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# Integrating Landslide Risk into Spatial Multi-Criteria Evaluation for Forest Land Suitability Planning in Sukabumi, Indonesia

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**Abstract:** Sustainable forest planning in disaster-prone landscapes requires the integration of ecological risk considerations into spatial decision-making frameworks. In this study, a spatial modeling framework was developed to integrate landslide risk into forest land suitability evaluation in Sukabumi, Indonesia, a region that has experienced the highest recorded landslide frequency in West Java over the past decade. Foundational spatial data were derived from forest site typologies and subsequently restructured to isolate environmental variables associated with landslide susceptibility. A spatial multi-criteria evaluation approach was implemented to integrate both qualitative and quantitative criteria within a unified spatial decision-support framework. Criterion prioritization and weighting were determined through the analytical hierarchy process, enabling structured expert judgment to be incorporated into the evaluation process. The resulting spatial suitability map delineated seven optimal forest land-use categories across the study area: pine resin production (19,485.81 ha; 35.03%), teak timber production (8,083.95 ha; 14.45%), agroforestry systems (7,130.91 ha; 12.82%), protection forest zones (2,258.62 ha; 4.06%), biomass cultivation areas (2,117.12 ha; 3.81%), ecotourism development zones (480.28 ha; 0.86%), and biomass processing facility sites (16.90 ha; 0.03%). Spatial prioritization emphasized areas where landslide susceptibility is minimized while maintaining high economic potential for forest-based production systems. The results demonstrate that the systematic incorporation of landslide hazard information can significantly improve the reliability of forest land suitability assessments, providing a more balanced decision-support tool for forest management planning. The approach offers practical value for policymakers and land managers seeking to enhance sustainable forest land-use planning in mountainous and disaster-sensitive regions.

**Keywords:** Spatial multi-criteria evaluation; Analytical hierarchy process; Landslide risk integration; Forest land suitability; Forest management planning; Sukabumi, Indonesia

## 1 Introduction

The Sukabumi Forest Management Unit, under Perhutani's West Java and Banten Regional Division, is one of the most financially productive forest management units, with revenues from teak, pine, resin tapping, and agroforestry. Despite its economic achievements, existing forest planning frameworks, such as the 2023–2032 Forest Management Plan, still lack explicit consideration of disaster risk, especially landslides, in land-use classification. This study addresses that gap by pioneering the integration of landslide susceptibility into spatial multi-criteria evaluation for forest land suitability. To our knowledge, this is the first study in Indonesia to systematically classify 22 forest business typologies into seven optimized land-use zones while incorporating slope stability and social conflict variables. The main objective is to design a spatially explicit decision-support model that improves forest planning in Sukabumi. Previous studies have applied spatial multi-criteria evaluation for landslide risk assessment. For instance, Huy Duong et al. [1] demonstrated its use in landslide susceptibility mapping but without employing management-specific parameters at the forest management unit scale. Similarly, spatial multi-criteria evaluation has been applied for landslide mapping in Romania and validated with the receiver operating characteristic curve analysis, but the unit of analysis is a watershed, not a forest management unit. These approaches provide valuable methodological insights, yet they remain limited to regional-scale hazard mapping [2].

The novelty of this study lies in applying spatial multi-criteria evaluation at the forest management unit level, the smallest operational unit of forest management in Indonesia, where land-use planning is directly linked to business typologies and local socio-ecological dynamics. By explicitly incorporating disaster risk parameters, this research introduces a disaster-mitigation perspective into forest planning, which has not previously been addressed in forest management unit-based studies. The main objective is to design a spatially explicit decision-support model that improves forest planning in Sukabumi by integrating landslide susceptibility mapping with economic and social criteria, thereby generating site-specific recommendations for multifunctional forest landscapes that are both productive and resilient.

## 2 Methods

### 2.1 Tools and Materials

The tools used in this study included smartphones and laptops equipped with software such as ArcGIS 10.8, MS Excel, and Zoom for online consultations. Primary datasets used in this research included forest resource evaluation records, digital spatial data (shapefiles) of the Sukabumi Forest Management Unit, and structured questionnaires designed for analytical hierarchy process-based analysis. Respondents were drawn from the full spectrum of forest managerial staff, including unit heads, deputy administrators, and primary administrators. Their responses also served as expert input for variable classification and scoring.

Data sources included the Forest Management Plan, site typologies, and forest inventory evaluations. Land classifications contained in the PDE-2 database were used to identify zones such as access roads, agricultural fields, conflict areas (tenure disputes), rocky terrain, tourism assets, and forest areas designated as Special Purpose Forest Management Areas (KHDPK) under Ministerial Decree SK.287/MenLHK/Setjen/PLA.2/4/2022. The KHDPK are allocated for specific objectives: community forestry, forest reorganization, utilization zones, rehabilitation, protection, and ecosystem services.

### 2.2 Study Area

This study was conducted in the Sukabumi Forest Management Unit, one of the management units under the Perhutani Regional Division of West Java and Banten. The Sukabumi Forest Management Unit comprises six BKPH: Bojong Lopang, Cikawung, Jampang Kulon, Lengkong, Pelabuhan Ratu, and Sagaranten, as shown in Figure 1. Administratively, the Sukabumi Forest Management Unit is located within Sukabumi Regency, West Java Province, Indonesia.

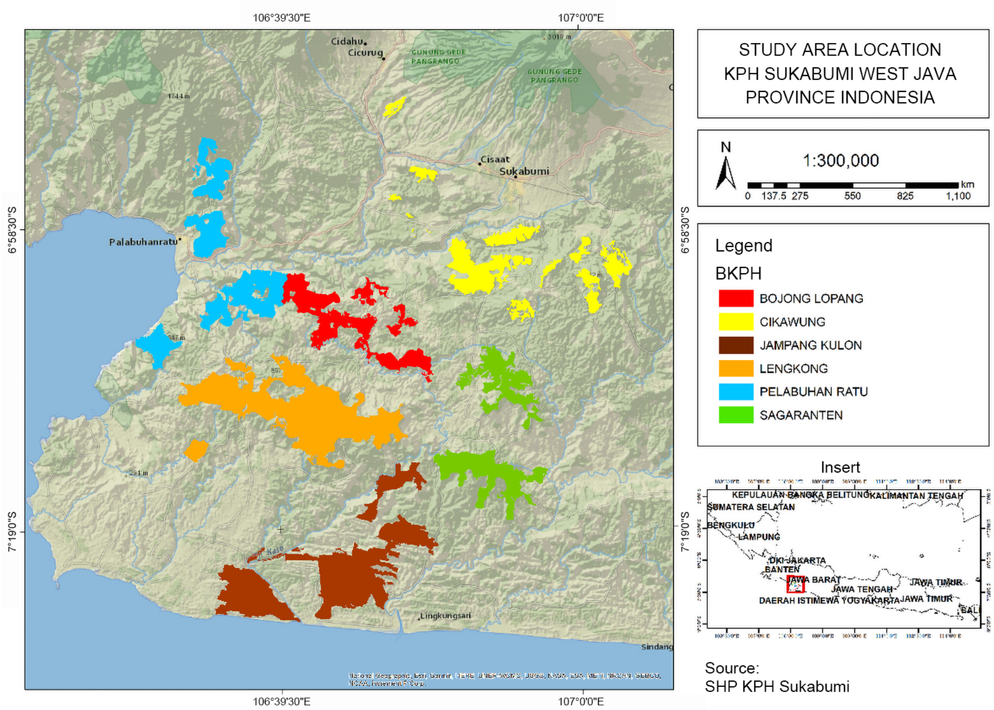


**Figure 1.** Location of the study area

## 2.3 Spatial Multi-Criteria Evaluation

Spatial multi-criteria evaluation is a technique that integrates geographic information systems with multi-criteria decision-making methods. It is widely applied in areas such as transportation planning, land-use allocation, and hazard mapping. The strength of spatial multi-criteria evaluation lies in its ability to handle both spatial and non-spatial data concurrently. Spatial multi-criteria evaluation [3] includes three important phases: intelligence, design, and evaluation. This approach provides decision-makers with composite models that prioritize spatial alternatives based on weighted criteria.

Sequential steps in spatial multi-criteria evaluation [4]:

1. Define objectives (goals, aims, and expected outcomes).
2. Identify and group criteria (relevant factors and constraints).
3. Score each criterion based on data or expert judgment.
4. Standardize scores to ensure comparability among criteria.
5. Assign weights to each criterion reflecting their relative importance.
6. Generate suitability maps based on stakeholder preferences and feasible land-use alternatives.
7. Support decision-making by selecting the most appropriate spatial alternative.

A five-step implementation framework for spatial multi-criteria evaluation in the study [5]:

1. Problem definition (structuring the decision-making problem).
2. Standardization (normalizing variables across different units and scales).
3. Weighting (assigning relative importance to each criterion).
4. Suitability mapping (generating spatial suitability layers).
5. Site identification (determining specific priority locations for intervention or implementation).

## 2.4 Model Formulation

The spatial model can be built based on scores and weights derived from both qualitative and quantitative data. Scores for each land unit were determined through expert judgment using intensity scales, while weights were obtained through pairwise comparison. Therefore, the spatial model for selecting management options, incorporating multiple criteria and weighted scores for each variable, is expressed mathematically through a weighted linear combination, as shown in Eq. (1).

$$\begin{aligned} Y = {} & A\left(a_1 \cdot x_1 + a_2 \cdot x_2 + \cdots + a_n \cdot x_n\right) \\ & + B\left(b_1 \cdot y_1 + b_2 \cdot y_2 + \cdots + b_n \cdot y_n\right) \\ & + C\left(c_1 \cdot z_1 + c_2 \cdot z_2 + \cdots + c_n \cdot z_n\right) \end{aligned} \tag{1}$$

where, $Y$ denotes the total score, $A$ denotes the weight of the landslide parameter criterion, $B$ denotes the weight of the economic criterion, $C$ denotes the weight of the social criterion, $a_1, a_2, \ldots, a_n$ denote the weights of the landslide parameter variables, $b_1, b_2, \ldots, b_n$ denote the weights of economic variables, $c_1, c_2, \ldots, c_n$ denote the weights of social variables, $x_1, x_2, \ldots, x_n$ denote the scores of the landslide parameter variables, $y_1, y_2, \ldots, y_n$ denote the scores of the economic variables, and $z_1, z_2, \ldots, z_n$ denote the scores of the social variables.

Although the weighted linear combination formula is presented in Eq. (1), further clarification is required on how expert judgments were processed into final scores. In this study, expert scores for each criterion and sub-criterion were averaged to obtain a representative weight value. This averaging approach was used to minimize individual subjectivity and provide a consensus-based weighting scheme, ensuring consistency in the scoring process. The identification of criteria is also necessary for building the spatial model in management option selection. The criteria used in this study include landslide-related parameters, economic indicators, and social factors.

## 2.5 Scoring Method

The classification criteria presented in Table 1 were used as variables to assign scores for each management option. Each variable was given a score from 1 (least suitable or acting as a constraint) to 3 (most suitable or supportive of the selected option) [6]. For example, in landslide-prone areas within the Sukabumi Forest Management Unit, the scoring based on elevation is shown in Table 1. Elevation classes below 500 meters above sea level were assigned a score of 1 because these areas are not prone to landslides. Elevation classes between 500 and 1,000 meters above sea level were assigned a score of 2, as they are moderately susceptible to landslides. Elevation classes above 1,000 meters above sea level were given a score of 3 due to their high vulnerability to landslides.

Areas with high elevation and steep slopes are highly susceptible to landslides. Landslides occur due to changes in topographic structure that affect the stability of soil and rock. The higher and steeper the area, the more vulnerable it becomes to landslides. Slope gradient has a significant impact on soil damage; the steeper the slope, the faster and more voluminous the landslides [6–8].

**Table 1.** Criteria and variables used in constructing the spatial model

| Criteria | Variable | Unit | Level | | | | |
|---|---|---|---|---|---|---|---|
| | Elevation | Meters above sea level (m asl) | $< 500$ | 500–1,000 | $> 1,000$ | - | - |
| | Soil type | - | Latosol (moderately sensitive) | Goumssol (sensitive) | - | - | - |
| | Texture | - | Clay | Sandy clay | Soil texture | - | - |
| Landslide parameters | Structure | - | Slightly clayey | Clay | - | - | - |
| | Solum | cm | Shallow ($< 30$) | Medium (30–60) | Deep ($> 60$) | - | - |
| | Rainfall | mm/hour | Low (0–100) | Moderate (100–300) | High (300–500) | Very high ($> 500$) | - |
| | High conservation value ( HCV ) | - | None | HCV6 | - | - | - |
| | Topography/slope | - | Flat/gentle | Slightly steep | Steep | Very steep | - |
| | Understory density | - | Sparse | Moderate | Dense | - | - |
| | Understory type | - | Imperatagrass | Harendong | Others | - | - |
| | Stand density | - | Sparse | Moderate | Dense | - | - |
| Economy | Main tree species | - | Teak | Pine | Mahogany | Rubber | Cajeput |
| | Tourism | - | Camping ground | Cave | Waterfall | - | - |
| | Theft intensity | - | None | Low | High | - | - |
| | Illegal clearing intensity | - | None | Occasional | Continuous | - | - |
| Social | Cultivation intensity | - | None | Seasonal | Continuous | - | - |
| | Cultivated commodities | - | Rice | Secondary crops | Coffee | - | - |
| | Grazing intensity | - | None | Occasional | Continuous | - | - |

Table 1 shows that the criteria used in spatial modeling not only include landslide-causing factors but also include other factors such as economic and social factors. This assumes that landslides in a location are not only caused by natural factors but also by human activity. Therefore, three criteria are used to represent the conditions of the landslide.

### 2.6 Weighting Method

Weight determination was carried out using pairwise comparisons through the analytical hierarchy process, which is a measurement theory based on pairwise comparisons and expert judgments to derive priority scales [9–11]. The steps for calculating weights are as follows:

Step 1: Develop a pairwise comparison matrix for each criterion. The comparison scale, indicating the relative importance of one element over another, is shown in Table 2.

Step 2: Sum all elements in each column of the matrix and determine the normalized relative weights by dividing each scale value by the column total.

Step 3: Calculate the eigenvalue (priority vector) of the criteria by summing the row values of the matrix and dividing by the number of criteria.

Step 4: Compute the maximum eigenvalue ($\lambda_{\max}$) using Eq. (2):

$$\lambda_{\max} = \text{ sum of column weights } \times \text{ criteria weights} \tag{2}$$

Step 5: Calculate the consistency index using Eq. (3):

$$CI = \frac{\lambda_{\max} - n}{(n-1)} \tag{3}$$

where, $CI$ denotes the consistency index, and $n$ is the number of criteria.

Step 6: Determine the consistency ratio by comparing the consistency index to the random index. The consistency ratio is acceptable if it is less than 0.1.

Step 7: Calculate the consistency ratio to assess the consistency of pairwise comparisons. The consistency ratio value must be less than 0.1 (10%) to be considered acceptable. The calculation follows Eq. (4) [12]:

$$CR = \frac{CI}{RI} \tag{4}$$

where, $CR$ denotes the consistency ratio, $CI$ denotes the consistency index, and $RI$ is the random index, which can be approximated as $RI = 1.98(n-2)/n$.

**Table 2.** Scale of relative importance in pairwise comparisons

| Value | Degree of Importance |
|---|---|
| 1 | Weakly important |
| 3 | Moderately important |
| 5 | Important |
| 7 | Very important |
| 9 | Extremely important |
| 2, 4, 6, 8 | Intermediate values between the two adjacent judgments |

The scale of values in Table 2 represents the relative degree of importance used in the analytical hierarchy process when making pairwise comparisons between criteria or alternatives. A value of 1 indicates weak importance, meaning that the two elements are considered equally or nearly equally important. A score of 3 suggests moderate importance, where one element is moderately more important than the other. A value of 5 reflects strong importance, indicating that one element is clearly preferred over the other. A score of 7 denotes very strong importance, showing that one element dominates significantly, while a value of 9 represents extreme importance, where one element is overwhelmingly more important than its counterpart. Intermediate values of 2, 4, 6, and 8 are used to capture judgments that fall between the adjacent categories, allowing greater flexibility in expressing expert opinions. This scaling system provides a structured approach for translating qualitative expert judgments into quantitative values that can be further processed in the weighting procedure of the analytical hierarchy process.

### 2.7 Mapping Management Option Patterns

The results from the scoring and weighting were integrated using a weighted linear combination. This produced a total suitability score for each spatial unit, which was then categorized into three classes: not suitable, moderately suitable, and highly suitable. Class intervals were calculated using the interval method based on Eq. (5).

$$\text{Equal interval} = \frac{\text{Maximum score} - \text{Minimum score}}{\text{Number of classes}} \tag{5}$$

The final total scores were derived for each generalized management option and grouped into the three suitability classes. Seven management options were evaluated in this study, each with a distinct scoring range due to variations in expert judgments on each criterion. These differences resulted in varying maximum and minimum scores across options. The class interval for each management option was used as a class separator for either not suitable, moderately suitable, or highly suitable classes. The class intervals are shown in Table 3.

The outputs for each management option were spatially aggregated using geographic information systems to generate a composite suitability map for the Sukabumi Forest Management Unit. This was accomplished by overlaying all individual suitability maps of the management options with Perhutani's forest plot map. The most suitable option for each spatial unit was selected. If both 'high suitability' and 'moderate suitability' existed within the same unit, the more favorable one was chosen automatically. In cases of conflict where two or more management options showed the same suitability level (e.g., moderate suitability for both Option 1 and Option 2), a spatial decision support system was used to resolve it. This system applied neighborhood similarity analysis to determine the dominant land-use type surrounding the conflicted unit. Parameters and decision variables were adjusted through simulation and model behavior evaluation [13, 14]. The dominant surrounding option was then selected for the target spatial unit. This modeling process was carried out using geographic information systems by performing spatial operations such as overlay and scoring on the attribute table of each parameter.

The stages of management option modeling in the Sukabumi Forest Management Unit began with an assessment by expert judgment to weight with the Excel software. Finally, spatial operations were carried out. The flow is presented in Figure 2.

**Table 3.** Land suitability class intervals for each management option

| Management Option | Score Range | Suitability Class |
|---|---|---|
| 1. Land suitability for timber production | $< 1.84$ | Not suitable |
| | 1.84–2.24 | Moderately suitable |
| | $> 2.24$ | Highly suitable |
| 2. Land suitability for resin tapping | $< 1.72$ | Not suitable |
| | 1.72–2.15 | Moderately suitable |
| | $> 2.15$ | Highly suitable |
| 3. Land suitability for biomass cultivation | $< 1.58$ | Not suitable |
| | 1.58–2.15 | Moderately suitable |
| | $> 2.15$ | Highly suitable |
| 4. Land suitability for agroforestry/understory land utilization (PLDT) | $< 1.70$ | Not suitable |
| | 1.70–2.11 | Moderately suitable |
| | $> 2.11$ | Highly suitable |
| 5. Land suitability for ecotourism | $< 1.61$ | Not suitable |
| | 1.77–1.93 | Moderately suitable |
| | $> 1.93$ | Highly suitable |
| 6. Land suitability for biomass factory | $< 1.60$ | Not suitable |
| | 1.60–1.97 | Moderately suitable |
| | $> 1.97$ | Highly suitable |
| 7. Land suitability for protection zone | $< 1.78$ | Not suitable |
| | 1.78–2.11 | Moderately suitable |
| | $> 2.11$ | Highly suitable |

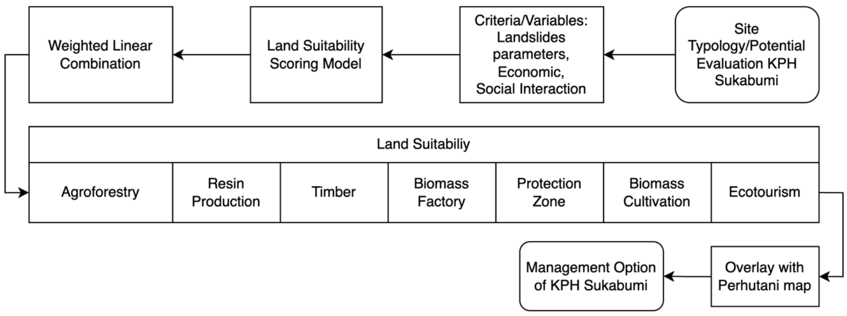


**Figure 2.** Stages of spatial modeling in management option selection management

The diagram illustrates the overall framework of the land suitability analysis for forest management in the Sukabumi Forest Management Unit. The process begins with the weighted linear combination method, which is applied within the land suitability scoring model. This model integrates multiple criteria and variables, including landslide-related parameters, economic indicators, and aspects of social interaction. These inputs are derived from the site typology and potential evaluation of the Sukabumi Forest Management Unit.

The outcome of this assessment produces several land suitability categories, namely agroforestry, resin production, timber production, biomass factory development, protection zones, biomass cultivation, and ecotourism. These categories represent the optimal land-use options identified through the multi-criteria evaluation. Subsequently, the results are linked to the management options of the Sukabumi Forest Management Unit, ensuring that the land-use recommendations align with practical forest management objectives. Finally, the spatial results are validated and contextualized through an overlay with the Perhutani map, allowing integration into official land management and planning processes.

## 3 Work Procedures

The modeling process consisted of several stages: identifying the management options, selecting and defining criteria and indicators, assigning scores based on variable intensity levels, determining criterion weights via the analytical hierarchy process method, and combining all variables through a weighted linear combination to produce the final suitability classification. These classifications were then spatially applied to forest management zones in the Sukabumi Forest Management Unit using the geographic information systems software.

The results indicate that the locations generated from spatial scoring still include spatially scattered areas. Therefore, an additional analysis was conducted, namely proximity analysis of management functions. This aims to ensure that the management of an area can be carried out in one management option by prioritizing the most dominant characteristics from the results of the expert judgment assessment.

### 3.1 Identification of Spatial Planning Criteria and Indicators

The determination of management options was based on the conditions available at the research site. Each criterion was assessed by expert judgement such as that of stakeholders and experts in the field of the criteria. Expert judgement gave a score according to the perception of their knowledge of the conditions to be obtained. The score results from several expert judgements were averaged to obtain a final score from all expert judgements as the basis for making spatial models of management options.

Figure 3 illustrates the sequence used to establish criteria and indicators for spatial land-use modeling. Three overarching categories were identified: landslide risk, economic viability, and social relevance. Each category contained a set of variables that were then scored based on expert judgment. Scores from different experts were calculated by taking a geometric mean of a series of numbers to produce a single number as the final weight.

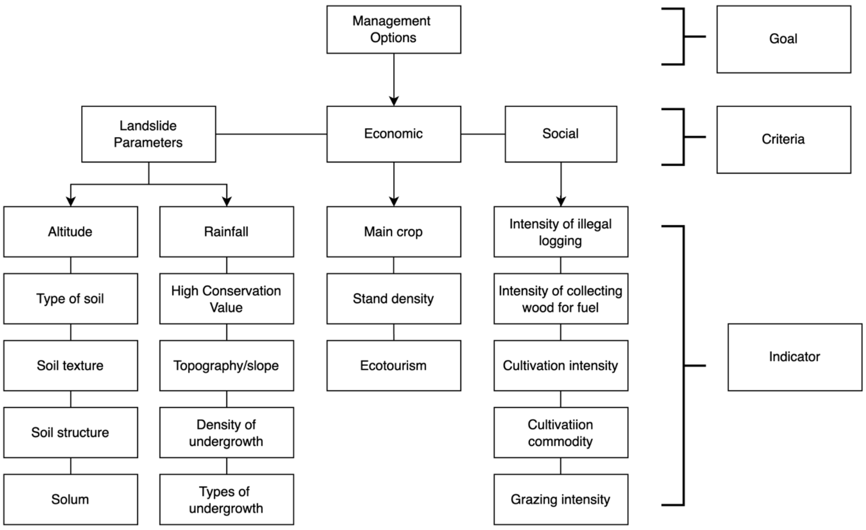


**Figure 3.** Schematic process of identifying criteria and indicators

### 3.2 Assignment of Weights to Criteria and Indicators

The study applied the analytical hierarchy process to evaluate criteria and indicators, assigning priority weights through expert judgment based on methodologies utilized by Mendoza and Prabhu [15]. Three main dimensions guided spatial decision-making: landslide risk parameters, economic viability, and social sensitivity. The landslide dimension included ten biophysical variables (elevation, soil type and texture, stability, solum depth, rainfall, conservation value, slope, vegetation density, and understory species) to represent ecological vulnerability. The economic dimension comprised stand density, dominant tree species, and tourism potential, reflecting productive and recreational values. The social dimension covered theft, illegal clearing, cultivation frequency, commodity type, and grazing pressure, capturing local socio-economic dynamics.

These multi-dimensional variables formed a comprehensive scoring system under the spatial multi-criteria evaluation framework, ensuring a balanced integration of ecological, economic, and social considerations in forest land-use planning.

## 4 Results

This study successfully developed and implemented a spatially explicit decision-support model using spatial multi-criteria evaluation that integrates landslide risk, economic viability, and social sensitivity to assess land suitability in Sukabumi's forest management context. The approach has shown significant relevance and replicability, particularly in regions prone to natural hazards. Validation results demonstrated strong alignment (over 80%) between the model output and stakeholder perspectives. This finding is align with geographic information systems-based multi-criteria analysis conducted in Nigeria for soybean production confirmed the feasibility of integrating biophysical and socio-economic factors in land suitability assessment [16].

Land suitability analysis conducted in Nepal [17] and Malaysia [18] emphasized the importance of integrating biophysical and socio-economic criteria, echoing this study's approach. Change detection and land suitability assessment in Indonesian forest regions [19] further support the use of multi-temporal spatial data to improve zoning accuracy. Furthermore, agroforestry suitability mapping using geographic information systems and nutrient availability data [19] and food susceptibility mapping using geographic information systems and the analytical hierarchy process in Iran [20] demonstrate how similar multi-criteria frameworks can be successfully adapted to diverse environmental and socio-economic settings. The weighted linear combination method adopted in this study enabled nuanced prioritization of land-use options and resolved spatial conflicts effectively. The weighted linear combination model used in this study allowed a nuanced prioritization of land-use options, resulting in seven distinct classifications. The model emphasized pine resin tapping (35.03%), timber production (14.45%), and agroforestry (12.82%) as the most suitable uses. The final maps facilitated by the geographic information systems ensured conflict resolution in overlapping suitability zones using spatial decision-support logic.

Overall, the integration of spatial criteria with expert-based weighting under spatial multi-criteria evaluation has demonstrated practical applicability for hazard-informed forest management. This model supports both productivity and sustainability, with transferability potential for similar forest management units across Indonesia.

### 4.1 Scoring Results

The Sukabumi Forest Management Unit consists of diverse land units with varied social, economic, and biophysical characteristics. In terms of topography, the region includes flat to steep slopes. The soil types are predominantly latosol and grumosol, with textures ranging from clay to sandy loam and soil structures that vary from clayey to moderately clayey. Soil depth also ranges from shallow ($<$ 30 cm) to deep ($>$ 60 cm). The region exhibits diverse economic and social conditions, as reflected in stand density, primary crop types, and the presence of ecotourism sites. There is also variation in the intensity of theft, encroachment, land cultivation, and livestock grazing.

This heterogeneous data must be standardized using scoring methods. Scores represent probability assessments based on the neutrality principle [21, 22]. Scoring is used to standardize variables with different units and characteristics, so they can be combined in thematic information development [23]. The diverse land units were assessed by expert judgment using an intensity scale for each management option. The assigned scores influenced the decision-making process for selecting appropriate management options. Tables 4 and 5 below present the scores used in the spatial modeling process.

**Table 4.** Scores assigned to economic and social criteria in the management options

| Criterion | Variable | Variable Class | Score |
|---|---|---|---|
| Economic | Stand density | Dense | 2 |
| | | Moderate | 2 |
| | | Sparse | 2 |
| | Main crop species | Teak | 3 |
| | | Pine | 2 |
| | | Mahogany | 2 |
| | | Rubber | 2 |
| | | Cajeput | 2 |
| | Tourism type | Waterfall | 2 |
| | | Camping ground | 2 |
| | | Cave | 2 |
| Social | Theft intensity | Low | 2 |
| | | None | 3 |
| | | High | 2 |
| | Land encroachment intensity | Occasional | 2 |
| | | Continuous | 1 |
| | | None | 3 |
| | Cultivation intensity | Seasonal | 2 |
| | | Continuous | 2 |
| | | None | 2 |
| | Cultivated commodities | Rice | 3 |
| | | Coffee | 2 |
| | | Secondary crops | 2 |
| | Grazing intensity | Occasional | 2 |
| | | Continuous | 1 |
| | | None | 3 |

Table 5. Key parameters of our model

| Criterion | Variable | Variable Class | Score |
|---|---|---|---|
| Landslide parameter | Elevation | $< 500$ | 3 |
| | | 500–1000 | 2 |
| | | $> 1000$ | 1 |
| | Soil type | Latosol | 3 |
| | | Grumosol | 1 |
| | Texture | Clay | 2 |
| | | Sandy clay | 2 |
| | Structure | Slightly clayey | 2 |
| | | Clay | 2 |
| | Solum | Shallow ( $< 30$ cm ) | 2 |
| | | Moderate ( 30–60 cm ) | 2 |
| | | Deep ( $> 60$ cm ) | 2 |
| | Rainfall | Low ( 0–100 mm/hour ) | 2 |
| | | Moderate (100–300 mm/hour ) | 2 |
| | | High (300–500 mm/hour ) | 2 |
| | | Very high ( $> 500$ mm/ hour) | 2 |
| | High conservation value (HCV) | HCV6 (cultural) | 2 |
| | | None | 1 |
| | Topography/slope | Slightly steep | 2 |
| | | Steep | 1 |
| | | Flat/gentle | 2 |
| | | Very steep | 2 |
| | Understory density | Dense | 2 |
| | | Moderate | 2 |
| | | Sparse | 2 |
| | Understory type | Imperata grass | 2 |
| | | Harendong | 2 |
| | | Others | 2 |

For clarity of presentation, this study presents the complete scoring matrix only for the timber management option (Tables 4 and 5), which includes all landslide-related, economic, and social variables. Similar scoring matrices were also developed for other land-use options, such as pine resin, agroforestry, biomass cultivation, biomass factory, protection, and ecotourism. These follow the same structure as the timber matrix but differ in the specific scores, which were assigned according to expert judgment.

### 4.2 Weighting Result

Each variable carries a specific level of importance, which was quantified as scores and weights in the spatial model for management option selection. Weighting was performed using pairwise comparisons through the analytical hierarchy process method, as shown in Table 6.

Among the criteria, the landslide parameter criterion was considered the most important with the highest weight (53%). However, economic (21%) and social (26%) criteria also played significant roles and were taken into account. This can lead to different values if the use of management objectives for production forests or social forestry has a tendency for higher economic or social values than environmental or landslide criteria.

The spatial model was constructed using both quantitative and qualitative data expressed as scores and weights. The values come from the processing of values given by expert judgment in determining management options that are in accordance with the designation of the area in the Sukabumi Forest Management Unit. Accordingly, the relationship between management option selection through spatial multi-criteria analysis and the weights in Table 6, along with the scores for each variable, is mathematically represented using a weighted linear combination in Eq. (6). Land suitability maps were prepared for each management alternative. Each land unit with different characteristics

**Table 6.** Criteria and variable weights used in the spatial model

| Criterion | Criterion Weight | Variable | Variable Weight |
|---|---|---|---|
| Landslide parameter | 0.53 | Elevation ( $x_1$ ) | 0.11 |
| | | Soil Type ( $x_2$ ) | 0.09 |
| | | Texture ( $x_3$ ) | 0.09 |
| | | Soil structure ( $x_4$ ) | 0.09 |
| | | Soil solum ( $x_5$ ) | 0.11 |
| | | Rainfall (x6) | 0.12 |
| | | High conservation value ( $x_7$ ) | 0.15 |
| | | Topography/slope ($x_8$) | 0.12 |
| | | Understory density ($x_9$) | 0.08 |
| | | Understory type ( $x_{10}$ ) | 0.06 |
| Economy | 0.21 | Stand density ($y_1$) | 0.35 |
| | | Main crop species ($y_2$) | 0.41 |
| | | Tourism ($y_3$) | 0.24 |
| Social | 0.26 | Theft intensity ( $\mathrm{z}_1$ ) | 0.21 |
| | | Land encroachment intensity ($\mathrm{z}_2$) | 0.22 |
| | | Cultivation intensity ($\mathrm{z}_3$) | 0.22 |
| | | Cultivation commodity ( $\mathrm{z}_4$ ) | 0.16 |
| | | Grazing intensity ($\mathrm{z}_5$) | 0.19 |

was given a score that varied according to the alternatives considered. The scores were then reprocessed using the weighted linear combination in Eq. (6) to produce a land suitability map for one management alternative.

$$
\begin{aligned}
\text{Total score } =& 0.53\,(0.11\ score_{x1} + 0.09\ score_{x2} + 0.09\ score_{x3} + 0.09\ score_{x4} + 0.11\ score_{x5}\\
&+ 0.12\ score_{x6} + 0.15\ score_{x7} + 0.12\ score_{x8} + 0.08\ score_{x9} + 0.06\ score_{x10})\\
&+ 0.21\,(0.35\ score_{y1} + 0.41\ score_{y2} + 0.24\ score_{y3})\\
&+ 0.26\,(0.21\ score_{z1} + 0.22\ score_{z2} + 0.22\ score_{z3} + 0.16\ score_{z4} + 0.19\ score_{z5})
\end{aligned}
\tag{6}
$$

The weighted linear combination model is a geographic information systems-based multi-criteria analysis approach widely used in land suitability assessments.

### 4.3 Final Management Pattern Mapping

The land suitability maps for all management options were aggregated to produce a comprehensive pattern of management options for the Sukabumi Forest Management Unit. This process involved overlaying the land suitability maps for each management option. Given the presence of multiple options, overlapping areas with the same options were identified. In these cases, automatic selection was not feasible. To address this, a decision support system was applied using spatial neighborhood similarity analysis. For spatial units with two or three equally suitable options, the selected option was based on the dominant type in neighboring areas.

The existence of functions or characteristics in the Sukabumi Forest Management Unit can be used as a basis for selecting options. For example, in the Lengkong BKPH, there is a plant biomass processing plant. Although the spatial analysis allocated only a limited area for this option, the biomass processing plant can still be supported by nearby locations, despite the fact that the spatial suitability results do not prioritize the plant's current location. This applies to other management options based on the analysis of proximity and existing conditions in the Sukabumi Forest Management Unit. This procedure is carried out using geographic information systems. The results of mapping management options for management patterns in the Sukabumi Forest Management Unit are shown in Figure 4.

The results of the management option analysis are illustrated in Figure 4. Forest management within the Sukabumi Forest Management Unit is not uniform across all areas; instead, it is determined by site-specific characteristics and the evaluation of expert judgment, which identifies the most appropriate management strategy for each condition. Figure 4 also highlights zones categorized as unsuitable for all management options. These areas represent special-purpose forest zones, where functions and management practices cannot be altered, even if existing conditions suggest alternative uses. Such restrictions are maintained in accordance with expert judgment and regulatory mandates. The distribution of management dominance is presented in Table 7.

Among the seven options, the largest proportion is land suitable for pine resin extraction (35.03%), followed by timber production (14.45%) and agroforestry (12.82%). The table also presents areas unsuitable for any option.

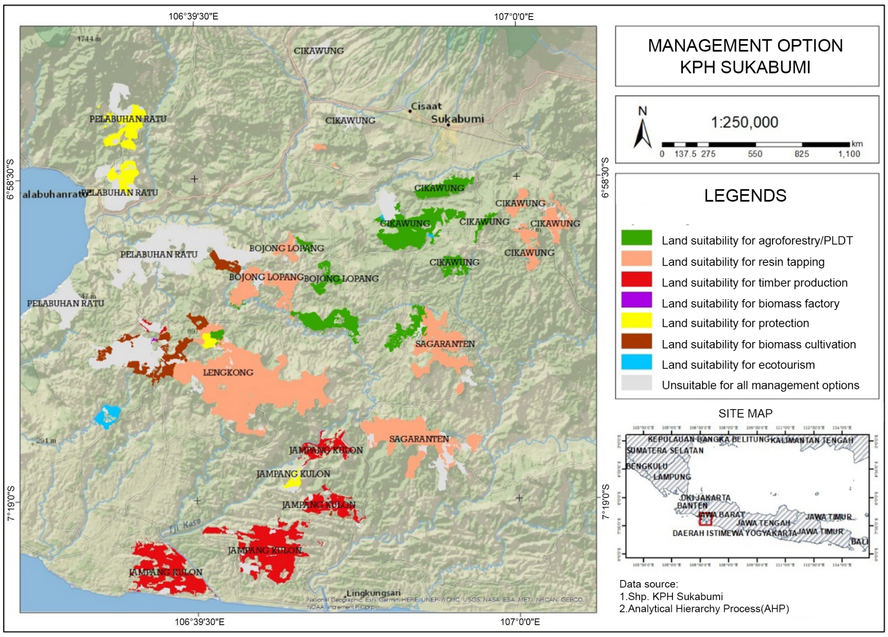


**Figure 4.** Final spatial model of management option patterns in the Sukabumi Forest Management Unit

**Table 7.** Area distribution of land suitability options in the Sukabumi Forest Management Unit

| Management Option | Area (ha) | Percentage (%) |
|---|---|---|
| Land suitability for agroforestry/understory land utilization (PLDT) | 7,130.91 | 12.82 |
| Land suitability for resin tapping | 19,485.81 | 35.03 |
| Land suitability for timber production | 8,038.95 | 14.45 |
| Land suitability for biomass factory | 16.90 | 0.03 |
| Land suitability for protection | 2,258.62 | 4.06 |
| Land suitability for biomass cultivation | 2,117.12 | 3.81 |
| Land suitability for ecotourism | 480.28 | 0.86 |
| Unsuitable for all management options | 16,089.69 | 28.93 |
| Total area | 55,618.28 | 100.00 |

These include regions excluded from the model due to data limitations and those classified under the KHDPK, which are not part of the management domain of the Sukabumi Forest Management Unit. The following figures illustrate actual field locations where the modeled management options have already been implemented.

The current existing condition includes several types of forest plants used for biomass products such as calliandra and pine resin production and for wood such as teak. The condition of the stands is shown in Figure 5.


**Figure 5.** (a) Pine stand, (b) Teak stand, (c) Calliandra stand, (d) Gliricidia stand

Figure 5a shows the existing condition of pine (*Pinus merkusii*) stands in the Sukabumi Forest Management Unit. Pine has been established as a dominant species due to its ecological role in slope stabilization and soil conservation, which is critical in areas prone to landslides. Economically, pine stands are primarily utilized for resin tapping, providing a major source of non-timber forest products that contribute both to forest management unit revenues and local livelihoods. Beyond resin, pine wood also holds economic value, although its use is generally secondary to ensure sustainable management. Figure 5b illustrates the condition of teak (*Tectona grandis*) stands. Teak is among the most valuable timber species due to its strength, durability, and high market demand. Within the Sukabumi Forest Management Unit, teak contributes to long-term timber production strategies, supporting both industrial needs and local economies. Teak plantations also provide ecosystem services such as soil protection and biodiversity habitat.

Figure 5c presents the existing stands of *Caliandra calothyrsus*, a fast-growing species widely known for its high biomass production. Currently, caliandra is mainly used as a source of fuelwood and household energy, while its potential as raw material for biomass energy industries is increasingly recognized. In addition, caliandra improves soil fertility through nitrogen fixation, making it important for land rehabilitation and agroforestry systems. Figure 5d depicts *Gliricidia sepium*, a multipurpose leguminous tree. In the Sukabumi Forest Management Unit, gliricidia is widely used as fodder for livestock, as well as for firewood. Its ability to fix nitrogen also supports soil improvement, particularly in mixed farming and agroforestry practices. As a fast-growing and resilient species, gliricidia provides both ecological and economic benefits, especially in supporting sustainable livelihoods for surrounding communities. Together, these four figures highlight the multifunctional nature of forest resources in the Sukabumi Forest Management Unit, where pine, teak, caliandra, and gliricidia are managed not only for their economic contributions but also for their ecological functions in sustaining forest landscapes.

## 5 Discussion

This study demonstrates that integrating landslide susceptibility into forest land suitability analysis enhances spatial decision-making at the forest management unit level. By combining ecological, economic, and social criteria through spatial multi-criteria evaluation, the model provides a more balanced approach that aligns productive uses with disaster mitigation. The findings highlight the importance of embedding disaster mitigation into forest management unit planning frameworks like the Forest Management Plan. Allocating high-susceptibility areas for protective functions and lower-risk zones for economic use reduces potential conflicts and strengthens resilience. The use of the analytical hierarchy process with averaged expert judgment further supports transparency and consensus in weight assignment. Overall, this study advances the methodological application of spatial multi-criteria evaluation in forestry by linking land-use planning with disaster risk reduction, offering a replicable model for sustainable and resilient forest management.

## 6 Conclusions

This study developed and implemented a spatially explicit decision-support model for land suitability analysis, specifically tailored for multi-functional forest management in landslide-prone areas. By integrating spatial multi-criteria evaluation with expert-based scoring and weighting techniques, the model evaluated and classified 22 forest business typologies into seven actionable land-use categories. Key criteria incorporated landslide risk parameters—such as slope gradient, soil structure, and solum depth—alongside economic (stand density, dominant commodity, and tourism potential) and social factors (tenure conflict, illegal logging, encroachment, and grazing pressure). The novelty of this study lies in its integration of geohazard risks into spatial forest zoning, a domain rarely explored in previous Indonesian forest planning models. It is the first known model to prioritize disaster risk reduction within forest land allocation while maintaining economic productivity and social compatibility. The resulting suitability maps provide an evidence-based basis for selecting the most resilient and feasible land-use types—primarily pine resin extraction (35.03%), teak wood production (14.45%), and agroforestry (12.82%).

The model's application to the Sukabumi Forest Management Unit offers a replicable framework for other forest management units across Indonesia, particularly in regions exposed to climate-sensitive hazards. This study recommends that Perhutani and the Ministry of Environment and Forestry integrate risk-based spatial modeling into their national forest planning systems (e.g., the Forest Management Plan and KHDPK). Future research could further strengthen this approach by incorporating dynamic hazard monitoring (e.g., rainfall-triggered landslide alerts), participatory mapping with local communities, and machine learning-based calibration of variable weights. This would ensure greater adaptability and resilience of forest landscapes under changing environmental and socioeconomic conditions.

## Data Availability

The data used to support the research findings are available from the corresponding author upon request.

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**Conflicts of Interest**

The authors declare no conflicts of interest.

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