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Integration of GIS and Environment-Based Machine Learning Variables for Flood and Landslide Analysis Sirimau Sub-District, Ambon City, Indonesia

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Abstract: Sirimau District often experiences floods and landslides during the rainy season. This study uses environmental variables and the coordinates of flood and landslide locations for MaxEnt modeling. The results show that elevation and land use/land cover are the most influential factors for floods (70.3% and 22.9%, respectively) and landslides (80.9% and 10.3%), consistent with hydrology and physical geography theories. The flood and landslide vulnerability levels are divided into three classes, with low and moderate risk areas dominating, while high-risk areas require special attention for stricter management. Model validation with high Area Under Curve (AUC) values (0.973 for floods and 0.845 for landslides) ensures prediction reliability, which can serve as a basis for adaptive spatial data-based mitigation policy making. Policy recommendations include strengthening early warning systems, spatial planning based on risk zoning, and community capacity building, which are expected to reduce social and economic impacts from disasters in this area sustainably.

Keywords: Flood, GIS, Sirimau, Landslide, Machine Learning

1. Introduction

Hydrometeorological disasters, particularly floods and landslides, have become a significant global challenge due to the impacts of climate change and uncontrolled urbanization (Badan Nasional Penanggulangan Bencana 2025). In island regions like Ambon City, particularly Sirimau District, vulnerability to this disaster increases exponentially due to the steep topography and extreme rainfall intensity (Rakuasa and Khromykh 2025; Rifai et al., 2025). The integration of Geographic Information Systems (GIS) and data-driven approaches is crucial in mitigation efforts, considering that conventional methods are often limited in handling the complexity of interactions between environmental variables (Rakuasa and Rifai 2025). Previous studies conducted in various regions have emphasized that precise risk mapping is the cornerstone of urban resilience in developing countries.

In recent years, the application of machine learning algorithms has revolutionized disaster spatial analysis due to its ability to handle non-linear and multivariate data (Park 2015). One method that shows superior performance is Maximum Entropy (MaxEnt)

(Suhermat et al. 2024). Although initially developed for species distribution modeling, research in the journal Heliyon shows that MaxEnt is highly effective for disaster prediction because it only requires presence-only data (location of events), which is highly relevant for regions with limited historical disaster inventory data but available environmental variables (Ramos-Bernal, Vázquez-Jiménez, and Rojas 2024).

Flood analysis in this study requires the integration of variables representing the physical and hydrological conditions of the area (Rakuasa et al. 2022). The main variables involved include slope, elevation, Topographic Wetness Index (TWI), soil type, precipitation, land use type, river density, and distance to river. Flood location data is used as training samples for the algorithm. The use of TWI and river density is very critical, as explained in the research conducted by Rakuasa & Pertuack (2025), because these variables determine the soil infiltration capacity and the accumulation of surface water flow, which are the main triggers of flooding in urban areas (Sajid et al. 2025).

Simultaneously, the analysis of landslides in Sirimau District requires different parameters to capture the slope failure mechanism. Variables such as slope, slope aspect, TWI, soil type, precipitation, land use type, distance to river, and distance to fault are the main controlling factors. The addition of the distance to fault and slope aspect variables is very important because slope stability in Ambon is highly influenced by tectonic activity and exposure of sunlight to soil moisture. This approach aligns with the methodology used by Tayyab et al. (2024), which emphasizes the importance of geological aspects in landslide modeling.

The research gap filled by this study lies in the integration of multiple hazards using a single MaxEnt framework in a densely populated small island region. Most previous studies tend to separate the analysis of floods and landslides, even though both often share the same trigger: extreme rainfall (Hao et al. 2024). By utilizing GIS as an integration platform, this research is able to produce more holistic probability maps. Research conducted by Huang et al. (2024), proves that the synergy between environmental variables and machine learning results in higher prediction accuracy compared to traditional statistical models.

Overall, this research not only contributes to the scientific development of geospatial science but also provides practical solutions for the Ambon City Government in risk-based spatial planning. The results of this modeling are expected to serve as a scientific reference in formulating more precise disaster adaptation policies at the sub-district level in Indonesia in the future.

2. Methods

This research was conducted in Sirimau District, Ambon City, Maluku Province, Indonesia (Figure 1). For flood modeling, variables included elevation, soil type, rainfall, land use type, river density, and distance to rivers. For landslide modeling, variables comprised elevation, slope gradient, soil type, rainfall, land use type, and distance to active faults. Elevation and slope data were sourced from the Digital Elevation Model (DEM) of the Geospatial Information Agency of Indonesia, soil type data from the Agriculture Service, rainfall data from the Meteorology, Climatology, and Geophysics Agency (BMKG), and land use data were interpreted from 3-meter resolution PlanetScope satellite imagery from Planet Labs. Spatial analysis of river networks and active faults was performed to derive river density and buffer distances to active faults. Presence data for flood events (20 locations) and landslides (16 locations) from 2015 to 2025 were obtained from the National Disaster

Management Agency (BNPB) and served as the basis for the probabilistic risk mapping model.

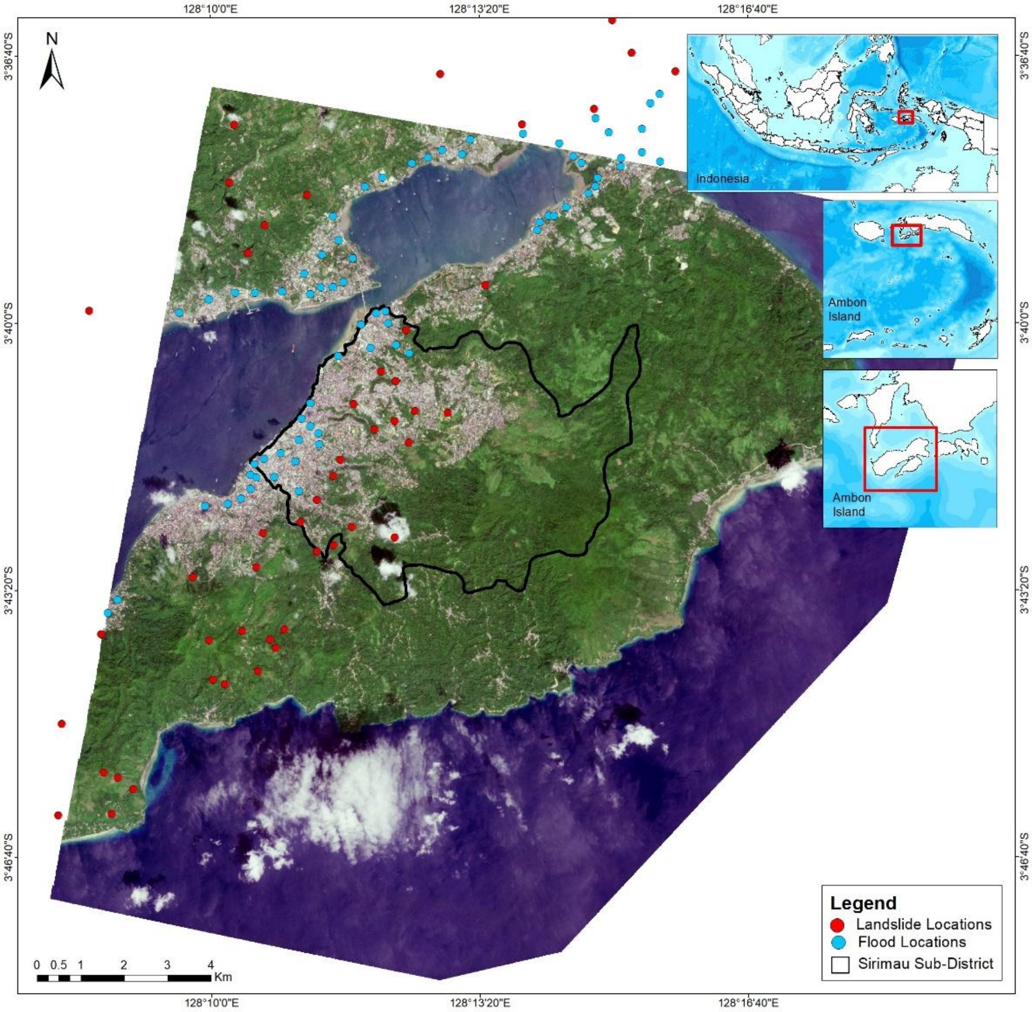

Figure 1. Study Area Location

The selection of environmental variables was based on previous studies and the physical conditions of the research area. This research began with variable processing done in ArcGIS Pro software and MaxEnt modeling for floods and landslides performed in Maximum Entropy Species Distribution Modeling software. The Maximum Entropy (MaxEnt) algorithm is a statistical-probabilistic modeling scheme initially initiated by Phillips et al., (2006), to predict species spatial distributions. In a geospatial context, this model adopts a presence-only methodology that effectively extracts correlations between actual event points and supporting environmental variables, making it a highly robust instrument for analyzing geological factors causing disasters (Javidan et al. 2021). Through the principle of maximum entropy, MaxEnt transforms the limitations of observational data into a comprehensive probability distribution without exceeding the available information constraints (Javidan et al. 2021). Fundamentally, the primary goal of this approach is to estimate the probability of an event across the entire spatial domain of the study area, where various causal factors act as moment constraints in forming a coherent predictive distribution (Zuo et al. 2023).

The concept and theory of MaxEnt were explained by Sharma et al. (2024). The MaxEnt model was developed for ecological modeling and species dispersal evaluation. The MaxEnt model operates based on machine learning and generates spatial predictions using partial data (Zhang et al. 2018). The mathematical concept of MaxEnt can be seen in the formula below:

$$H = -C \sum_{i=1}^{n} p_i \, lnp_i \qquad (1)$$

where H represents data entropy, ρ_i denotes the probability of presence occurrence, and C is a positive constant. Entropy H, as a function of p_i, is maximized under empirical constraints. According to the Maximum Entropy (ME) principle and the Lagrange multiplier approach, the distribution is obtained when entropy is maximized at 1. Assuming the occurrence parameters x are $x_1, x_2, \ldots . x_n$ with probabilities $p_1, p, \ldots . p_n$.

$$\sum_{i=1}^{n} pi = 1, p_i \geq 0 \qquad (2)$$

The averge Fk is as follows:

$$Fk = \sum_{i=1}^{n} f_x\,(x_1) p_i = 1.2 \ldots \ldots m\;(m < n) \qquad (3)$$

According to the constraint conditions of Eqs. (2) and (3), indefinite multiplicators (α and α and β_k) are to create a new function to locate the dispersion when entropy is at its maximum: $H - \alpha - \beta_1 F_1 - \beta_2 F_2 - \cdots - \beta_m F_m$:

$$H - \alpha - \sum_{k=1}^{m} \beta_k F_k = -\sum_{i=1}^{n} p_{ilnpi} - \propto \sum_{i=1}^{n} p_i - \sum_{k=1}^{m} \beta_k$$
$$= \sum_{i=1}^{n} p_i \; ln \left\{ \frac{1}{p_i} \; exp \left[- \propto - \sum_{k-1}^{m} \beta_k f_k\;(x_1) \right] \right\} \qquad (4)$$

Utilizing inequality lnx ≤ x − 1 Eq. (4) changes into:

$$H \leq \sum\nolimits_{i=1}^{n} p_1 \left\{ \frac{1}{p_1} \; exp \left[-\propto - \sum\nolimits_{k=1}^{m} \beta_k F_k\;(x_i) \right] - 1 \right\} + \propto \sum\nolimits_{k=1}^{m} \beta_k \, F_k \qquad (5)$$

To acquire H as the most priority, the upper mathematical notion should be transformed into an equation, and Pi is as follows:

$$P_i = \exp \left[-\propto \sum_{k=l}^{m} \beta_k F_k\;(x_i) \right] . i = 12 \ldots \ldots n \qquad (6)$$

Equations (2) and (6) give as follows:

$$\propto = ln\left\{\sum_{i=l}^{n} exp\left[\left[-[-\sum_{k=1}^{m} \beta_k f_k\ (x_i)\right]\right]\right\} .\, if Z = e^{\propto}.\, then\ it\ changes\ into$$

$$z = ln\sum_{i=l}^{n} exp\left[\left[-\sum_{k=1}^{m} \beta_k f_k\ (x_i)\right]\right] .\, where\ Z\ is\ the\ partion\ function$$

Consequently:

$$pi = \frac{\{exp\,[-\ \sum_{k=1}^{m} \beta_k f_k\,(x_i)]\}}{z} \qquad (7)$$

To acquire the value of β_k, Eq. (7) is substituted into constraint Eq. (3):

$$Fk = \sum_{i=l}^{n}\left\{-f_k(x_i) exp\left[-\sum_{i=l}^{m} \beta_k f_k\ (x_i)\right]\right\}/_z \qquad (8)$$

In Eq. (8), both Fk and fk (xi) are known; however, the true unknowns are m values of β *(β1, β2…βm)*. The m expressions contain mβ values, resulting in the value of pi when entropy is at its maximum (Cabrera and Lee 2020). The results from discrete conditions might also be applied to continuous situations (Cabrera and Lee 2020).

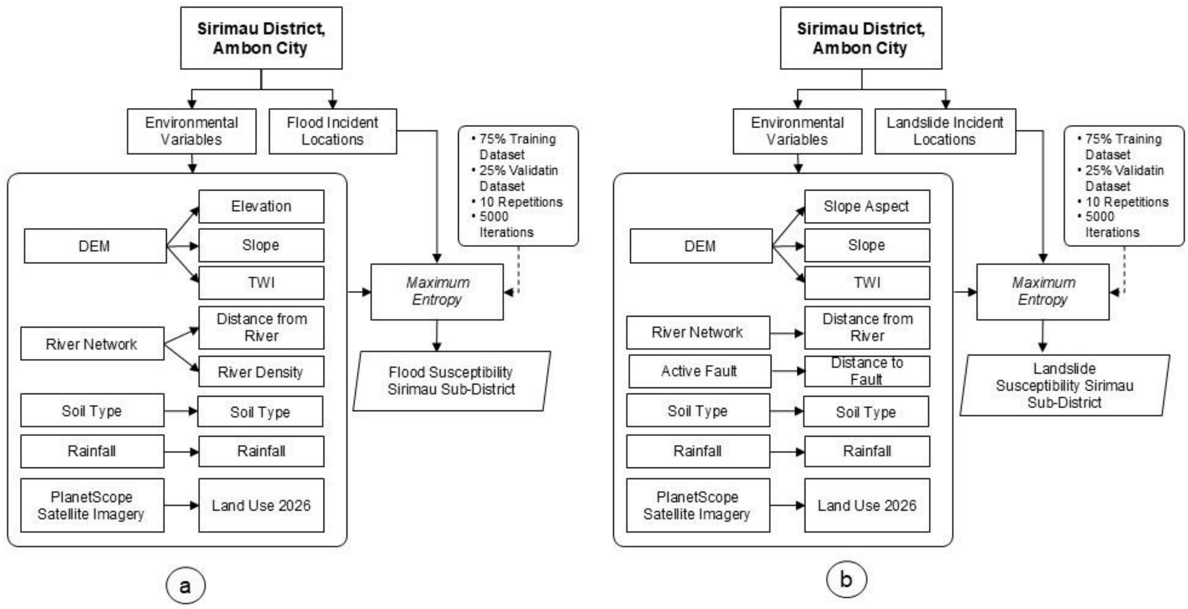

Figure 2. Model Workflow: (a) Flood, (b) Landslide

The process begins with the preparation of environmental variables that cause floods and landslides, followed by the classification and collection of event data. These environmental variables, along with the coordinates of the flood and landslide locations, were input into the MaxEnt software for flood modeling. The MaxEnt model was configured with 75% of the data for training and 25% for testing/validation (Kalmar et al. 2024). The collected flood and landslide occurrence data were used to train the MaxEnt model to learn the relationship between the presence of floods/landslides and environmental variables. Validation data is used to test the accuracy of the model through performance parameters such as Area Under the Curve (AUC). After training and validation, MaxEnt generated flood and landslide vulnerability distribution maps classified into high-, medium-, and low-risk zones based on probability scores. The model's output data was analyzed to identify the main factors influencing flood vulnerability and the most vulnerable areas. These results are presented in the form of maps and statistics to support future flood mitigation decision-making. The entire working process is illustrated in Figure 2.

3. Results and Discussion

3.1. Environmental Variables

The contribution of environmental variables to flood occurrences in Sirimau District, Ambon City, shows that elevation has a dominant influence of 70.3%. This aligns with hydrological theory stating that elevation affects water flow and relative position to water sources that trigger floods. land use/land cover (LUCL) contributes a significant 22.9%, indicating the importance of LULC in accelerating or obstructing surface water flow, especially in urban areas and regions experiencing land use changes. Rainfall contributes 3.3%, which, though relatively small in this model, remains an important factor as the primary water source causing floods. River flow density, distance to rivers, and soil type each contribute less than 2%, but still remain relevant in determining the flow and storage of floodwater.

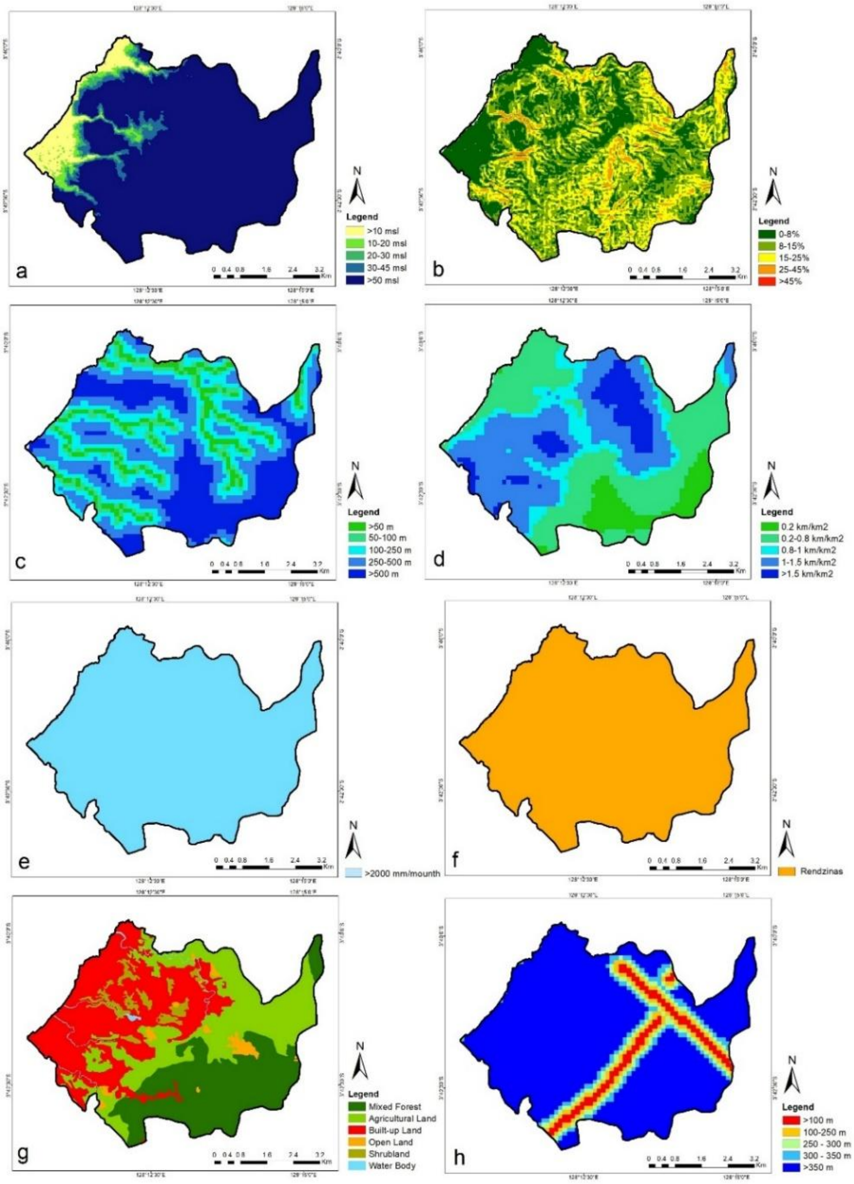

Figure 3. Environmental variables: a) elevation, b) slope, c) distance from river, d) stream density, e) rainfall, f) soil type, g) LULC, h) distance from fault

In landslide occurrences, LULC contributes the most at 80.9%, reflecting the role of vegetation cover in maintaining slope stability and reducing the risk of erosion and slope failure. Elevation contributes 10.3%, indicating that the elevation position of the slope remains important in landslide events, supported by slope gradient at 4.2%, which determines the potential for soil movement. Soil type contributes 2.6%, related to the physical characteristics and strength of the soil in bearing load. Distance to active faults contributes only 1%, showing a spatial relationship with fault zones that can trigger slope failure. Rainfall contributes just 1%, indicating that although precipitation is an important trigger, the long-term influence of vegetation condition and terrain characteristics is more dominant in landslide modeling in Sirimau (Rakuasa & Pertuack 2025). The full set of variables used can be seen in Figure 4.

Thus, the dominance of elevation and LULC for floods and landslides highlights the importance of integrating variables that describe physical conditions and land use in spatial disaster risk modeling . This also aligns with literature findings that rapid land use change and topographic instability are key factors to consider in disaster mitigation. The MaxEnt-based spatial approach allows risk mapping that effectively accounts for the relative contributions of these variables for adaptive and evidence-based disaster management.

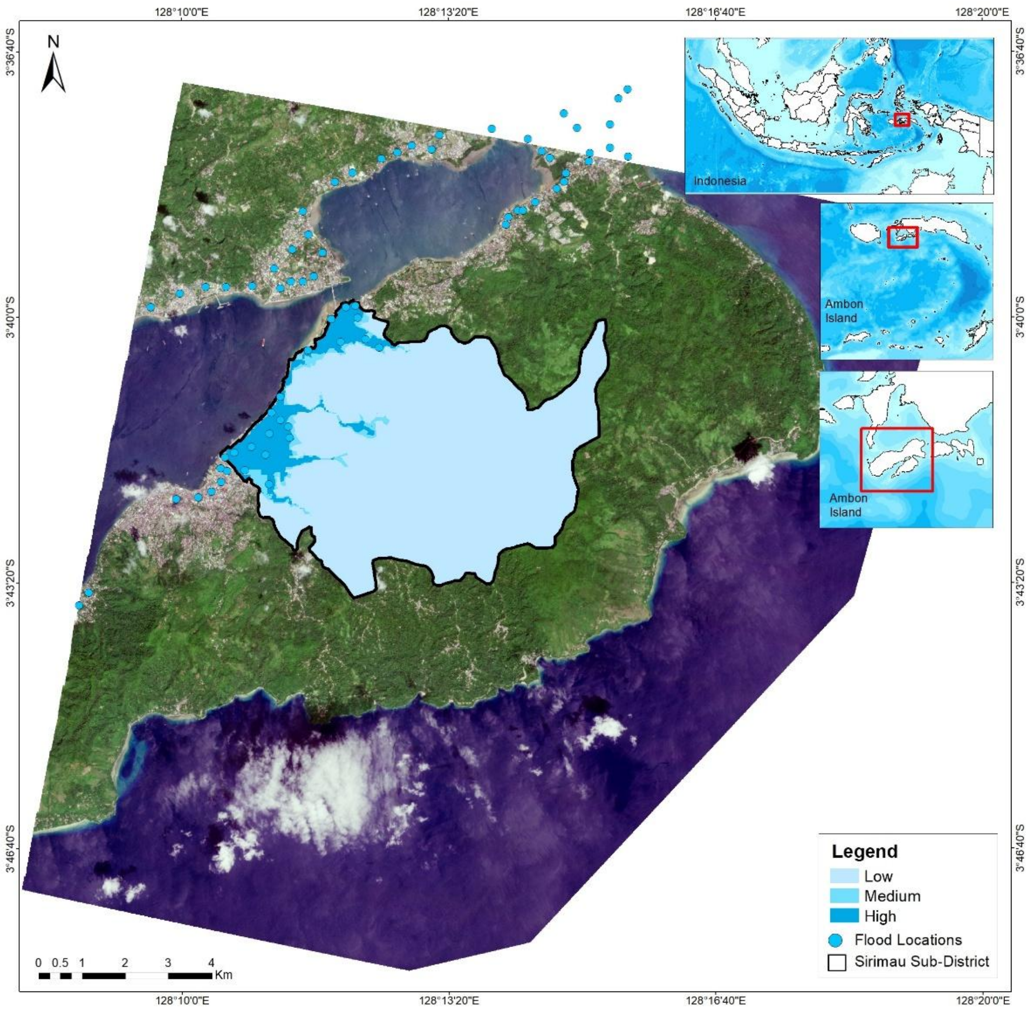

Figure 4. Flood Vulnerability Levels

3.2. Flood vulnerability in Sirimau District

The flood hazard vulnerability levels in Sirimau District are divided into three classes: low, medium, and high. Data shows that the area classified as low flood hazard is the most dominant, covering 3,299.18 hectares, followed by the medium class with 125.69 hectares, and the high class with 259.41 hectares (Figure 2). This situation reflects that most of Sirimau District has a relatively low flood risk, closely related to the region's topography dominated by hills and mountains, which reduces the potential for extensive water pooling. However, the high hazard class area, approximately 259.41 hectares, requires special attention due to its greater flood risk potential. The complete flood area in Sirimau Subdistrict can be seen in Figure 1.

Table 1. Flood Area in Sirimau District

Flood Class	Area (ha)	%
Low	3.299.18	89.55
Medium	125.69	3.41
High	259.41	7.04
Total area	3.684.28	100.00

Understanding the distribution of hazard classes is crucial for flood disaster risk management in Sirimau District. Information on flood vulnerability distribution enables appropriate policy-making in spatial planning and disaster mitigation, such as settlement arrangement and flood control infrastructure development (Latue et al., 2023). Generally, areas with low hazard levels can be considered safer zones for development, while medium and high hazard areas require greater attention in supervision and mitigation efforts to minimize disaster impacts (Allafta and Opp 2021). GIS-based and multi-criteria approaches are widely recommended in flood risk literature to produce reliable hazard maps that support effective decision-making (Demissie et al. 2024).

3.3. Landslide Vulnerability in Sirimau District

The landslide hazard vulnerability in Sirimau District is divided into three classes: low, medium, and high, covering areas of 1,943.66 hectares for the low class, 1,510.61 hectares for the medium class, and 227.73 hectares for the high class. The complete landslide area in Sirimau Subdistrict can be seen in Figure 2. This distribution reflects that areas with low and medium landslide risk dominate the Sirimau region, while the high hazard area is relatively small. This condition is closely related to topographic and slope characteristics, high rainfall intensity, and varied land use types (Rakuasa et al., 2022). Areas with high hazard levels require special attention in spatial utilization management and mitigation efforts to minimize landslide disaster risk. Landslide-prone areas can be seen in Figure 5.

Table 2. Landslide Area Extent in Sirimau Sub-District

Landslide Class	Area (ha)	%
Low	1943.66	52.76
Medium	1510.64	41.00
High	229.98	6.24
Total area	3684.28	100.00

A thorough understanding of landslide vulnerability levels is crucial in planning and implementing disaster mitigation strategies in Sirimau District (Somae et al. 2022). Spatial data on landslide vulnerability enables local governments and stakeholders to create more effective land use control policies, strengthen early warning systems, and apply technical measures for slope stabilization (Souisa, Hendrajaya, and Handayani 2016). The application of spatial planning guidelines based on vulnerability levels is supported by relevant regulations and scientifically tested disaster risk models, providing a solid foundation for reducing landslide disaster risk in vulnerable areas (Rakuasa et al., 2025).

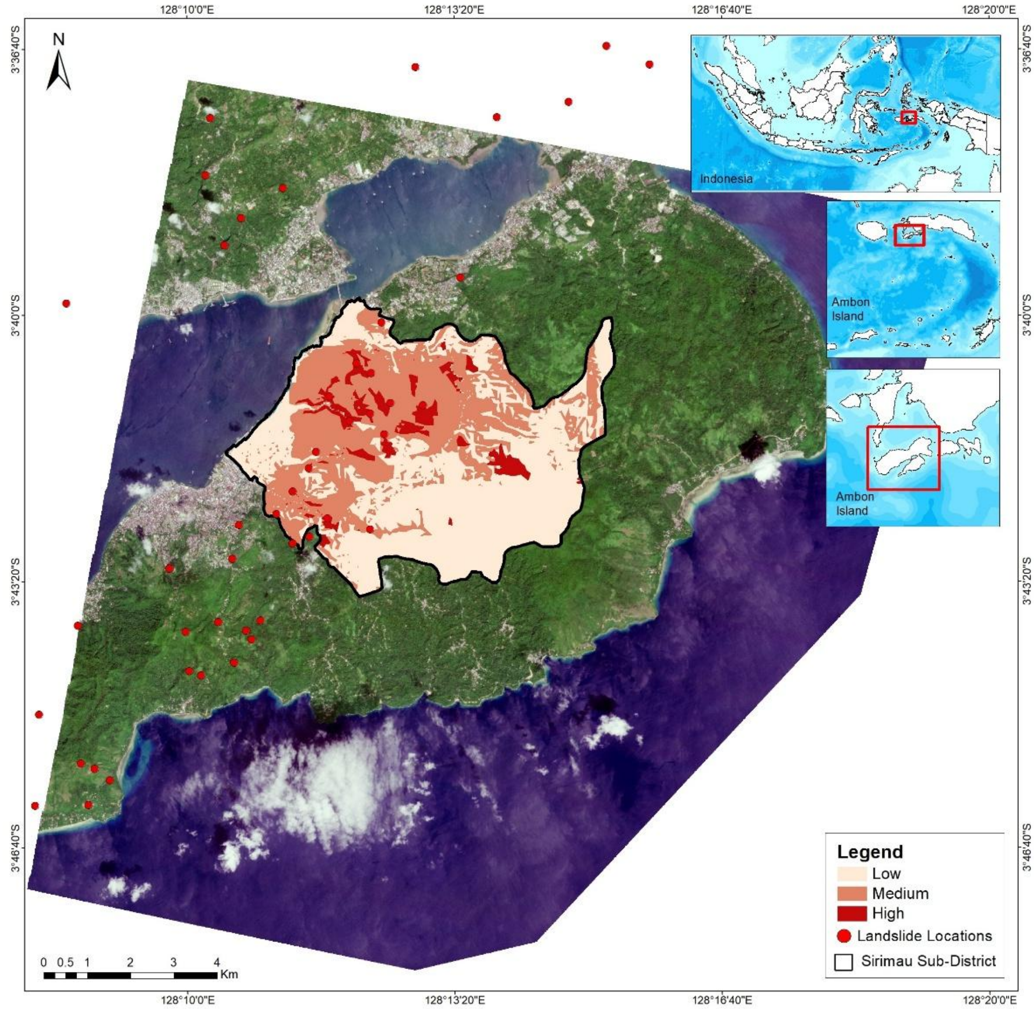

Figure 5. Landslide Vulnerability Levels

3.4. Flood and Landslide Model Validation Test

The Area Under Curve (AUC) value is an important indicator for measuring the accuracy of disaster hazard prediction models, including floods and landslides. In the validation test of the flood model in Sirimau District, an AUC value of 0.973 indicates that this model has a very good ability to distinguish between flood-prone and non-flood-prone locations. An AUC value close to 1 signifies high sensitivity and specificity of the model, making it reliable for mitigation planning and policy-making in flood disaster management (Kalmar et al. 2024).

Meanwhile, the landslide model validation with an AUC value of 0.845 also demonstrates good model performance in predicting areas at risk of landslides. An AUC value above 0.8 is categorized as a good model according to standards in geography and disaster mitigation literature (Hu, Pang, and Deng 2025). This model utilizes various topographic variables, land use, and other environmental factors to produce landslide vulnerability maps that can serve as strategic tools in risk management for vulnerable areas, including Sirimau District.

The use of AUC in model validation provides scientific assurance regarding the reliability of prediction results and forms the basis for developing targeted mitigation policies. With flood and landslide models validated by high AUC values, mitigation efforts can be more focused on high-risk areas, reducing potential social and economic losses due to disasters (Harshasimha and Bhatt 2023). This is particularly important given the complexity of geographic characteristics and the dynamic environmental conditions influencing flood and landslide occurrences in tropical regions such as Sirimau District.

4.5. Policy Recommendations

Policy recommendations for managing flood and landslide disasters in Sirimau Sub-District, Ambon City, Maluku must be based on a comprehensive understanding of the vulnerability and risk levels identified spatially. First, local governments need to strengthen integrated early warning systems and rapid response to extreme weather events that could trigger floods and landslides (Bosher & Chmutina, 2017). This includes enhancing rainfall monitoring, river conditions, and slope stability, as well as disseminating information through local media and digital platforms so the community can take preventive measures early (Shi et al. 2020).

Second, spatial planning must adopt a strict disaster risk zoning approach, especially avoiding development in high vulnerability areas such as steep slopes and riverbanks prone to flooding (Kamil et al. 2020). The construction of flood control infrastructure, such as retaining walls, adequate drainage channels, and revegetation in critical areas, must be carried out to stabilize slopes and reduce the potential for erosion and landslides (Masocha et al. 2025). Repair and normalization of access routes affected by landslides should also be prioritized to ensure community mobility is not disrupted.

Third, increasing community capacity through education and disaster preparedness training is very important. Communities must be engaged to understand danger signs, evacuation procedures, and the importance of following instructions from disaster management authorities (Rakuasa, Latue, and Pakniany 2024). In addition, the provision of logistical aid and emergency support facilities for affected residents must be maintained to ensure a quick and effective response. To strengthen mitigation efforts, cross-sector collaboration between city and provincial governments, the National Disaster Management Agency (BNPB), and non-governmental organizations needs to be intensified for the implementation of sustainable and holistic programs.

Conclusions

Environmental variable analysis shows that floods and landslides in Sirimau Sub-District, Ambon City are influenced by different dominant factors elevation for floods (70.3%) and LULC for landslides (80.9%) reflecting the complex disaster risk dynamics in the region. Vulnerability levels for both hazards mostly fall within low to medium risk categories, but high-risk zones, though smaller, require special mitigation attention. Model validation using high AUC values (0.973 for floods and 0.845 for landslides) confirms the reliability of the MaxEnt method in accurately predicting vulnerable areas with minimal error and good sensitivity. Effective risk management should integrate spatial data with early warning systems, risk zoning in spatial planning, and community capacity building for disaster preparedness to sustainably reduce social and economic impacts.

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