A Blockchain-based Landslide Mitigation Recommendation System for Decision-Making

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ABSTRACT

Landslides are catastrophic natural disasters that could threaten the structural integrity of a building, imposing hazards to engineering and human life. This study proposes a TOPSIS landslide disaster mitigation recommendation system integrated with blockchain. New approaches to data provenance, transparency, and informed decision-making are explored in the context of geospatial blockchain. The decision-making process is carried out using the multicriteria evaluation method, which considers soil stability, rainfall, vegetation density, proximity to rivers, and slope. The results yielded promising precision, recall, accuracy, and F1 scores (91%, 93%, 95%, and 95%, respectively), suggesting that the model could make accurate and impartial prioritization predictions. Blockchain ensures data transparency, immutability, and security, and TOPSIS ranks mitigation strategies from worst to best to determine the better solution. The proposed approach is essential to predict regions that are prone to landslides and enables the appropriate management of relaxation measures. This application of blockchain technology can provide trust, reliability, and speed in decision-making while reducing landslides.

Keywords-blockchain technology; landslide mitigation; decision-making system; TOPSIS method; data integrity

I. INTRODUCTION

Landslides are among the most destructive natural hazards, as they can cause severe damage to the environment and infrastructure and threaten human life. Decisions about mitigation are complicated by many criteria and environmental factors. There are also issues with data manipulation and inefficiencies, making the process even more vulnerable, as there is no reliable way to verify the data [1]. This study proposes an innovative blockchain-integrated algorithm to provide protection against landslides and ensure data security and transparency to reinforce decision-making. An algorithm uses a distributed ledger system and collects data from various environmental monitoring hardware devices (e.g., geospatial sensors and telecommunication devices) to provide a solid basis for unbiased decision-making. This system is well suited for contexts that focus on mitigating landslide risks because it employs the TOPSIS method, a specialized approach to convert multicriteria data into actionable insights [2].

This research aims to create reference datasets and standardized workflows for machine learning and statistical approaches to modeling landslide vulnerabilities over the long term. Its main objective is to facilitate standardized comparisons among geoscientists. For example, an integrated technique known as TOPSIS-Mahalanobis was presented in [3], which was employed to evaluate multihazard vulnerabilities in Golestan Province, Iran. The results showed that this method could enhance prediction accuracy and improve prioritization in risk management efforts. In [4], an effective risk prediction model was developed for land-use planning, combining GIS, Frequency Ratios (FR), and the analytical hierarchy process. The results showed that this method was very promising in identifying landslide vulnerability zones more effectively. In [5], statistical, machine learning, and multicriteria decision analysis approaches were used in Bafoussam, Cameroon, to develop an accurate map of landslide risk, which is crucial to developing risk mitigation plans. In [6], Naïve Bayes (NB) and Logistic Regression (LR) methods were based on GIS to assess landslide susceptibility in the Red Sea Mountains. This study integrated the information value with the MCDA process, improving the predictive accuracy over AHP. In [7], a landslide vulnerability model was developed for the Kulfo River Basin based on statistical analysis and geospatial methods. The FR-based model led to an Area Under the Curve (AUC) score of 79.6%, demonstrating high efficacy. This method was also used in [8] to assess social vulnerability to landslides in several small towns in China. This approach significantly improved vulnerability assessment, providing additional information on disaster management strategies. GIS was combined with TOPSIS to produce a reliable landslide vulnerability map, showing that this method was feasible on the practical level.

However, these studies have a noticeable gap, as none of them describes how blockchain technology and GIS can be used together to make mapping landslide risk more accurate, open, and safe. A blockchain-based approach could make a significant difference, especially in increasing both the reliability of data and collaboration across different sectors. This gap underscores the potential for further investigation into the integration of existing assessment methods with blockchain technology. This study introduces blockchain to provide a land-based solution and system to discover and reduce landslide possibilities. Data integrity has been ensured in some areas using blockchain, but limited studies have used it to mitigate disasters. Using blockchain, with its data immutability and decentralized nature, can help make judgments under extreme weather conditions and landslides to ensure the quality of decision-making. Far from relying on a single database system, this system can keep and check data in an immutable way. This method also uses TOPSIS to assess landslide protective measures in three aspects, namely slope stability, rainfall intensity, and vegetation cover-based topography. This approach brings these technologies together to offer an unprecedented solution that can deliver more precise recommendations, making operations transparent and distributing power through a trusted environment where everyone has stakes in the operation. The system also uses real-time data from areas prone to landslide processes.

This study presents an ideal blockchain-based landslide prevention and recommendation system that can be efficient in decision-making. The system is designed to maintain the integrity of environmental data, including soil site stability, rainfall, and slope, which are crucial to this planning. This study compiles data from landslide areas and uses TOPSIS for multicriteria analysis and blockchain to authenticate the data and protect them from tampering. The efficacy of the system was evaluated to provide a solid advance for disaster management in seeking a societal transition toward structured and reliable formations for disaster prevention processes.

II. PROPOSED BLOCKCHAIN-BASED LANDSLIDE MITIGATION RECOMMENDATION SYSTEM

This approach recommends blockchain ecosystems for landslide mitigation to cover confidential information on landslide risks. In the proposed method, an MCDM-based analytical method was combined with blockchain to protect the dependability of the advice provided. Blockchain subchains permanently store all transactions or data generated during our systems' operational cycle, allowing anyone involved to verify their authenticity. Figure 1 illustrates the workflow for improving decision-making in landslide risk management using geospatial data and blockchain technology. The analysis looks at soil stability (a benefit criterion, since compact or consolidated soils are resistant to gravity), rainfall density (a cost criterion, since heavy rain makes landslides more likely), vegetation cover index (a benefit, since it acts as a binding agent and affects ground testability by reducing some gravitational effects), river proximity costs in headwater areas, and damage potential modeling based on the above criteria for slope steepness. These parameters help determine the likelihood that landslides will occur and what steps should be taken to prevent them.

The feature node helps transform landslide vulnerability datasets into usable forms in the system. Raw data was processed and then analyzed in the context of key features, i.e., soil stability, amount of rainfall received, vegetation density, distance from a river, and slope. The feature node approach focuses on eliminating less-or-no significant information from landslide occurrence. After discovering vital features, these data are processed and regrouped into transactional blocks that describe landslide susceptibility. These transaction blocks can be inserted into a blockchain-based ledger, providing transparent, secure, and immutable data for the analysis and decision-making processes. This approach creates a verifiable and auditable record of every data processing step, ensuring accountability for relevant stakeholders.

```
Algorithm 1: Inserting a Feature Landslide
Block into Ledger
Input: features(landslide data)
Output: Updated ledger with the new block

# Define the Feature Landslide Block
Function createFeatureLandslideBlock
  features, previousHash)
Initialize block as:
index = getNextBlockIndex()
timestamps = getCurrentTimestamp()
features = features (input feature
  data)
previousHash = previousHash
hash = ""
Compute block["hash"] =
  calculateHash(block)
Return block.
```

```
# Validate and Add Block to Ledger
Function insertBlockToLedger(features)
Retrieve previousHash =
   getLatestBlockFromLedger()["hash"].
Create newBlock =
   createFeatureLandslideBlock(features,
   previousHash).
Retrieve latestBlock =
   getLatestBlockFromLedger().
IF validateBlock(newBlock,
   latestBlock) is True THEN:
  Execute
  appendBlockToLedger(newBlock).
  Print "Block successfully added to
  the ledger."
 ELSE:
   Print "Block validation failed. Not
   added to the ledger."

   # Calculate Hash Function for the
   Block
Function calculateHash(block)
Convert block contents to a string
   and calculate hash:
Return sha256(block["index"] +
   block["timestamp"] +
   JSON.stringify(block["features"]) +
   block["previousHash"]).

#Validate the Block
Function validateBlock (block,
   latestBlock)
IF block["previousHash"] !=
   latestBlock["hash"] THEN return False
   (Invalid previous hash).
IF block["index"] !=
     latestBlock["index"] + 1 THEN return
     False (Invalid index).
IF block["hash"] !=
     calculateHash(block) THEN return
     False (Invalid hash).
Return True.
# Append the Block to the Ledger
Function appendBlockToLedger(block)
Execute ledger.append(block).
Return True.
END.
```

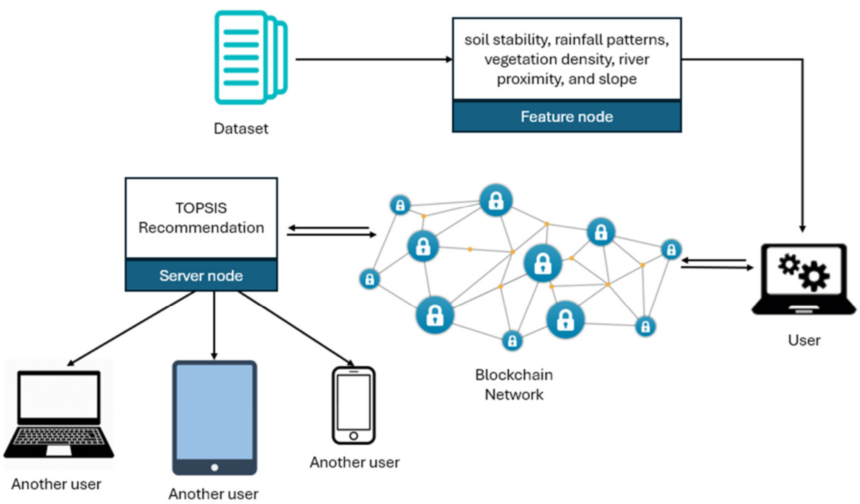

Fig. 1. Proposed blockchain-based integration with recommendation system.

The server node uses the TOPSIS method to generate suggestions based on previously analyzed data. The server node further processes the data received from the feature node using an MCDM approach to determine its priority level or vulnerability ranking. In every alternative, the entropy variation must be found using the TOPSIS approach [10]. The method calculates the closeness to the ideal solution for each alternative based on attribute weights and their values. Suppose that stepping down the slope, where its surface immediately results in cliff faces leading in opposite directions, there are factors such as soil stability, rainfall, and vegetation density. These recommendations are stored on a blockchain. The server node ensures that tractable and reliable data are available to all concerned in making decisions about landslide mitigation.

The formulation of TOPSIS is as follows:

- The decision matrix:

$$Z = \begin{bmatrix} z_{11} & z_{12} & \cdots & z_{1n} \\ z_{21} & z_{22} & \cdots & z_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ z_{n1} & z_{n2} & \cdots & z_{nn} \end{bmatrix} \quad (1)$$

- Normalization is performed to convert the original values into unitless ones using:

$$r_{ij} = \frac{z_{ij}}{\sqrt{\sum_{z=1}^{m} z_{ij}^2}} \quad (2)$$

and:

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nn} \end{bmatrix} \quad (3)$$

- In the weighted mormalized matrix, for each criterion, a weight w_j indicates its significance.

$$v_{ij} = w_j \cdot r_{ij} \quad (4)$$

Then,

$$V = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & v_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ v_{n1} & v_{n2} & \cdots & v_{nn} \end{bmatrix} \quad (5)$$

- Determine Positive Ideal Solution (A^+):

$A^+ = \{v_1^+, v_2^+, \dots\dots, v_n^+\}$,

with:

$$v_j^+ = \begin{cases} \max(v_{ij}), & if\ j\ is\ a\ benefit\ criterion, \\ \min(v_{ij}), & if\ j\ is\ a\ cost\ criterion. \end{cases} \quad (6)$$

Negative Ideal Solution (A^-):

$A^- = \{v_1^-, v_2^-, \dots\dots, v_n^-\}$,

with:

$$v_j^- = \begin{cases} \max(v_{ij}), & if\ j\ is\ a\ benefit\ criterion, \\ \min(v_{ij}), & if\ j\ is\ a\ cost\ criterion. \end{cases} \quad (7)$$

- Calculate the alternative distance to the ideal solution:

Distance to True ideal solution (S_i^+):

$$S_i^+ = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^+)^2} \quad (8)$$

Distance to False ideal solution (S_i^-):

$$S_i^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^-)^2} \quad (9)$$

- Proximity (C_i) is calculated by:

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad (10)$$

The C_i value is between 0 and 1. The closer to 1, the better the alternative.

- The alternatives are ranked based on C_i (relative closeness to the ideal solution) final value, and higher C_i means higher importance. Graphically, C_i denotes the trade-off between benefit and cost criteria. The larger the C_i, the more applicable or optimal behaviors exist for the final goal. The TOPSIS method leaves an exact and bias-free degree of order over the different options for correlating the handled information. This allows for decisions to be more data-driven and transparent, and for stakeholders to choose those that best address their needs and priorities. C_i can be regarded as the core metric that translates into evaluation and alternative ranking in any TOPSIS-based system.

The following TOPSIS formulation includes the complete decision matrix up to the calculation steps. Table I shows an example of a dataset.

TABLE I. SAMPLE DATASET

Loc	Stability	Rainfall	Vegetation	River	Slope
	C1	**C2**	**C3**	**C4**	**C5**
A1	70	200	40	10	25
A2	60	150	60	15	20
A3	80	100	50	12	30

- Initial decision matrix (*Z*): This matrix contains the original values for each criterion at each location (1).

$$Z = \begin{bmatrix} 70 & 200 & 40 & 10 & 25 \\ 60 & 150 & 60 & 15 & 20 \\ 80 & 100 & 50 & 12 & 30 \end{bmatrix}$$

Description:

Rows: Alternatives (A1, A2, A3)

Columns: Criteria (C1: Stability, C2: Rainfall, C3: Vegetation, C4: Distance to river, C5: Slope)

- Normalization matrix (R) using (2) and (3) as follows:

$$R = \begin{bmatrix} 0.573 & 0.801 & 0.456 & 0.451 & 0.455 \\ 0.491 & 0.601 & 0.684 & 0.677 & 0.364 \\ 0.655 & 0.400 & 0.570 & 0.541 & 0.546 \end{bmatrix}$$

- Weighted normalization matrix (V): Each normalization value is multiplied by the weight of the criteria, using (4). $w = \{0.3, 0.2, 0.25, 0.15, 0.1\}$. The result of the weighted matrix through (5) is:

$$V = \begin{bmatrix} 0.172 & 0.160 & 0.114 & 0.068 & 0.046 \\ 0.147 & 0.120 & 0.171 & 0.102 & 0.036 \\ 0.196 & 0.080 & 0.143 & 0.081 & 0.055 \end{bmatrix}$$

- Positive (A^+) and Negative (A^-) ideal solutions: Positive and negative ideal solutions are calculated based on the type of criteria (benefit or cost) according to (6) and (7): The results are:

$A^+ = \{0.196, 0.080, 0.171, 0.102, 0.036\}$

$A^- = \{0.147, 0.160, 0.114, 0.068, 0.055\}$

- Distance to ideal solution (S^+ and S^-): Equations (8) and (9) give:

$$S^+ = \begin{bmatrix} 0.280 \\ 0.215 \\ 0.095 \end{bmatrix} \qquad S^- = \begin{bmatrix} 0.115 \\ 0.129 \\ 0.280 \end{bmatrix}$$

- Proximity (C_i) is calculated using (10).

$$C_i = \begin{bmatrix} 0.290 \\ 0.375 \\ 0.746 \end{bmatrix}$$

- The ranking of alternatives based on C_i is: A3 (0.746), A2 (0.375), A1 (0.291). Therefore, location A3 is a top priority for landslide mitigation.

As shown in Figure 2, the landslide features are processed and stored in the blockchain. Transaction data from the user is passed to the feature node, with soil stability, rainfall patterns, vegetation density, river proximity, and slope according to flow status. The feature node checks the data, sending it to the Proof of Recommendation (crypto-spatial) layer [11]. This layer validates whether the data are authentic and related correctly to the criteria space. Immediately, if successful, the Proof of Recommendation sends back to the feature node an authentication state that will process the transactions in hand and store them in the blockchain ledger [12]. The feature node gets a notification that the data has been included in the blockchain. The whole process shows how to use blockchain-based [13] data validation and storage methods to ensure the reliability of landslide feature data.

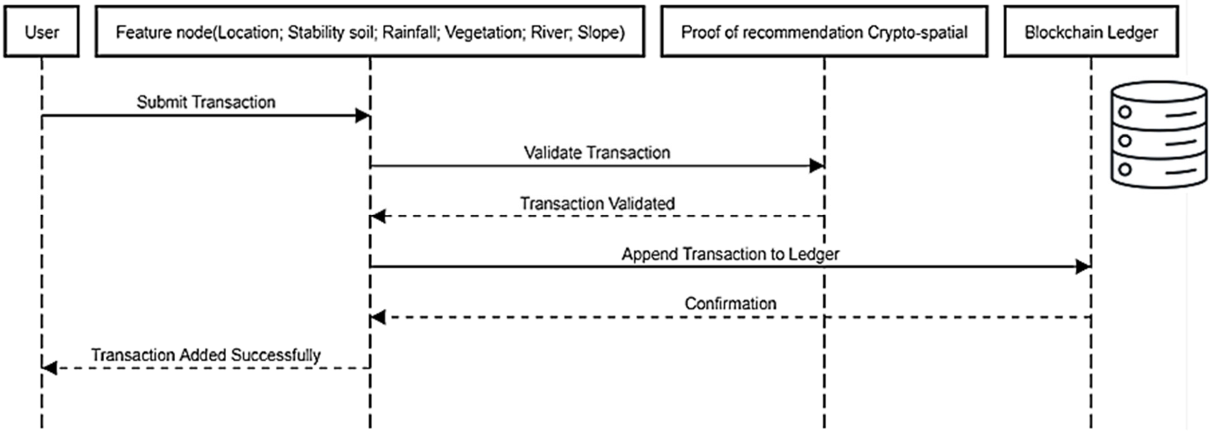

Fig. 2. Sequence diagram for inserting a feature landslide block to ledger.

III. EXPERIMENTAL ANALYSIS

A. *Landslide Dataset*

Synthetic data was generated to replicate specific situations related to the risk of landslides, including soil, slope, and rainfall. Online data are collected from platforms that provide geospatial datasets or verified datasets about the environment, such as weather reports, satellite image data, and geological records. The goal is to coalesce two types of data for a sample dataset for analysis. This is beneficial in addressing gaps in online data, such as sectors that cannot be measured directly. This enables the dataset to be effectively utilized in risk-based simulations and decision-making for landslide applications. Table II shows some examples of the landslide dataset.

The dataset consists of fundamental parameters for determining soil stability, rainfall, vegetation density, distance to rivers, and slope in the region of Bogor Regency, Indonesia. Geospatial data processing and visualization improvements relied on access to additional datasets through the Google Earth Engine platform [14]. Having this connection between the local data and geospatial platforms provides all the information needed to perform a more thorough analysis for landslide risk assessment. The datasets can be accessed in [15].

TOPSIS involves assigning weights to these criteria to indicate their importance in reducing the risk of landslides. In this case, the weights assigned are [0.3, 0.2, 0.2, 0.1, 0.2]. Benefit criteria include soil stability and vegetation density, while cost criteria include rainfall, proximity to rivers, and slope. By balancing positive impacts and potential hazards, these weights help establish priority.

B. *Inserting Landslide Block into the Ledger*

Figure 3 shows the implementation of a smart contract written in Solidity for storing landslide information on the blockchain. The landslide structure is used to store important attributes, such as soil stability, rainfall, vegetation density, distance from rivers, and slope hash range, to maintain data integrity. LandslideData provides landslide data, hashes the data, and adds the data to the landslide Records array. In addition, this function emits the DataAdded event as a transparent log [16].

TABLE II. DATASET LANDSLIDE SYNTHETIC

Location	Stability soil	Rainfall	Vegetation	River	Slope
1	80	120	70	500	30
2	75	150	60	300	45
3	90	100	85	800	20
4	85	140	75	450	40
5	70	110	65	350	35
6	65	130	50	600	50
7	95	105	90	700	25

Figure 4 illustrates a smart contract execution log in the data storage process. Figure 4 also shows the input parameters submitted (including location data and relevant attributes) with the blockchain response that the data was successfully stored. Figure 4 also contains information on the block hash to validate the information, the status of the transaction (whether it succeeded or failed), the address of the sender of the transaction, and the DataAdded event that was triggered to ensure transparency. These two logs act as audit trails to verify that data was written to the blockchain in a secure and trusted manner.


```
// SPDX-License-Identifier: MIT
pragma solidity ^0.8.0;
contract GIS_Landslide_Ledger {
    struct LandslideData {
        uint location;
        uint stability;
        uint rainfall;
        uint vegetationDensity;
        uint riverProximity;
        uint slope;
        string hash; // Data hash for integrity
    }
    LandslideData[] public landslideRecords;
    uint public recordCount = 0;
    event DataAdded(uint location, string hash);
    function addLandslideData(
        uint stability,
        uint rainfall,
        uint vegetationDensity,
        uint riverProximity,
        uint slope,
        string memory dataHash
    ) public {
        landslideRecords.push(LandslideData({
            location: recordCount,
            stability: stability,
            rainfall: rainfall,
            vegetationDensity: vegetationDensity,
            riverProximity: riverProximity,
            slope: slope,
            hash: dataHash
        }));
        recordCount++;
        emit DataAdded(recordCount, dataHash);
```

Fig. 3. Smart contract to insert block into ledger.

Fig. 4. Log smart contract insert block.

TABLE III. STATUS LOG INSERTION BLOCK TO LEDGER

Description	Indicators_Log
Status_log	succeed
Transaction_hash_log	0x8f25d4ea708495e367f12a9f602c680591b3aeba046df5e49ea7220eeebef2ed
Block_hash_log	0x9990fc9f579de0b7d706bed360e747fc02c719302ecab775a22d41499a7f1642
blocknumber	100
from	0x5B38Da6a701c568545dCfcB03FcB875f56beddC4
to	GIS_Landslide_Ledger.addLandslideData(uint256,uint256,uint256,uint256,uint256,string) 0xc2955A581b9481B8e56374dBf78adDA30D7dEc11
gas	237678 gas
transaction cost	206676 gas
execution cost	184468 gas

Table III provides detailed information on the status log of the data insertion process in the blockchain ledger. The transaction status indicates that the process was successful. The Transaction_hash_log column records a unique hash for each transaction, enabling a specific identification of the transaction. The Block_hash_log also maintains the unique hash of the data-storing block. The sender of the transaction can be seen in the From column, and the destination address refers to the smart contract in which the data were received and the addLandslideData function was run. Suppose a function with multiple parameters: a number type uint256 and a text type string. The gas is logged, which denotes computational resources. In total 237,678 gas was allocated. The actual transaction cost was 206,676 gas, which also accounts for the overhead of the function execution. The smart contract function itself recorded a cost of 184,468 gas, demonstrating efficient resource usage. The information in this table is crucial for tracking transactions, verifying data accuracy, and assessing the efficiency of blockchain systems.

C. Landslide Calculation Using the TOPSIS Method

The TOPSIS approach is used to choose the mitigation spots. Before that, decision matrix normalization was performed to ensure that each criterion (soil stability, rainfall, slope, etc.) would not exceed the maximum standards scale. This is measured by how far true and false ideal solutions are, and thus, the best and worst values of each criterion and the best alternative are found. The relative closeness value is produced as the output of the prioritization indicator, and an alternative with the highest value is chosen as a mitigation site.

The results were calculated to measure the positions between the true and false ideal solutions given in Table IV to order these locations. So, the higher the C_i value, the better this ranking, since it is closest to the perfect solution. As shown in Table IV, the best was location 3 (C_i = 0.686). Location 4 got rank 2 (C_i = 0.569), and location 1 got rank 3 (C_i = 0.555). Location 2 had the lowest C_i value and was ranked last. An assessment enables an objective basis for determining the most appropriate site based on the selected parameter.

The experimental results were used to evaluate the predictive priority of slope landslide mitigation sites, as represented by the ground truth and model prediction for 50 sites. Ground truth indicates the real data regarding the order of priority for mitigation, and prediction displays the outcome of the model. Ground truth and prediction were occasionally differing, which shows model errors in the prediction of the prioritization. These errors could be: (i) False Positives (FP) - sites that would not be a priority but are predicted as priorities, and (ii) False Negatives (FN) - sites that are real priorities but not predicted as priorities. The best predictions are very similar to ground truth, indicating that the model can predict reliably under actual conditions.

TABLE IV. CALCULATION RESULTS WITH THE TOPSIS METHOD

Location	S^+ (Distance to positive)	S^- (Distance to negative)	C_i (Relative closeness)	Rating
1	0.0552	0.0689	0.555	3
2	0.1111	0.0510	0.315	6
3	0.0510	0.1111	0.686	1
4	0.0645	0.0850	0.569	2
5	0.0889	0.0587	0.398	5
6	0.1215	0.0450	0.270	7
7	0.0490	0.0920	0.652	4

Precision quantifies how accurate are the positive predictions, i.e., how many of the locations predicted as priorities are truly priorities in the ground truth:

$$Precision = \frac{TP}{TP+FP} \tag{11}$$

Recall measures the ability of the model to capture priorities from ground truth:

$$Recall = \frac{True\ Positive}{Ture\ Positif + False\ Negative} \tag{12}$$

Accuracy is the ratio of total accurate positive and negative predictions to the total data:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{13}$$

F1 score balances between true positives and the system's ability to detect priority levels in the ground truth:

$$F1\ score = 2 \times \frac{Precision\ x\ Recall}{Precison+Recall} \tag{14}$$

The precision was 91%, indicating the model's effective prediction of accurate prioritization with few false positives. A 93% recall indicates that the model was able to capture almost all the priorities that were present in the ground truth. The model showed excellent overall performance, predicting priorities and non-priorities with 95% accuracy and 95% F1 score. These results demonstrate that it is suitable for implementation in landslide risk mitigation based on prioritization data.

IV. DISCUSSION

This study developed a landslide dataset using blockchain technology to protect the integrity of geospatial data from tampering. Assessment of landslide risk utilizes geospatial information and benefits from the immutable and decentralized characteristics of blockchain. The synthetic data were enriched with data from the Google Earth Engine platform for experimental purposes. This allowed the generation of realistic conditions to evaluate the robustness of the proposed approach.

This study contributes to solving the critical problems of data authenticity, reliability, and access with the following:

- To ensure data security, blockchain stores and makes all raw data available.
- Synthesize it with other datasets.
- Cloud platforms such as Google Earth Engine offer preprocessed geospatial products, contributing to the advancement of landslide risk analysis.

Table V illustrates a performance comparison with previous studies. The comparison uses not only non-machine learning methods but also machine learning methods. This study achieved the best accuracy (95%), recall (93%), and F1 score (95%) by combining Promethee 2 with GIS and blockchain, surpassing the results of previous studies. Although previous studies such as [17] and [19] showed excellent accuracy for non-ML methods, they are not quantitatively representative of recall and F1 scores. Similarly, the study in [20] relied on a machine learning strategy that provided a high level of precision but a lower F1 score (0.74). The proposed approach offers higher performance compared to previous works, along with improved data integrity and transparency through blockchain, which fills one of the significant gaps in previous methods.

TABLE V. COMPARISON ACCURACY, PRECISION, RECALL, AND F1 SCORE

Ref.	Method	ML or non-ML	Result Score			
			A	P	R	F1
[17]	HFSM + DWT	Non-ML	0.78	0.80	0.96	0.87
[18]	AHP + GIS	Non-ML	0.89	0.87	-	-
[19]	GIS + FAHP + Promethee 2	Non-ML	0.90	0.75	-	-
[20]	GIS + CNN	ML	0.88	0.94	0.87	0.74
This study	TOPSIS + GIS + Blockchain	Non-ML	0.95	0.91	0.93	0.95

V. CONCLUSIONS

Traditional approaches often face obstacles, such as data limitations, security vulnerabilities, and complexity in multicriteria decision-making. To address these challenges, this study proposed a new framework that integrates blockchain technology with the TOPSIS method. The system utilizes geospatial data to evaluate and mitigate landslide strategies. Blockchain technology ensures data reliability through its immutability and decentralized nature, thus enabling secure data sharing and recommending mitigation strategies for security risks.

The proposed approach collects environmental datasets, including parameters such as soil stability, rainfall patterns, vegetation density, river proximity, and slope. These features are processed and analyzed using the TOPSIS method, which ranks landslide-prone areas based on their similarity to an ideal solution, considering multiple criteria simultaneously. To ensure security and transparency, the resulting data and recommendations are stored on a blockchain network. The decentralized nature of blockchain allows real-time updates, allowing stakeholders, ranging from government agencies to local communities, to access reliable and tamperproof data through various devices. This integration of blockchain and TOPSIS offers a secure, transparent, and scalable solution for landslide risk management.

This blockchain-integrated TOPSIS framework provides substantial benefits from environmental, social, and technical perspectives. By ensuring data integrity and preventing tampering, it strengthens the reliability of decision-making processes, while real-time geospatial sensor data ensure timely warnings and anomaly detection. The system prioritizes efforts to minimize environmental damage and empowers local communities to participate in risk management. Acting as a bridge between theoretical disaster models and practical applications, the framework achieves impressive performance metrics, including a precision of 91%, a recall of 93%, an accuracy of 95%, and an F1 score of 95%. With its ability to provide actionable insights and foster collaboration between stakeholders, this framework represents a transformative step forward in the management of landslide risks.

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