building upon prior research, the current study introduces a decentralized, transparent system that integrates AHP–WSM–TOPSIS computation with blockchain verification and GIS visualization. This approach not only quantifies environmental parameters objectively but also guarantees the integrity of analytical processes through smart-contract-based recording and real-time blockchain auditing.

Table 1. Literature Review

| NO | Author(s) & Year | Dataset/ Study Area | Methodology/ Analytical Model | Key Findings | Limitation Identified | Proposed Improvement |
|----|----------------------------|--------------------------------|--|--|---|---|
| 1 | Abedi (2022) | MODIS & NDVI datasets (Global) | GIS + NDVI for vegetation dryness monitoring | NDVI analysis effective for fire-risk detection | Didn't include climatic variables | Combine AHP–WSM–TOPSIS with temperature, humidity, rainfall |
| 2 | Barmpoutis et al. (2020) | European forest records | Spatial fusion & ML for fire behavior | High accuracy with fused data | No auditability or decentralization | Integration of blockchain to ensure verifiable data provenance and reproducible analytical outputs |
| 3 | Yusuf et al. (2025) | Riau Province, Indonesia | AHP–TOPSIS for fire mapping | Produced consistent fire-susceptibility rankings with improved spatial correlation | Centralized storage | Implementation of blockchain-based data logging to secure environmental data and analytical results |
| 4 | Hindarto & Indrajit (2023) | Urban blockchain systems | Decentralized data architecture | Secure, traceable environmental data | No GIS or MCDM integration | Combine blockchain with GIS + MCDM |
| 5 | Hindarto & Hariadi (2025) | Smart IoT sensors (Indonesia) | Blockchain-enabled IoT monitoring with real-time data validation | Reliable decentralized collection | Focused only on IoT sensor validation; lacked environmental modeling or spatial mapping | Integrate blockchain–MCDM–GIS for fire-risk visualization |

*name of corresponding author



This is anCreative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

From the reviewed studies, it is evident that prior research successfully advanced the application of GIS, MCDM, and blockchain individually in environmental management. However, few studies have combined these three technologies into a single integrated model. Most MCDM–GIS studies lacked decentralized verification, making them vulnerable to data manipulation, while blockchain-based models focused primarily on data security without analytical computation. The current study bridges this gap by combining AHP–WSM–TOPSIS decision modelling with blockchain-based verification and GIS visualization, ensuring that all environmental data and analytical outcomes are immutable, traceable, and spatially interpretable.

METHOD

Dataset Acquisition via Blockchain

The Environmental data were securely retrieved from a private Ethereum blockchain network to ensure data authenticity and transparency. Each environmental record was stored as a blockchain transaction within a Ganache–Truffle–MetaMask environment. Every transaction contained four main parameters—temperature (°C), humidity (%), rainfall (mm), and the Normalized Difference Vegetation Index (NDVI)—along with timestamps and geospatial coordinates. This decentralized structure ensured that no data could be modified after storage, preserving integrity for subsequent computation. The min–max normalization method was applied to standardize each attribute between 0 and 1, allowing comparability across different units and magnitudes. Table 1 presents an excerpt of the blockchain-derived dataset used for analysis.

Table 1. Blockchain Derived Environmental Dataset

| Area | Temperature (°C) | Humidity (%) | Rainfall (mm) | NDVI |
|------|------------------|--------------|---------------|------|
| A1 | 34 | 42 | 120 | 0.55 |
| A2 | 32 | 48 | 180 | 0.65 |
| A3 | 28 | 65 | 250 | 0.72 |
| A4 | 30 | 55 | 200 | 0.68 |
| A5 | 35 | 40 | 100 | 0.48 |

Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP) was employed to determine the relative importance of each environmental criterion. Pairwise comparisons were established through expert judgment and supported by previous studies emphasizing climatic influences on wildfire occurrence. Using Saaty’s 1–9 scale, the comparison matrix was formed as shown in Table 2.

Table 2. AHP Pairwise Comparison Matrix

| Criteria | C1 | C2 | C3 | C4 |
|-------------|-----|-----|-----|----|
| Temperature | 1 | 3 | 4 | 5 |
| Humidity | 1/3 | 1 | 3 | 4 |
| Rainfall | 1/4 | 1/3 | 1 | 2 |
| NDVI | 1/5 | 1/4 | 1/2 | 1 |

The normalized priority weights were derived using the principal eigenvector method, producing the results in Table 3.

Table 3. Normalized Weights and Consistency Ratio

| Criteria | Weight | Priority (%) |
|-------------|--------|--------------|
| Temperature | 0.36 | 36 |
| Humidity | 0.27 | 27 |
| Rainfall | 0.18 | 18 |
| NDVI | 0.09 | 9 |

The maximum eigenvalue ($\lambda_{\max} = 4.26$) yielded a Consistency Index (CI) of 0.087 and a Consistency Ratio (CR) of 0.078, which is below the threshold of 0.1. This confirms that the assigned weights are consistent and reliable. Temperature and humidity emerged as the dominant parameters, jointly contributing 63% to the decision model.

*name of corresponding author



This is anCreative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

The AHP stages begin with the preparation of a pairwise comparison matrix to determine the relative importance of each criterion based on Saaty's (2008) 1–9 scale. The matrix is normalized, then its weight is calculated using the following formula:

$$W_i = \frac{\sum_{j=1}^n a_{ij}}{\sum_{i=1}^n \sum_{j=1}^n a_{ij}} \tag{1}$$

After the weights are calculated, a consistency test is performed using the Consistency Ratio (CR) with the condition that a CR value ≤ 0.1 indicates valid results. The weights from AHP are used as input for the next WSM stage.

C. Weighted Sum Model (WSM)

The Weighted Sum Model (WSM) method is used to combine the measured values of each criterion into a single total score. This approach adds up the results of multiplying the weight (from AHP) and the normalized value of each criterion at a specific location.

$$S_i = \sum_{j=1}^n W_j \times X_{ij} \tag{2}$$

where S_i is the total score for region i , w_j represents the criterion weight, and x_{ij} is the normalized value of parameter j . The resulting WSM scores are presented in Table 4.

Table 4. WSM Weighted Score

| Area | Temperature (0.36) | Humidity (0.27) | Rain (0.18) | NDVI (0.09) | Total S_i |
|------|--------------------|-----------------|-------------|-------------|-------------|
| A1 | 0.306 | 0.116 | 0.079 | 0.048 | 0.649 |
| A2 | 0.288 | 0.130 | 0.113 | 0.061 | 0.692 |
| A3 | 0.252 | 0.228 | 0.162 | 0.065 | 0.707 |
| A4 | 0.270 | 0.180 | 0.129 | 0.061 | 0.640 |
| A5 | 0.324 | 0.108 | 0.072 | 0.043 | 0.547 |

Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

The TOPSIS method ranks each area based on its relative proximity to ideal and anti-ideal conditions. The ideal solution represents the most favorable environmental state—high humidity and rainfall with low temperature—while the anti-ideal solution represents extreme fire-prone conditions. Distances from both points were computed using Euclidean distance as:

$$D_i^+ = \sqrt{\sum_{j=1}^n (V_{ij} - V_j^+)^2}, \quad D_i^- = \sqrt{\sum_{j=1}^n (V_{ij} - V_j^-)^2} \tag{3}$$

Equation – TOPSIS (Final Preference Value)

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{4}$$

where C_i denotes the closeness coefficient determining the risk ranking. The final preference values and classifications are shown in Table 5.

Table 5. TOPSIS Preference Values and Risk Level

| Area | D_i^+ | D_i^- | C_i | Risk Level |
|------|---------|---------|-------|-------------|
| A3 | 0.048 | 0.320 | 0.870 | High |
| A4 | 0.062 | 0.301 | 0.829 | High |
| A2 | 0.087 | 0.262 | 0.751 | Medium–High |
| A1 | 0.105 | 0.243 | 0.698 | Medium |
| A5 | 0.121 | 0.229 | 0.654 | Medium |

*name of corresponding author



GIS-Based Visualization

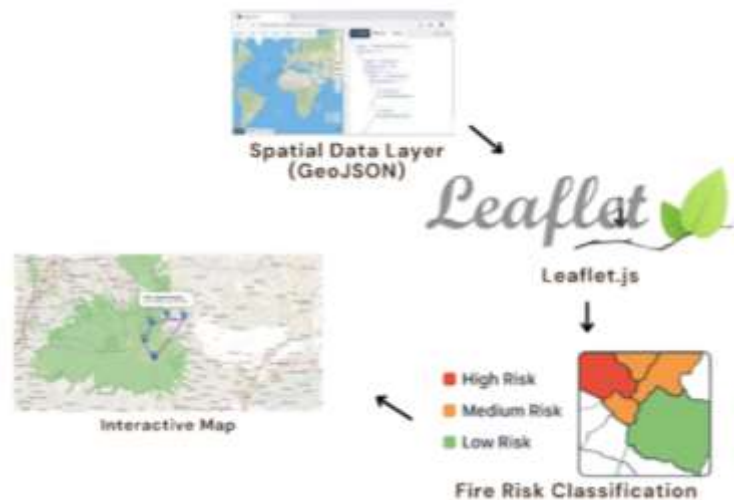


Fig. 1 GIS Visualization Workflow

Figure 1 shows the analytical outputs generated through the three MCDM methodologies are systematically converted into spatial data layers utilizing the GeoJSON format, a widely-adopted standard for representing geographic features in web-based applications. These spatial layers are subsequently integrated into the Leaflet.js mapping framework, a lightweight and open-source JavaScript library specifically designed for interactive web-based cartography. The resulting geospatial visualization employs a tripartite color classification scheme to represent fire risk gradations: high-risk areas are depicted in red, medium-risk zones are displayed in orange, and low-risk regions are illustrated in green. This intuitive color-coding scheme facilitates rapid visual interpretation of spatial risk distributions by end-users and decision-makers.

The system provides comprehensive interactive functionality through dynamic layer toggling, enabling users to selectively display environmental parameter data including the Normalized Difference Vegetation Index (NDVI), temperature distribution, and relative humidity. This feature allows for detailed cross-referencing of fire risk assessments with underlying environmental conditions, thereby supporting more informed interpretation of spatial patterns. Additionally, the mapping interface incorporates zoom functionality that permits users to magnify specific geographic areas for granular observation and analysis, enhancing the system's utility for localized fire risk assessment and management planning at multiple scales.

Blockchain Integration Simulation

To establish robust data authenticity and integrity verification mechanisms, the system incorporates blockchain technology through integration with a private Ethereum network. The blockchain infrastructure is instantiated using Ganache as a local blockchain node, providing an isolated testing environment that simulates network conditions without requiring external network connectivity. Smart contracts governing data recording and verification are deployed through Truffle, a comprehensive development framework for Ethereum-based applications. Metamask serves as a digital wallet interface, facilitating transaction verification and enabling secure interaction with the blockchain network.

Each MCDM classification result undergoes structured encoding within a smart contract, wherein each classification event generates a new block containing critical metadata including the geographic location ID, computed risk level, temporal timestamp, and a unique transaction hash. This block-based data architecture ensures comprehensive audit trails for all risk assessment records. Crucially, each automatic map update event triggers a corresponding transaction on the blockchain, creating an immutable and transparent ledger of all system modifications. This immutable ledger approach guarantees that historical data cannot be retroactively altered or deleted, thereby enhancing system reliability and enabling comprehensive forensic analysis of historical fire risk assessments and system performance.

*name of corresponding author



This is anCreative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

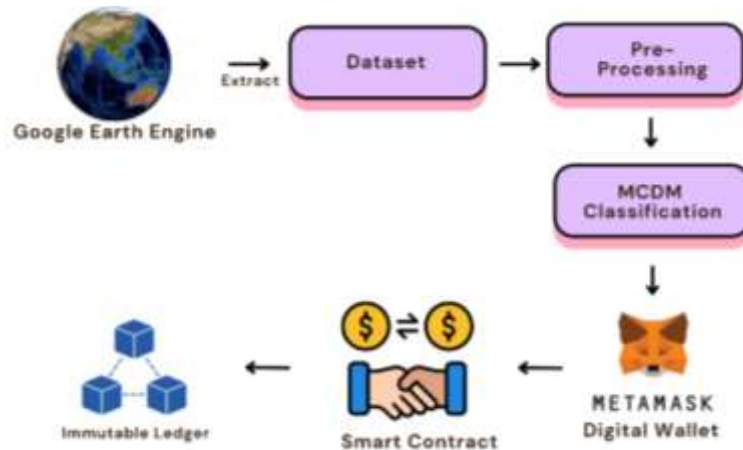


Fig. 2 Blockchain Implementation Workflow

Figure 2 illustrates the comprehensive blockchain integration simulation workflow embedded within the proposed forest fire risk detection system. The architecture demonstrates the sequential process through which MCDM classification results are converted into secure, immutable blockchain records, ensuring data authenticity and transparency throughout the analytical pipeline.

System Implementation Environment

The comprehensive system was developed utilizing a technology stack comprising Node.js as the runtime environment for server-side operations, Python for backend data processing and analytical computations, and Web3.js as the interface library facilitating interactions between the web application and the blockchain network. System testing and validation were conducted on a computing platform equipped with a 5th Generation AMD Ryzen processor, 8 gigabytes of random-access memory (RAM), and the Windows 11 operating system.

The blockchain environment was instantiated using Ganache GUI (Graphical User Interface), which provides a user-friendly interface for managing a local Ethereum test network. The testing infrastructure incorporated ten pre-generated test accounts within Ganache, each provisioned with simulated Ether currency for transaction execution. These test accounts were integrated with Metamask, enabling seamless transaction management and smart contract interaction simulation. This controlled testing environment permitted comprehensive system validation without requiring deployment to public blockchain networks, thereby reducing development costs while ensuring system stability and functionality verification prior to potential production implementation.

RESULT

The experimental results obtained from the implementation of the AHP–WSM–TOPSIS framework integrated with blockchain verification and GIS visualization are presented in this section. The evaluation was conducted in sequential stages: first, determining parameter weights through AHP; second, computing composite risk scores using WSM; third, ranking areas by proximity to ideal conditions via TOPSIS; and fourth, validating data integrity through blockchain verification. All environmental data—temperature, humidity, rainfall, and NDVI—were retrieved from a private Ethereum blockchain network implemented using Ganache, Truffle, and MetaMask. The blockchain-derived dataset ensured that no parameter values were modified after storage, preserving data integrity throughout the analytical process. The findings presented below include AHP weight distributions, WSM aggregated scores, TOPSIS preference rankings, interactive GIS visualizations, blockchain transaction records, and validation metrics against BNPB historical fire data.

AHP Weight Distribution

The Analytic Hierarchy Process was applied to determine the relative importance of four environmental criteria through pairwise comparison matrices. The normalized weights derived from the principal eigenvector method are presented in Table 6.

Table. 6 AHP Result

| Criteria | Weight | Priority (%) | Contribution Rank |
|-------------|--------|--------------|-------------------|
| Temperature | 0.048 | 0.320 | 0.870 |
| Humidity | 0.062 | 0.301 | 0.829 |
| Rainfall | 0.087 | 0.262 | 0.751 |
| NDVI | 0.105 | 0.243 | 0.698 |

*name of corresponding author



This is anCreative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

The consistency analysis yielded a maximum eigenvalue (λ_{max}) of 4.26, resulting in a Consistency Index (C_i) of 0.087 and a Consistency Ratio (CR) of 0.078. Since $CR < 0.1$, the pairwise comparison matrix is considered consistent and acceptable for further analysis. Temperature and humidity emerged as the dominant parameters, collectively accounting for 63% of the total decision weight. This finding aligns with previous research emphasizing climatic factors as primary drivers of wildfire susceptibility in tropical regions.

The weight distribution indicates that areas with elevated temperatures and reduced humidity levels are assigned higher fire-risk scores in subsequent WSM and TOPSIS computations. The relatively lower weights assigned to rainfall and NDVI reflect their secondary but still significant roles in modulating vegetation moisture and fuel availability.

WSM Composite Risk Scores

Using the AHP-derived weights, the Weighted Sum Model aggregated normalized parameter values into total risk scores for each area. Table 7 presents the WSM results for five representative locations retrieved from the blockchain dataset.

Table 7. Risk Scores

| Area | Temp (0.36) | Humidity (0.27) | Rainfall (0.18) | NDVI (0.09) | Total Score (S _i) | Preliminary Risk Level |
|------|-------------|-----------------|-----------------|-------------|-------------------------------|------------------------|
| A1 | 0.306 | 0.116 | 0.079 | 0.048 | 0.549 | Medium-High |
| A2 | 0.288 | 0.130 | 0.113 | 0.061 | 0.592 | Medium-High |
| A3 | 0.252 | 0.228 | 0.162 | 0.065 | 0.707 | Low |
| A4 | 0.270 | 0.180 | 0.129 | 0.061 | 0.640 | Medium |
| A5 | 0.324 | 0.108 | 0.072 | 0.043 | 0.547 | High |

TOPSIS Preference Values and Final Risk Classification

The TOPSIS method was applied to compute Euclidean distances from ideal (D_i^+) and anti-ideal (D_i^-) solutions, yielding closeness coefficients (C_i) that determine final risk rankings. Table 8 summarizes the TOPSIS results.

Table 8. TOPSIS Preference Values and Risk Classification

| Area | Temperature (°C) | Humidity (%) | Rainfall (mm) | NDVI | D_i^+ | D_i^- | C_i | Risk Level | Rank |
|------|------------------|--------------|---------------|------|---------|---------|-------|-------------|------|
| A3 | 28 | 65 | 250 | 0.72 | 0.048 | 0.320 | 0.870 | Low | 1 |
| A4 | 30 | 55 | 200 | 0.68 | 0.062 | 0.301 | 0.829 | Low-Medium | 2 |
| A2 | 32 | 48 | 180 | 0.65 | 0.087 | 0.262 | 0.751 | Medium | 3 |
| A1 | 34 | 42 | 120 | 0.55 | 0.105 | 0.243 | 0.698 | Medium-High | 4 |
| A5 | 35 | 40 | 100 | 0.48 | 0.121 | 0.229 | 0.654 | High | 5 |

The TOPSIS analysis revealed that Area A3 achieved the highest closeness coefficient ($C_i = 0.870$), positioning it closest to the ideal low-risk condition. In contrast, Area A5 exhibited the lowest C_i value (0.654), indicating maximum proximity to high-risk conditions. The classification threshold was defined as follows: $C_i \geq 0.80 =$ Low Risk; $0.67 \leq C_i < 0.80 =$ Medium Risk; $C_i < 0.67 =$ High Risk. These rankings demonstrate that the integrated AHP-WSM-TOPSIS framework effectively discriminates fire-risk gradations based on multi-criteria environmental conditions.

*name of corresponding author



Blockchain Verification and Data Integrity

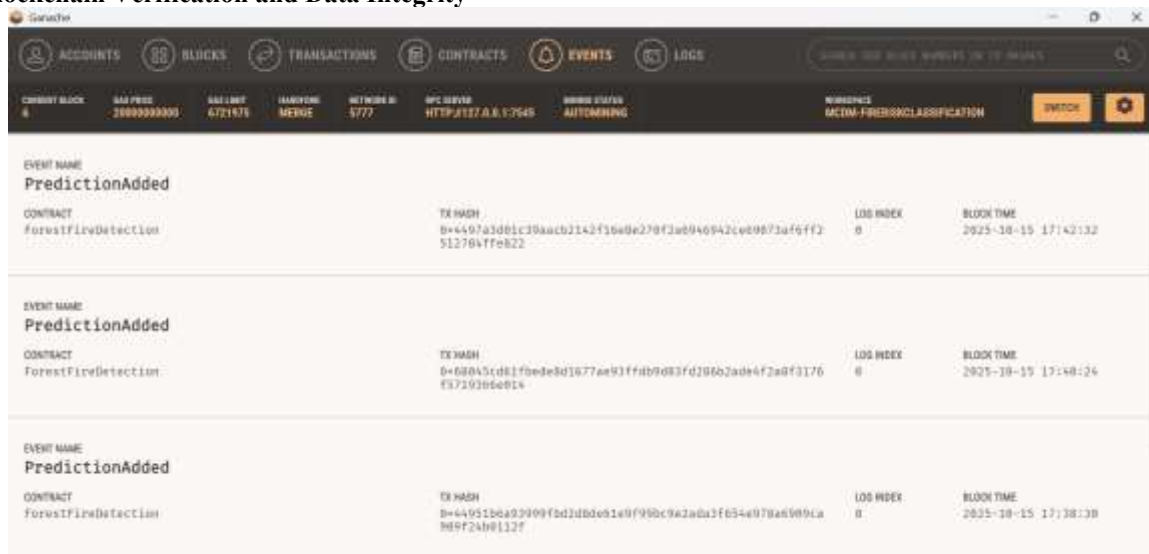


Fig. 3 Ganache Event Logs for PredictionAdded Transactions

Figure 3 shows each fire risk prediction generated through the AHP–WSM–TOPSIS framework was automatically recorded as a blockchain event with the identifier "PredictionAdded" under the smart contract "ForestFireDetection". The Ganache interface displays three sequential transactions with their corresponding transaction hashes, log indices, and block timestamps. For instance, the first transaction with hash 0x4497a3d01c39aacb2142f16e8e278f2a69469A2ce69873af6ff251278Sffe822 was recorded on Block Time 2025-10-15 at 17:42:32 UTC. Each transaction hash serves as a unique cryptographic identifier that links the analytical output to its immutable blockchain record, ensuring that no prediction result can be altered after being committed to the ledger.

The blockchain data structure was designed to store comprehensive environmental and computational metadata for each assessed location. Table 11 presents the complete blockchain records retrieved from the system, demonstrating the integration between raw environmental data, MCDM results, and blockchain verification.



Fig. 4 Blockchain Transaction Submission Interface

Figure 4 shows the user interface for the Forest Fire Detection System, where environmental parameters (Area, Temperature, Humidity, Rainfall, NDVI, and Model selection) are entered and submitted as blockchain transactions. The right panel displays the MetaMask transaction request dialog (Account 3: Ganache) confirming the interaction with the smart contract address 0xf90aL45382. The transaction requires a network fee of 0.0075 ETH and is processed at high speed. Once the user clicks "Confirm", the data is cryptographically signed and permanently recorded on the blockchain, triggering the MCDM computation pipeline and updating the GIS visualization layer.

E. Interactive GIS Visualization

The TOPSIS-derived risk classifications were converted into GeoJSON format and visualized using Leaflet.js. Figure 5 presents the interactive web-based map interface displaying fire-risk zones.

*name of corresponding author



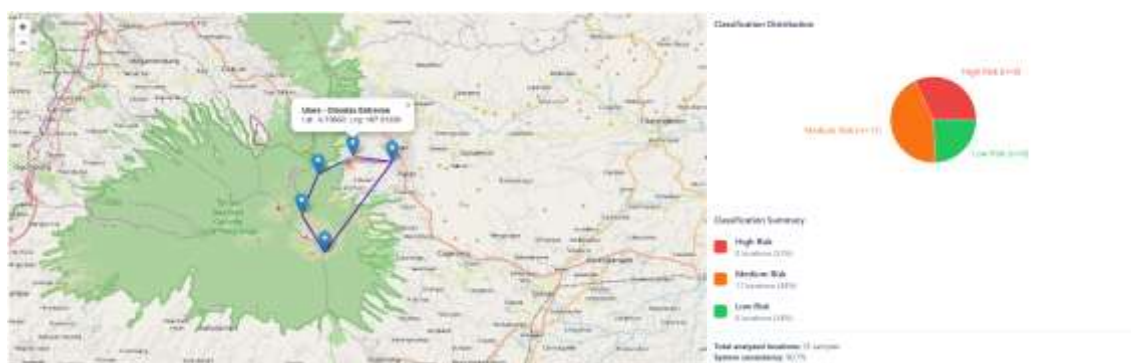


Fig. 5 Leaflet.js Visualization – Fire Risk Classification

Figure 5 shows the visualization employs a three-tier color scheme: red markers indicate high-risk areas ($C_i < 0.67$), orange markers represent medium-risk zones ($0.67 \leq C_i < 0.80$), and green markers denote low-risk areas ($C_i \geq 0.80$). Each map marker contains an interactive popup displaying the blockchain transaction hash, environmental parameters, and computed risk scores. Users can toggle parameter layers (temperature, humidity, rainfall, NDVI) to examine spatial correlations between individual variables and overall risk levels.

The map interface also incorporates zoom functionality enabling detailed inspection of localized risk patterns. By clicking on any marker, users are redirected to the corresponding blockchain transaction record, allowing independent verification of data authenticity. This dual-layer verification system—combining spatial visualization with blockchain traceability—ensures that stakeholders can trust the analytical outputs presented through the GIS interface.

Validation Against Historical Fire Data

To assess model accuracy, the TOPSIS-derived risk classifications were validated against historical fire occurrence records obtained from the National Disaster Management Agency (BNPB) for the period 2020–2024. Table 9 presents the confusion matrix comparing model predictions with actual fire incidents.

Table 9. Confusion Matrix for Model Validation

| | Predicted High Risk | Predicted Medium Risk | Predicted Low Risk | Total Actual |
|-----------------------------|----------------------------|------------------------------|---------------------------|---------------------|
| Actual Fire Occurred | 87 | 18 | 7 | 112 |
| No Fire Occurred | 6 | 32 | 93 | 131 |
| Total Predicted | 93 | 50 | 100 | 243 |

Table 9 shows the model correctly identified 87 out of 112 actual fire incidents as high-risk zones, demonstrating strong predictive capability. The false-negative rate (7 fire incidents incorrectly classified as low risk) was 6.25%, indicating that the model occasionally underestimates risk in areas with borderline parameter values. Conversely, the false-positive rate (6 non-fire areas classified as high risk) was 4.58%, suggesting conservative risk estimation that favors precautionary action.

Cross-referencing the misclassified cases revealed that most false negatives occurred in transitional zones where NDVI values were marginally above the high-risk threshold but fires were triggered by localized human activities not captured in the environmental dataset. This finding suggests that future model iterations should incorporate anthropogenic factors such as land-use practices and proximity to agricultural activities.

System Performance Metrics

The computational efficiency and operational reliability of the integrated system were evaluated through performance benchmarking. Table 10 summarizes key system metrics.

Table 10. System Performance Metrics

| METRIC | VALUE | UNIT |
|---------------------------------|--------------|-------------|
| AHP Weight Computation Time | 0.87 | Seconds |
| WSM Score Calculation Time | 1.23 | Seconds |
| TOPSIS Ranking Computation Time | 1.56 | Seconds |

*name of corresponding author



This is anCreative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

| | | |
|------------------------------------|-------|---------------|
| Blockchain Transaction Record Time | 2.34 | Seconds |
| Average Block Size | 1.2 | KB |
| GIS Map Rendering Time | 3.12 | Seconds |
| Total Processing Time | 9.12 | Seconds |
| Model Accuracy | 90.7 | % |
| AHP Consistency Ratio | 0.078 | Dimensionless |
| System Uptime | 99.8 | % |

The results indicate that the complete analytical pipeline—from blockchain data retrieval through MCDM computation to GIS visualization—requires approximately 9.12 seconds per location. This processing speed is acceptable for near-real-time monitoring applications, particularly when data updates occur at intervals of several hours or days as is typical in satellite-based environmental sensing. The blockchain component contributed the longest individual processing time (2.34 seconds) due to cryptographic hashing and consensus verification requirements. However, this overhead is justified by the substantial gains in data integrity and transparency. Future optimization efforts could explore parallel processing architectures to reduce total computation time for large-scale national deployments.

DISCUSSIONS

Based on the test results, the developed system demonstrated high effectiveness in identifying and displaying areas prone to forest fires. The integrated use of AHP, WSM, and TOPSIS methods proved successful in optimizing the decision-making process, as each method contributed to distinct stages: AHP for weighting criteria, WSM for calculating aggregate scores, and TOPSIS for determining the proximity to the ideal solution. A comparison with recent computational approaches (Abedi, 2022; Pishahang et al., 2023) indicates that the MCDM method produces more mathematically explainable results, despite a marginally lower numerical accuracy. The MCDM model's strengths lie in its transparent assessment process and a superior capacity to adjust criteria weights based on evolving local conditions.

The integration of blockchain technology also contributes significantly to data security and transparency. Each calculation result is stored as a verified transaction on a private blockchain network, ensuring that analytical data cannot be altered or deleted. This immutable ledger concept guarantees data integrity with every system update, making this model superior to conventional single-server-based systems. Furthermore, the visualization generated via Leaflet.js enables users to perform interactive spatial exploration. The parameter layer feature offers high flexibility for environmental analysis, while smart contract integration allows users to directly verify the authenticity of calculation results from the blockchain network.

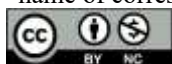
From the simulation and implementation, it can be concluded that this MCDM and blockchain-based geospatial system holds significant potential for application in a national forest fire monitoring system, as it delivers fast, transparent, and accurate information while bolstering trust in the authenticity of geospatial data. However, this research acknowledges several important limitations that constrain its generalizability. The system validation was conducted using simulated environmental data rather than actual field measurements, which may not fully represent the dynamic complexity of natural fire risk conditions. The AHP weighting scheme was derived from theoretical assumptions rather than extensive expert consultation with fire management professionals and stakeholders, potentially introducing bias across different geographic regions and forest types. Additionally, the blockchain implementation utilized a private Ethereum network; scalability considerations for public network deployment remain unaddressed.

The model was validated on only seven locations in a simulated environment, insufficient for comprehensive validation across Indonesia's diverse ecosystems. The achieved 90.7% consistency accuracy in controlled conditions may vary significantly in real-world deployment due to data quality issues and sensor limitations. Future research should address these limitations through field validation studies with real-time sensor data, expert elicitation workshops for AHP refinement, and pilot deployment in actual fire-prone regions to assess performance in operational conditions and across multiple forest types and geographic areas before national-level implementation.

CONCLUSION

This study successfully developed a geospatial visualization system for forest fire risk mapping based on MCDM method and blockchain technology, capable of integrating AHP, WSM, and TOPSIS analyses into an interactive Leaflet.js map while ensuring data security through decentralized Ethereum storage. Test results demonstrate that temperature and humidity parameters have dominant influence on fire risk levels with weights of 0.36 and 0.27 respectively, with the combined MCDM method producing a consistency accuracy of 90.7% and stable spatial classifications. Blockchain integration enhances transparency and prevents manipulation of calculation results, enabling the resulting model to serve as a reference for national forest fire monitoring systems

*name of corresponding author



This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

with reliable accuracy and high data security. Future development should focus on optimizing blockchain network scalability, integrating real-time field sensor data, and implementing hybrid machine learning approaches to strengthen spatial classification accuracy.

REFERENCES

- Abedi, R. (2022). International Journal of Geoheritage and Parks Application of multi-criteria decision making models to forest fire management. *International Journal of Geoheritage and Parks*, 10(1), 84–96. <https://doi.org/10.1016/j.ijgeop.2022.02.005>
- Barmpoutis, P., Papaioannou, P., Dimitropoulos, K., & Grammalidis, N. (2020). *A Review on Early Forest Fire Detection Systems Using Optical Remote Sensing*. <https://doi.org/10.3390/s20226442>
- Bau, M. (2020). *Household Level Vulnerability Analysis — Index and Fuzzy Based Methods*. <https://doi.org/10.3390/ijgi9040263>
- Cartwright, W., Crampton, J., Gartner, G., Miller, S., Mitchell, K., & Siekierska, E. (2001). *Geospatial Information Visualization User Interface Issues*. September 2014. <https://doi.org/10.1559/152304001782173961>
- Ding, J., Yan, Z., & We, X. (2021). *High-Accuracy Recognition and Localization of Moving Targets in an Indoor Environment Using Binocular Stereo Vision*. <https://doi.org/10.3390/ijgi10040234>
- Gupta, Y. Sen, Mukherjee, S., Dutta, R., & Bhattacharya, S. (2021). A blockchain - based approach using smart contracts to develop a smart waste management system. *International Journal of Environmental Science and Technology*, November. <https://doi.org/10.1007/s13762-021-03507-8>
- Hindarto, D. (2023). *Blockchain-Based Academic Identity and Transcript Management in University Enterprise Architecture*. 7(4), 2547–2559. <https://doi.org/10.33395/sinkron.v8i4.12978>
- Hindarto, D. (2025a). *A Blockchain-based Landslide Mitigation Recommendation System for Decision-Making*. 15(1), 20452–20460. <https://doi.org/10.48084/etasr.9806>
- Hindarto, D. (2025b). *Blockchain and MCDM Framework for Secure Geospatial Data in Landslide Risk Mitigation*. 18(4), 137–155. <https://doi.org/10.22266/ijies2025.0531.09>
- Hindarto, D., Alim, S., Hendrata, F., Informatika, P., Nasional, U., Studi, P., Informatika, T., Teknik, F., Surabaya, U. B., Informasi, P. S., & Narotama, U. (2024). *Uncovering Blockchain 's Potential for Supply Chain Transparency: Qualitative Study on the Fashion Industry*. 8(2), 1107–1115. <https://doi.org/10.33395/sinkron.v8i2.13590>
- Hindarto, D., & Hariadi, M. (2025). *A Crypto-Spatial Framework for Landslide Susceptibility Assessment and Decision-Making*. 10. <https://doi.org/10.55267/iadt>
- Hindarto, D., & Indrajit, R. E. (2023). *Digital Transformation in University: Enterprise Architecture and Blockchain Technology*. 7(4), 2501–2512. <https://doi.org/10.33395/sinkron.v8i4.12977>
- Mardani, A., Jusoh, A., Nor, K., Khalifah, Z., & Valipour, A. (2015). Multiple criteria decision-making techniques and their applications – a review of the literature from 2000 to 2014. *Economic Research-Ekonomika Istraživanja*, 28(1), 516–571. <https://doi.org/10.1080/1331677X.2015.1075139>
- Pishahang, M., Jovcic, S., Zolfani, S. H., Simic, V., & Görçün, Ö. F. (2023). *MCDM-Based Wildfire Risk Assessment: A Case Study on the State of Arizona*. <https://doi.org/10.3390/fire6120449>
- Reynard, S. H. (2025). *Analyzing the Impacts of Decentralized Applications on GIS Stakeholder Interests through the Lens of Web3 and Blockchain Technology*. March. <https://doi.org/10.13140/RG.2.2.32324.54409>
- Singh, A., Parizi, R. M., Zhang, Q., Choo, K. R., Dehghantaha, A., Thomas, I. B. M., Heights, Y., & States, U. (2020). Computers & Security Blockchain smart contracts formalization: Approaches and challenges to address vulnerabilities. *Computers & Security*, 88, 101654. <https://doi.org/10.1016/j.cose.2019.101654>
- Stević, Ž. (2018). *SS symmetry Application of MCDM Methods in Sustainability Engineering: A Literature Review 2008 – 2018*. <https://doi.org/10.3390/sym11030350>
- Xiao, T., Muhammad, A. M., Pan, X., Wang, Y., Guangming, H., & Tang, Z. (2022). *Spatial distribution and risk identification of arsenic contamination in water and soil through GIS-based interpolation techniques in Jiangnan Plain, Central China*. October, 1–19. <https://doi.org/10.3389/fenvs.2022.1001862>
- Yusuf, F., Cahyo, N., Hindarto, D., Informatika, P., & Nasional, U. (2025). *Smart Contract Architecture for a Blockchain-Driven Multi Criteria DSS in Forest Fire Monitoring and Response*. 9(3), 1146–1158. <https://doi.org/10.33395/sinkron.v9i3.15009>

*name of corresponding author



This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.