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Flood and Landslide Hazard Mapping in Teluk Ambon Baguala District, Ambon City, Indonesia

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Abstract. *Teluk Baguala District, Ambon City is frequently affected by flood and landslide disasters. This study uses the Maximum Entropy method to model flood and landslide hazard areas based on environmental variables and the spatial distribution of disaster occurrences. The flood mapping results show that areas with low vulnerability cover the largest area, totaling 5,296.07 hectares, while medium-risk areas cover only 188.84 hectares, and high-risk areas cover 493.97 hectares. The area with low landslide vulnerability reaches 2,595.19 hectares, whereas medium vulnerability areas are smaller at 2,327.26 hectares, and very vulnerable or high-risk areas cover only 694.73 hectares. The flood validation test shows an AUC value of 0.974, while the landslide AUC value is 0.851. These mapping results are expected to assist the government in flood and landslide disaster mitigation efforts in the future.*

Keywords: *Flood, landslide, maximum entropy, Teluk Baguala*

1. Introduction

Teluk Ambon Baguala District, Ambon City, is an area prone to hydrometeorological disasters such as floods and landslides due to its topography, high rainfall, and dynamic land use (Rakuasa & Khromykh, 2025). This flood and landslide disaster has had a significant impact on the lives of the community, infrastructure, and sustainable development in the region (Badan Nasional Penanggulangan Bencana, 2025). Therefore, mapping areas prone to flooding and landslides is crucial as an initial step in risk mitigation and better spatial planning (Rozaki et al., 2021). Previous studies have shown that coastal areas with erosion-prone topography and high rainfall require accurate vulnerability modelling to reduce disaster risk (Rakuasa et al., 2022).

Vulnerability modelling for flood and landslide areas has evolved with the use of remote sensing technology and Geographic Information Systems (GIS) as the primary tools for spatial analysis. Conventional methods often have limitations in processing complex data and variables that interact non-linearly (Cabrera & Lee, 2020). In this context, machine learning algorithms like Maximum Entropy (MaxEnt) become an effective choice because they can generate vulnerability probability maps with high precision based on environmental data and historical disaster events (Jiao et al., 2019; Norallahi & Seyed Kaboli, 2021).

The MaxEnt method, a probabilistic model based on the principle of maximum entropy, has been widely used in various hazard mapping studies, including for floods and landslides, with results recognised as effective and accurate (Davis & Blesius, 2015). MaxEnt utilises presence-only data from disaster events as input and correlates it with

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environmental variables such as elevation, slope, distance from rivers, and land cover type (Codru & Niacşu, 2022). The advantage of this method lies in its ability to process incomplete data and provide a vulnerability map output that is spatially well-interpretable (Kornejady et al., 2017; Huang et al., 2024).

To the best of our knowledge, the use of MaxEnt in this study is aimed at identifying and mapping flood- and landslide-prone areas in Teluk Ambon Baguala District, which is geographically vulnerable to hydrometeorological disasters. This method was chosen due to the complexity of factors influencing disasters in coastal and urban areas, which require an adaptive and data-driven modelling approach (Huang et al., 2024). The resulting vulnerability map will serve as a basis for policymakers in effectively determining priorities for disaster management and mitigation.

Additionally, the integration of spatial and temporal data in MaxEnt allows for dynamic modelling, enabling the monitoring of changes in disaster vulnerability due to environmental changes or human activities (Maerker et al., 2016). This approach becomes highly relevant in the context of Ambon City, which is experiencing rapid development with significant land cover changes, thereby increasing the potential risk of flooding and landslides (Javidan et al., 2021).

Overall, this research contributes to the development of GIS and machine learning-based disaster risk mitigation methodologies in tropical regions with specific characteristics. By utilising the MaxEnt model, it is hoped that the resulting flood- and landslide-prone area maps will be more accurate and scientifically accountable, while also serving as a foundation for sustainable development in Teluk Ambon Baguala District, Ambon City.

2. Methods

This research was conducted in Teluk Ambon Baguala District, Ambon City, Indonesia (Figure 1). The research method used is Maximum Entropy (MaxEnt). The environmental variables used for flood analysis consist of elevation, soil type, precipitation, land use type, river density, and distance to river. The variables used for landslide analysis are elevation, slope, soil type, precipitation, land use type, and distance to fault. There are 23 coordinates for flood locations and 6 coordinates for landslide locations. A complete list of environmental variables and their sources can be found in Table 1.

Table 1. Environmental variables

No	Environmental variables	Source	Flood	Landslide
1	Slope	Geospatial Information Agency	-	√
2	Elevation	Geospatial Information Agency	√	√
3	Soil Type	Food and Agriculture Organization	√	√
4	Precipitation	Meteorological and Climatological Agency	√	√
5	Land Use Type	Planet Labs	√	√
6	River Density	Geospatial Information Agency	√	-
7	Distance to River	Geospatial Information Agency	√	-
8	Distance to Fault	Indonesian Geological Agency	-	√
9	Flood and landslide location	National Disaster Management Agency	√	√

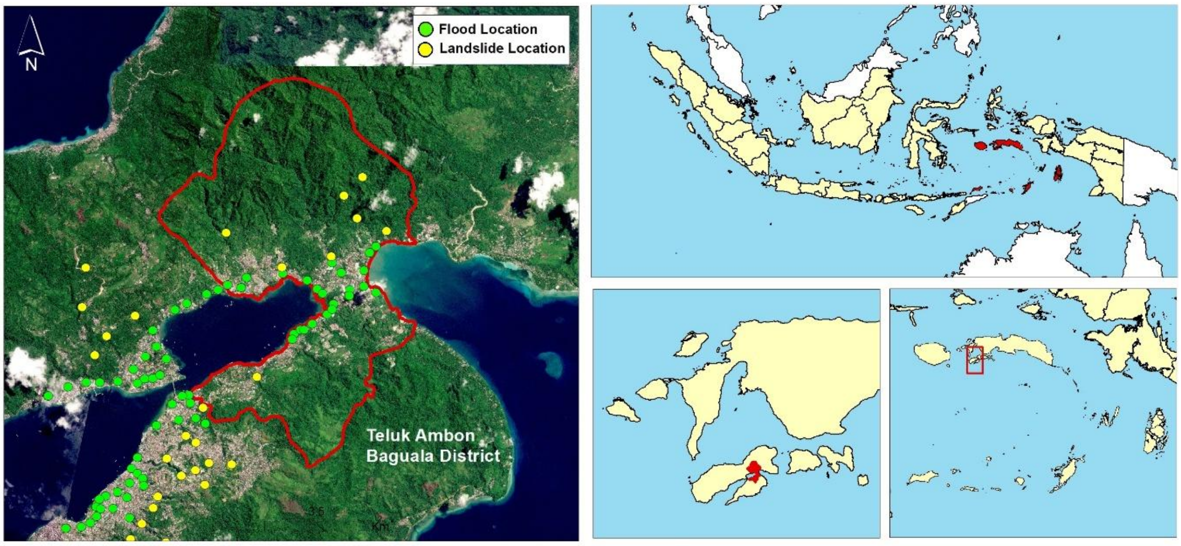

Figure 1. Research Location: Teluk Ambon Baguala District, Indonesia

The data processing begins with the collection of spatial data on environmental variables and historical data on flood and landslide events, which are then prepared in raster and vector formats with a uniform coordinate system to ensure accurate analysis. Environmental variables influencing disaster occurrence were selected based on their correlation with event data and then included in the MaxEnt model. MaxEnt is a machine learning method that uses the principle of maximum entropy to predict the spatial distribution of potential hazards using only presence-only data and relevant environmental variables (Kim et al., 2015; Ramos-Bernal et al., 2024). This model generates probability maps of areas prone to flooding and landslides, which are then classified based on vulnerability level. The software used in this study is ArcGIS, QGIS, and MaxEnt.

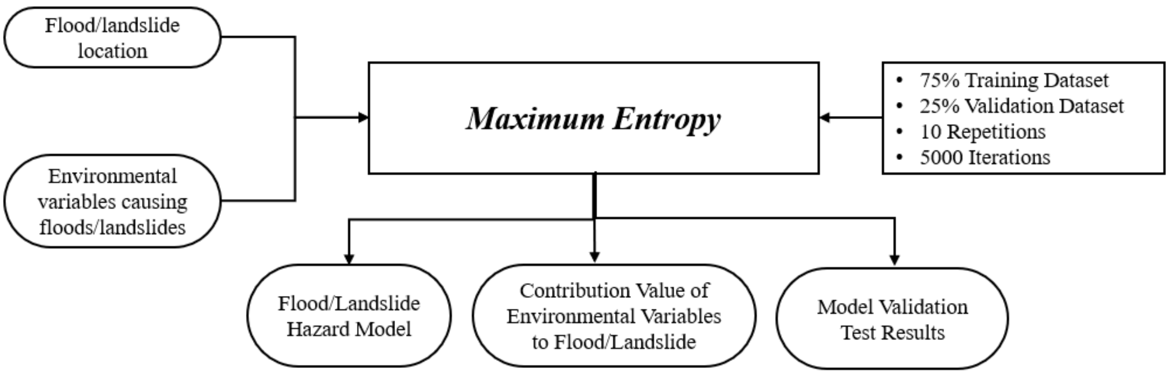

Figure 2. Research workflow

Model validation was performed using the statistical method Area Under Curve (AUC) on the Receiver Operating Characteristic (ROC) curve to measure the accuracy of the model's predictions. With this evaluation, a final map was obtained that can be used as a basis for making disaster mitigation policy decisions (Ramos-Bernal et al., 2024b). The MaxEnt model has been widely proven effective in mapping disaster vulnerability using environmental and historical event data and is capable of providing informative spatial outputs for scientific and accurate disaster risk management. This approach is highly relevant for the complex conditions in Teluk Baguala District, which faces the simultaneous risks of flooding and landslides. The complete workflow can be seen in Figure 2.

3. Results and Discussion

3.1. Influence of Environmental Variables on Floods and Landslides

The contribution of environmental variables to flood hazard in Figure 4 illustrates the different relative influence of each variable in determining an area's vulnerability to flooding. The elevation variable has the most dominant contribution, accounting for 70.3%, which indicates that the location's altitude is highly determinant of flood potential. Areas with low elevation tend to be more susceptible to flooding because water tends to flow to lower areas, making elevation determination a key factor in flood risk modelling. Spatially, the environmental variables influencing floods can be seen in Figure 3.

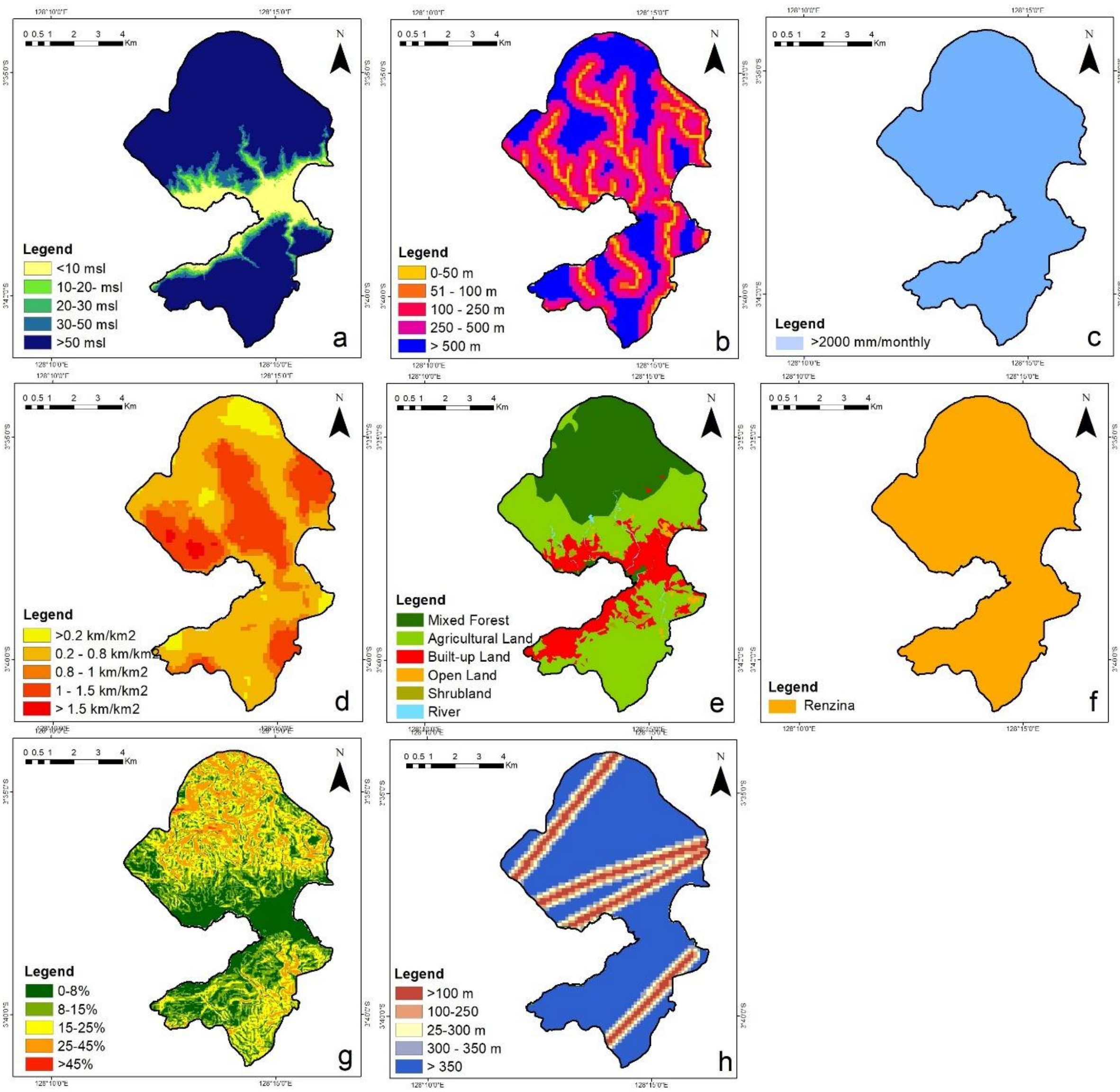

Figure 3. Environmental variables: a) elevation, b) distance from river, c) precipitation, d) stream density, e) land cover, f) soil type, g) slope, h) distance from fault

The contribution of land cover type is also quite significant at 22.9%. This reflects the important role of land surface use and conditions in influencing rainwater infiltration and surface runoff. Areas with dense cover or hard surfaces like asphalt and concrete will increase surface runoff and flood risk, while vegetation cover can absorb water and reduce these risks (Hu et al., 2025). Therefore, this variable is highly relevant for inclusion in the spatial analysis of flood vulnerability.

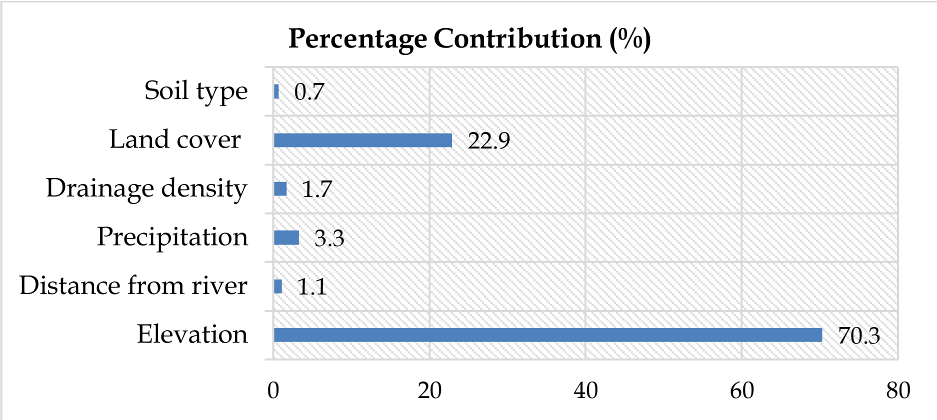

Figure 4. Contribution of Environmental Variables to Flood Hazard

Other variables such as rainfall, drainage density, distance from rivers, and soil type have relatively small contributions, accounting for 3.3%, 1.7%, 1.1%, and 0.7%, respectively. Although the figures are small, these variables are still important because they influence water flow patterns and the intensity of flood events. Rainfall, as the primary source of water, plays a role in determining the amount of runoff, while the distance and density of rivers are related to flow capacity and the potential for water overflow.

Overall, this table shows that in the context of flood hazard mapping, topographic factors, particularly elevation, are the most critical variables in determining regional vulnerability. However, other variables such as land cover and hydrology must still be considered integrally to produce an accurate and representative vulnerability map. This multidimensional approach allows for more effective mitigation decision-making based on the most influential environmental factors (Huang et al., 2024).

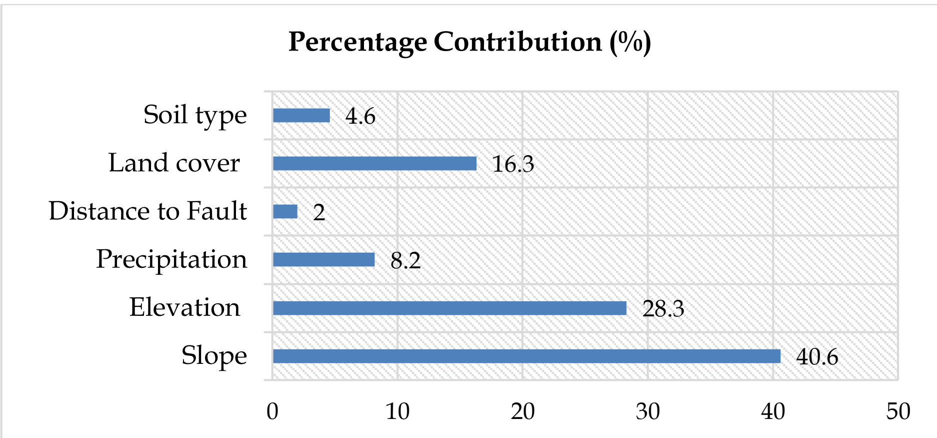

Figure 5. Contribution of Environmental Variables to landslide Hazard

The contribution of environmental variables to landslide hazard in Figure 5 shows that slope is the most dominant factor, contributing 40.6%. This confirms that the steepness of the ground surface significantly influences landslide triggers, as steep slopes tend to be more unstable and susceptible to soil mass movement, especially when combined with triggering factors such as high rainfall (Van Duong, 2024).

Elevation ranks second with a contribution of 28.3%, indicating that the height of a location influences landslide vulnerability. Elevation is related to the geomorphological characteristics and drainage patterns of an area, thus playing a role in determining slope stability and the potential for landslides (Codru & Niacşu, 2022). Areas with a specific elevation can have different risks depending on their combination with other variables such as slope and rainfall.

Rainfall contributed 8.2%, indicating its significant role as the main trigger for landslides. High rainfall intensity and duration can weaken soil cohesion and increase water load on slopes, thereby accelerating the process of landslides (Felícisimo et al., 2013). Although its contribution is less than slope and elevation, rainfall remains a major factor in landslide occurrences.

Other variables such as land cover (16.3%), soil type (4.6%), and distance to faults (2%) also contribute to landslide vulnerability. Land cover reflects the influence of human activities and vegetation conditions that affect slope stability, while soil type influences the physical and mechanical properties of the soil substrate. The distance to the fault indicates the potential for tectonic vibrations as a trigger for landslides, although its contribution is relatively small compared to other factors. All these variables are important to integrate in order to obtain a valid and accurate landslide susceptibility map.

3.2. Flood and landslide model based on MaxEnt

The flood model developed using the Maximum Entropy (MaxEnt) approach for the Teluk Ambon Baguala sub-district classifies flood risk levels into three vulnerability classes: low, medium, and high. The model results show that most of the 5,296.07-hectare area falls into the low-risk category. This area generally has a higher elevation and favourable land cover conditions, such as natural vegetation that allows for optimal water infiltration, thus reducing the potential for waterlogging and the risk of flooding. Conditions like this are important to maintain for disaster mitigation and sustainable environmental management (Rakuasa et al., 2022).

On the other hand, there are smaller areas with moderate and high-risk levels, covering 188.84 hectares and 493.97 hectares, respectively. These moderate- and high-risk areas are typically located in areas with lower elevations and more degraded land cover conditions, such as areas that have been converted to dense settlements or open land susceptible to surface runoff (Harshasimha & Bhatt, 2023). These areas are a priority focus in flood mitigation efforts, particularly in the planning of drainage infrastructure and land conservation (Huang et al., 2024).

The importance of this vulnerability classification is to provide a clear spatial overview of flood risk distribution, enabling policymakers and stakeholders to formulate the most effective mitigation strategies (Norallahi & Seyed Kaboli, 2021). Flood risk maps based on this class also serve as a tool for public outreach to raise awareness and preparedness in the face of potential floods (Zuo et al., 2023). With the MaxEnt approach, this model is able to utilise spatial flood presence data and environmental variables to generate accurate and informative probabilistic maps.

Overall, the use of MaxEnt in flood modelling in Teluk Ambon Baguala shows that the combination of elevation variables and land cover conditions is a major determinant in determining flood distribution and risk levels (Rakuasa & Latue, 2024). Therefore, maintaining land cover quality and implementing sustainable land management in low-risk areas can be a long-term strategy to reduce the impact of floods while increasing the region's resilience to climate change and human activities (Hao et al., 2024). This result reinforces the importance of data- and technology-driven approaches in modern disaster mitigation. The flood model in Teluk Ambon Baguala District can be seen in Figure 6.

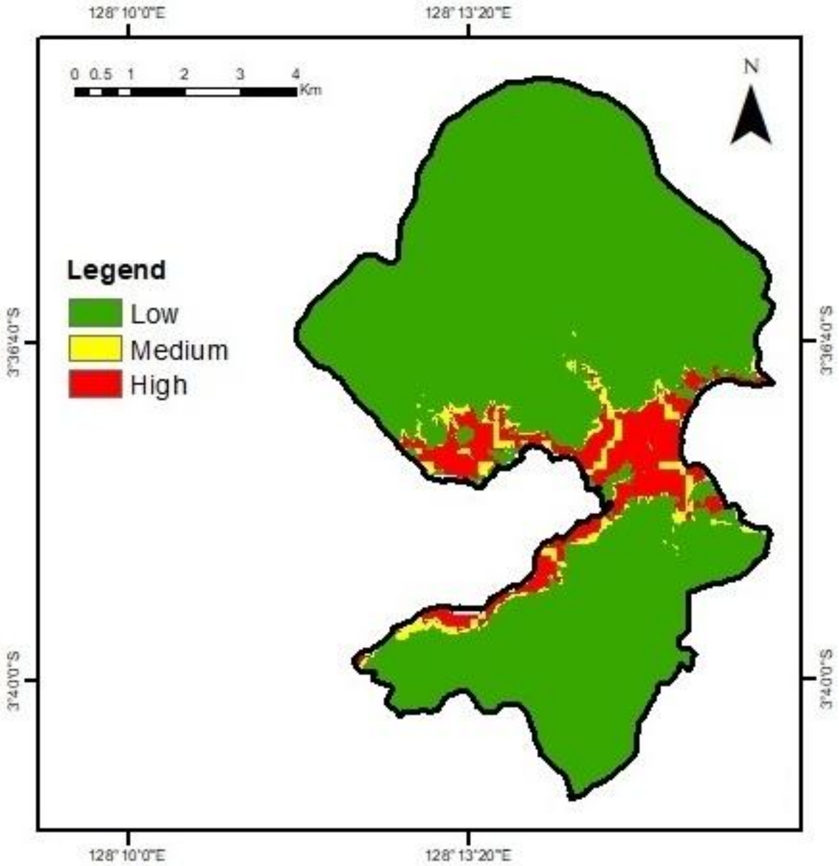

Figure 6. Flood vulnerability map

The landslide model developed using the Maximum Entropy (MaxEnt) approach in Teluk Ambon Baguala District classifies landslide susceptibility into three classes: low, medium, and high, with significantly different areas for each class. The area with low susceptibility covers the largest area, which is 2,595.19 hectares. This indicates that most of the area has relatively more stable environmental and topographic conditions and is less susceptible to landslides.

The area with moderate vulnerability, covering 2,327.26 hectares, which is a moderately risky region, signals the need for mitigation attention in this zone. This area may have certain environmental characteristics, such as a moderate slope and more degraded land cover compared to low-risk areas, potentially making it a transition zone that requires more careful management in the face of potential landslides (Rakuasa et al., 2025). The landslide model for Teluk Ambon Baguala District can be seen in Figure 7.

Meanwhile, areas with high vulnerability occupy the smallest area, which is 694.73 hectares, but are very important because this zone is the most prone to landslides and poses a high risk of causing damage and threatening public safety. This zone is usually located in areas with steep slopes and specific elevations and may be affected by extreme rainfall conditions as well as human activities that damage soil structure (Rakuasa, 2025).

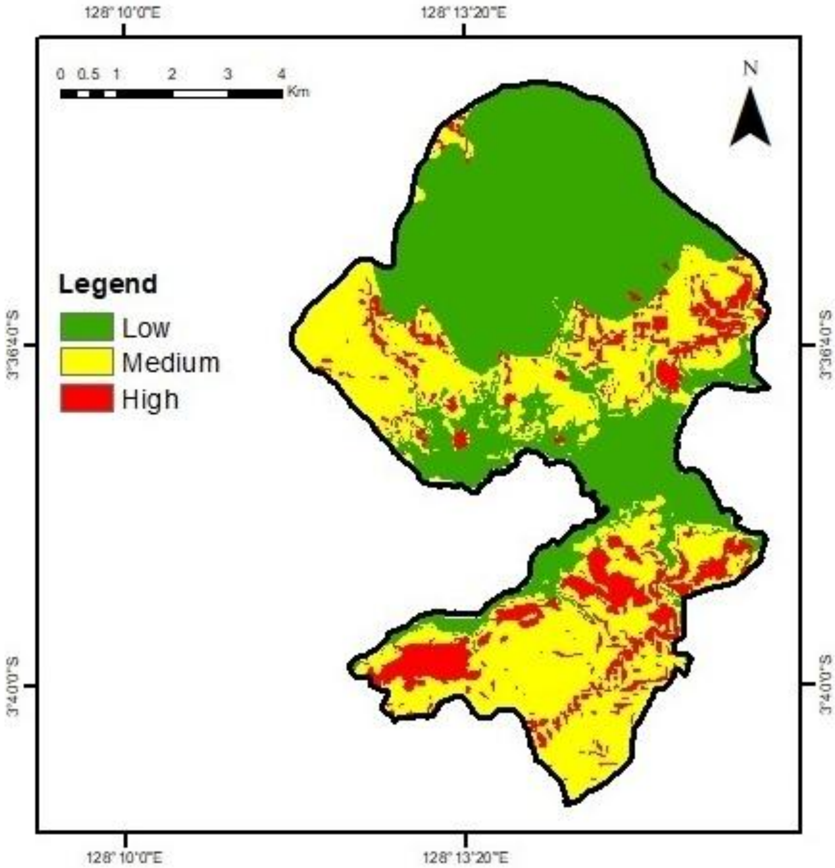

Figure 7. Landslide vulnerability map

Practically, the results of this classification provide clear spatial guidance for policymakers and disaster mitigation practitioners to prioritise flood and landslide risk management (Sugandhi et al., 2023). This risk mapping helps in spatial planning, the development of landslide control infrastructure, and public awareness campaigns to improve preparedness, particularly in areas with moderate to high vulnerability (Somae et al., 2022). The MaxEnt approach allows for adaptive and data-driven landslide vulnerability models, which are highly relevant for the dynamic conditions in Teluk Ambon Baguala.

3.3. Accuracy Test of Flood and Landslide Models

The accuracy test results of the flood model, evaluated using the omission method, area prediction, and sensitivity, with an Area Under Curve (AUC) value of 0.974, indicate excellent and reliable model performance. An AUC value close to 1 signifies that the MaxEnt model has a very high ability to spatially distinguish between flood-prone and non-flood-prone areas. This means the omission error rate, which is the model's failure to identify flood-prone areas, is very low (Norallahi & Seyed Kaboli, 2021). With a low omission rate, the majority of areas that are indeed prone to flooding are successfully predicted by the model, significantly reducing the risk of losing important data in critical regions (Lorente, 2019). The flood model validation test can be seen in Figure 8.

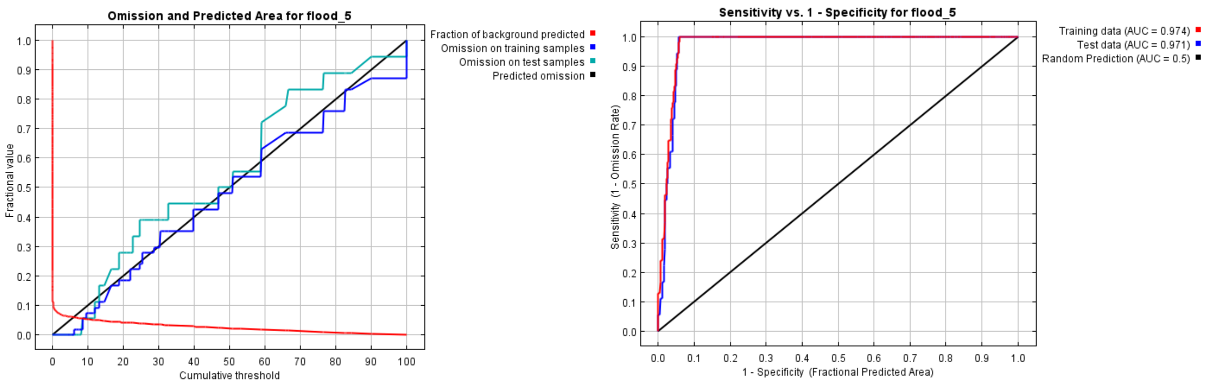

Figure 8. Flood model validation test

Additionally, the model's high sensitivity indicates that it is capable of detecting most of the actual flood events occurring in the study area without significant information loss. Good sensitivity indicates that the model effectively captures environmental signals and flood risk distribution based on the input variables used, thus providing realistic and applicable vulnerability maps to support disaster mitigation planning (Qasimi et al., 2024). This risk map can be used as a basis for decision-making in regional management, development planning, and prioritising resource allocation for flood prevention and mitigation measures (Huang et al., 2024).

Technically, the high performance of this model also reflects the quality of the environmental data used and the appropriateness of selecting important variables, especially the significant dominance of elevation and land cover variables that influence flood risk prediction. However, although AUC is a key indicator of model performance, it is recommended to supplement validation with other metrics and independent testing to further strengthen the model's reliability before large-scale implementation. Thus, an AUC value of 0.974 proves that the developed MaxEnt model is highly effective and accurate for mapping flood vulnerability in Teluk Baguala District, providing a strong foundation for more targeted risk reduction and mitigation strategies (Kalita et al., 2025).

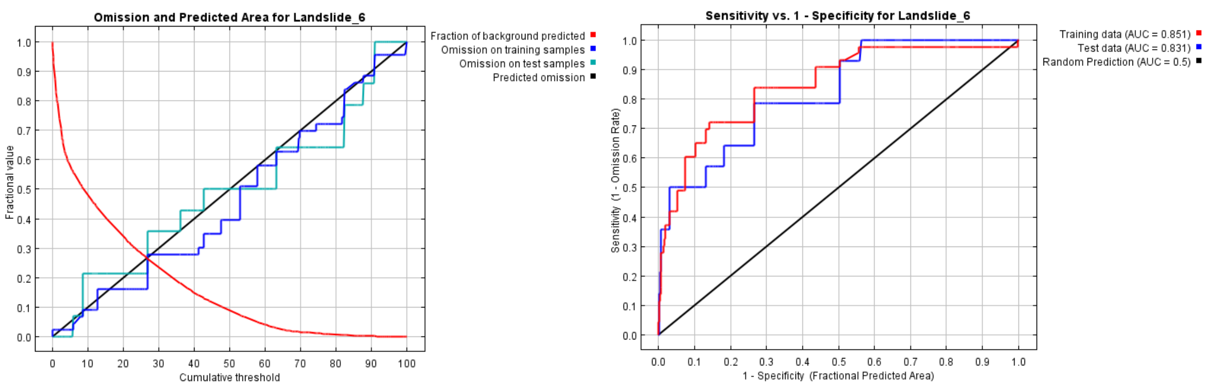

Figure 9. Landslide model validation test

The accuracy test results for the landslide model using the omission method, area prediction, and sensitivity show good performance, as indicated by an AUC value of 0.851 in Figure 9. This AUC value indicates that the model is able to distinguish quite well between landslide-prone and non-prone areas, although not as strongly as models with an AUC approaching 1. The small number of landslide event points, only 6, is a significant limitation for the statistical power of the MaxEnt model in this analysis. Although the AUC value of the landslide model reached 0.851 and was statistically acceptable, the limitations in the number of observation points affected the potential reliability and generalisability of the results (Maulita et al., 2024). Therefore, the results of the landslide modelling need to be interpreted with caution, with suggestions for adding more event points in future research to improve the model's validity (Maerker et al., 2016). The relatively low omission rate indicates that the model is able to identify most of the actual landslide locations, while adequate sensitivity confirms the model's effectiveness in detecting landslide-prone areas. Thus, this MaxEnt model can be used as a valid tool for landslide risk mitigation planning and land management in the study area.

3.4. Policy Recommendations

Policy recommendations regarding the mapping of flood- and landslide-prone areas in Teluk Baguala District, Ambon City, need to be directed toward strengthening the integration of MaxEnt-based mapping results into spatial planning and land use management. With accurate hazard maps, local governments can establish no-build zones in high-risk areas and direct development to safer locations, in line with the principle of spatial-based disaster risk reduction (Li et al., 2018). This is important given the dynamic land use changes in Ambon, which have the potential to increase disaster risk (Rana et al., 2021).

Additionally, mitigation strategies must integrate structural and non-structural approaches in a unified manner. The structural approach includes building disaster-resistant infrastructure such as drainage systems and slope reinforcement, while non-structural approaches like community education, local capacity building, and MaxEnt-based spatial data early warning systems are key to improving community preparedness and response. Coordination and socialisation by the Ambon City Regional Disaster Management Agency (BPBD) have already been carried out, but they need to be strengthened with monitoring and resource support to make mitigation efforts more optimal (Van Niekerk et al., 2018).

Mitigation policies must also be based on adaptive monitoring and evaluation that are responsive to environmental and social dynamics (Huang et al., 2024). With MaxEnt modelling that can be updated according to current conditions, policies become flexible and evidence-based in the face of climate change and human activities that affect flood and landslide risks. This is important to ensure that mitigation measures are always relevant and effective and that they support sustainable development in disaster-prone areas like Baguala Bay. Implementing policies like this will strengthen regional resilience to disasters while significantly reducing their negative impact.

Conclusions

The flood and landslide vulnerability mapping model in Teluk Baguala District using the Maximum Entropy (MaxEnt) approach successfully classified risk levels into low, medium, and high categories, with results showing that most of the area is considered safe, but important zones require special attention for mitigation. The flood model demonstrated excellent performance with an AUC value of 0.974, indicating high accuracy in distinguishing flood-prone areas, while the landslide model has an AUC value of 0.851, also valid for landslide risk mitigation planning use. The distribution of areas with medium and high risk levels is the main focus for risk management actions to minimize disaster impacts, making this MaxEnt model proven effective and reliable as a tool for disaster risk reduction planning in the study area.

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Conflicts of Interest

The authors declare no conflict of interest

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