# Flood modeling in the Ambon City Center River Basin using maxent model and environmental variables

*Susan E* Manakane[1*], *Heinrich* Rakuasa[2], and *Vadim V.* Khromykh[1]

[1]Geograpy Education Study Program, Universitas Pattimura, Ambon, Indonesia
[2]Faculty of Geology and Geography, Tomsk State University, Tomsk, Russian Federation

**Abstract.** The river basins in the Ambon city center area frequently experience annual flooding, which causes environmental damage and disrupts community social-economic activities. This study aims to model flood hazards using environmental variables, including elevation, slope, aspect, TWI (Topographic Wetness Index), soil type, precipitation, land use type 2026, river density, distance to river, and flood event location data. The MaxEnt method based on machine learning was employed in this research. The flood modeling results indicate that elevation (53.3%), land cover (42.3%), and drainage density (1.9%) have a significant influence on this disaster. The flood hazard model shows high-risk areas covering 590 ha, moderate-risk areas 1,528 ha, and low-risk areas 2,828 ha. The Wai Ruhu river basin has the largest extent in the high flood hazard class at 177 ha, followed by Wai Tomu (134 ha), Wae Batumerah (115 ha), Wae Batu Gajah (99 ha), and Wae Batu Gantung (66 ha). Overlay results of flood hazards with 2026 built-up land in the river basins reveal that settlements in high-risk classes cover 32%, moderate-risk 52%, and low-risk 16%. The research findings are expected to assist local government in future flood disaster mitigation efforts in the river basins.

## 1 Intoduction

Floods are a frequent hydrological disaster in urban areas such as Ambon City, particularly in the central city river basin, resulting from a combination of climatic, topographic, and anthropogenic factors [1]. Global climate change has intensified extreme rainfall events in eastern Indonesia [2], while rapid urbanization in Ambon has led to land conversion into settlements and infrastructure, reducing rainwater infiltration [3]. This phenomenon not only threatens human lives but also damages economic infrastructure and local ecosystems, necessitating accurate spatial modeling for mitigation [4].

Ambon City, as the administrative center of Maluku Province, faces high flood vulnerability in its central city river basin due to low elevation, gentle slopes, and proximity to major rivers [1]. Previous studies indicate that floods in this area are triggered by high rainfall, soil types prone to water saturation, and inadequate drainage density, exacerbated by urban land cover [1]. Historical data records recurrent flooding during the rainy season, with significant impacts on the dense urban population.

Traditional flood susceptibility modeling has relied on deterministic methods such as the Analytic Hierarchy Process (AHP); however, these approaches often lack accuracy when handling incomplete data or class imbalances [5]. Machine learning models like MaxEnt (Maximum Entropy) offer advantages as presence-only models that effectively predict flood occurrence distributions based on environmental variables, achieving high accuracy of up to 90% in similar studies [6]. MaxEnt has proven superior in urban flood susceptibility mapping across various contexts, including integration with GIS for spatial analysis [8].

The application of MaxEnt with these variables enables precise spatial mapping of flood susceptibility in the Ambon City Center River Basin. This approach has been widely adopted in many countries and proven to be highly effective, whereas its implementation in Indonesia remains very limited. This research is expected to fill the gap in local flood modeling in Ambon by optimizing MaxEnt using specific environmental variables, thereby providing a scientific basis for sustainable river basin management policies. The mapping results can support risk zoning, drainage planning, and land restoration, aligning with Indonesia's national priorities for disaster risk reduction.

## 2 Methodology

### 2.1 Research location

This research was conducted in the river basin in the Central Ambon City, Maluku Province, Indonesia. This river basin consists of Wai Ruhu (1,939.03 ha), Wai Batu Merah (655.03 ha), Wae Tomu (620.61 ha), Wai Batu Gajah (641.51 ha), and Wae Batu Gantung (1,089.86 ha), which frequently overflow and cause flooding in Ambon City during the rainy season. The spatial location of the study area can be seen in Figure 1.

* Corresponding author: uchanmanakane9782@gmail.com[1], heinrich.rakuasa@yandex.ru[2]

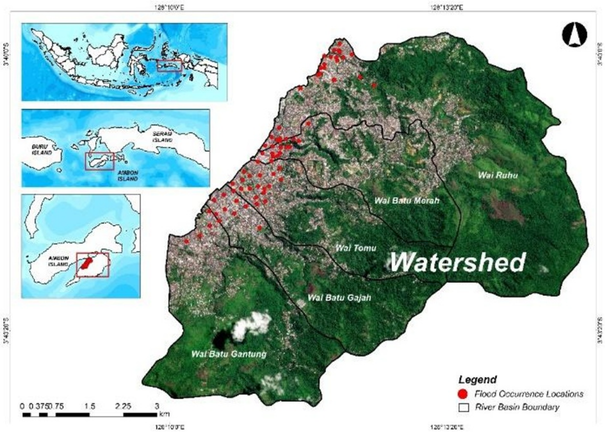


**Figure 1.** Research Location, Ambon Island, Indonesia.

### 2.2 Environmental Variables Data

Place The environmental variables contributing to flooding in the Ambon City river basin consist of elevation, slope, soil types, rainfall, distance from the river, land cover, drainage density, Topographic Wetness Index (TWI), and 70 historical flood location points. The elevation, slope, and Topography Wetness Index variables were derived from processing Digital Elevation Model (DEM) data from the Indonesian Geospatial Information Agency (BIG). The distance from the river and drainage density variables were obtained from processing the river network data from the Indonesian Geospatial Information Agency (BIG). Soil type data was sourced from the Ambon City Soil Type Map provided by the Ambon City Government. Land cover data were derived from the interpretation of PlanetScope satellite imagery for 2026, obtained from Planet Labs. Rainfall data were acquired from the Ambon City Meteorology, Climatology, and Geophysics Agency (BMKG) Station. The distribution of flood event locations (70 coordinates) from the past five years was obtained from the National Disaster Management Agency of Indonesia (BNPB). The spatial distribution of the environmental variables used can be seen in Figure 2.

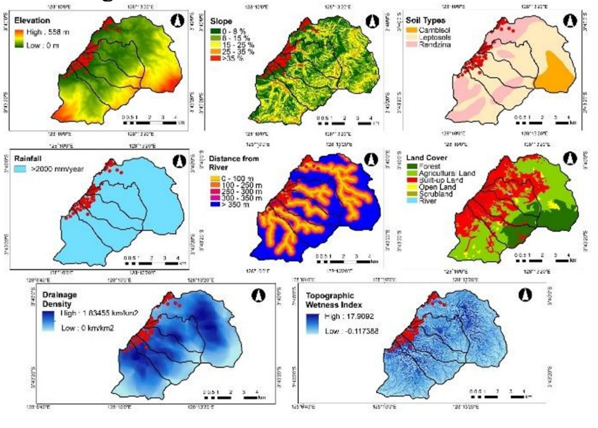


**Figure 2.** Environmental variables include elevation, slope, soil types, rainfall, distance from river, land cover, drainage density, and Topography Wetness Index (TWI).

All environmental variables were processed and analyzed using ArcMap GIS software, which was employed for the preparation of environmental variables. Flood modeling was conducted using MaxEnt software, an open-source machine learning-based tool.

### 2.3 MaxEnt for Flood Modeling

Flood modeling in this river basin uses MaxEnt. The Maximum Entropy (MaxEnt) model was originally developed as a statistical approach to model species' spatial distributions based on presence-only occurrence data and a set of constraining environmental variables [9]. Mathematically, MaxEnt seeks to find the probability distribution p(x) over the space X (e.g., pixels in a map) that maximizes the Shannon entropy $-\sum_x p(x) \log p(x)$, subject to the constraint that the expected value of each environmental feature $f_j$ (x)under p(x)equals the empirical average of that feature at the presence points [10]. The solution to this optimization problem takes the form of an exponential distribution.

$$p\,(x)= \frac{1}{Z}\exp\left(\sum_j \lambda_j\, f_j\,(x)\right) \qquad (1)$$

where $\lambda_j$ are the estimated coefficients and Z is the normalization factor. In practice, features $f_j$ can consist of linear, quadratic, product, or other transformations of environmental variables, making MaxEnt effectively function similarly to logistic regression models with high flexibility under constraints [10].

In flood susceptibility modeling, historical flood occurrence points (e.g., recorded inundation locations or those captured by satellite imagery) can be treated analogously to species presence points in ecological studies, while the environmental variables influencing floods (elevation, slope, distance to rivers, TWI, rainfall, land cover, etc.) serve as environmental features [8]. Thus, MaxEnt is used to estimate the relative probability distribution of flood susceptibility across the entire river basin, representing the relative likelihood that a given location will experience flooding given its environmental variables [11]. The results of this flood modelling were then overlaid with built up land data to predict the built-up areas that would be affected.

## 3 Results and discussion

### 3.1 Contribution of Environmental Variables

The contributions of elevation and land cover are highly dominant in the MaxEnt modeling results, with percent contributions of 53.3% and 42.3%, respectively, and permutation importance values of 93.5% and 2.5%. The percent contribution value reflects how much each variable is used during the model training process, whereas permutation importance indicates how sensitive the model performance is to randomization of a given variable's values in the training data. The dominance of elevation in both percent contribution and permutation importance indicates that differences in elevation within the Ambon watershed are the primary factor controlling flood susceptibility, for example low-lying areas and topographic depressions that tend to become zones of surface flow accumulation [1]. The major role of land cover shows that changes and types of land use (settlements, built-up areas, vegetation, and so on) significantly influence runoff processes and infiltration capacity, which is consistent with various studies that emphasize the strong impact of LULC changes on flood response in urban areas [11].

Conversely, other variables such as drainage density, slope, rainfall, distance from river, soil type, and TWI have relatively low percent contribution and permutation importance values (each below 3%), indicating that under the data configuration and spatial scale of this study, their additional contribution to improving model accuracy is more limited. The contribution of each variable can be seen in Table 1. This is in line with MaxEnt interpretation guidelines, which state that variables with low percent contribution are not necessarily "unimportant", but are often redundant or correlated with dominant variables such as elevation and land cover, so that the information they carry is largely represented already. In the context of flood modeling, this condition can be interpreted as indicating that topographic patterns and land cover types in the Ambon watershed are already strong enough to explain the spatial variation in flood susceptibility, while variables such as TWI, distance from river, and rainfall act more as fine-tuning factors that adjust the risk distribution.

**Table 1.** Font styles for a reference.

| No | Variable | Percent contribution | Permutation importance |
|---|---|---|---|
| 1 | Elevation | 53.3 | 93.5 |
| 2 | Land Cover | 42.3 | 2.5 |
| 3 | Drainage Density | 1.9 | 0.4 |
| 4 | Slope | 1.1 | 2.7 |
| 5 | Rainfall | 0.6 | 0.3 |
| 6 | Distance from River | 0.4 | 0.2 |
| 7 | Soil Type | 0.2 | 0.2 |
| 8 | TWI | 0.1 | 0.1 |

### 3.2 Contribution of Environmental Variables

The MaxEnt modeling results in Figure 4 show that the flood susceptibility levels in each watershed in Ambon City are dominated by the Low class, but the extents of the Medium and High zones cannot be ignored because they are concentrated in densely populated and strategically important low-lying areas. In Wae Batu Gantung, out of a total of approximately 1,090 ha, low susceptibility covers 740 ha, medium susceptibility 284 ha, and high susceptibility 66 ha, indicating that most parts of the watershed are still relatively safe, but there are pockets of critical zones that can cause severe impacts during extreme rainfall events. A similar pattern is observed in Wai Ruhu, where the low class reaches 1,214 ha, the medium 548 ha, and the high 177 ha, so although the low class is dominant, the total area of the medium–high classes is substantial enough to justify prioritizing both structural and non-structural measures.

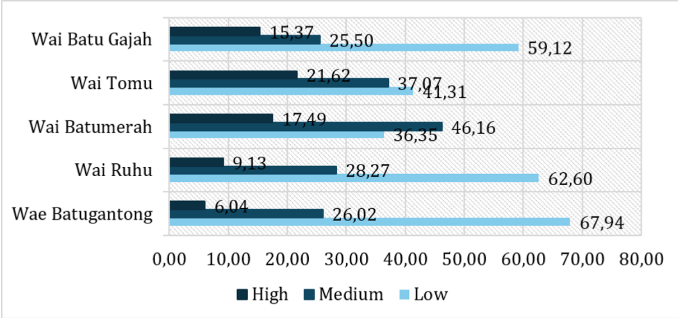


**Figure 3.** Percentage of flood susceptibility area (%).

In smaller watersheds such as Wai Batu Merah, Wai Tomu, and Wai Batu Gajah, the distribution of susceptibility classes is relatively more balanced, making the proportion of Medium and High areas more important from a management perspective. Wai Batu Merah has 238 ha of low, 302 ha of medium, and 115 ha of high; Wai Tomu has 256 ha of low, 230 ha of medium, and 134 ha of high; while Wai Batu Gajah has 379 ha of low, 164 ha of medium, and 99 ha of high, indicating that a significant portion of the watershed area falls within medium- to high-susceptibility conditions.

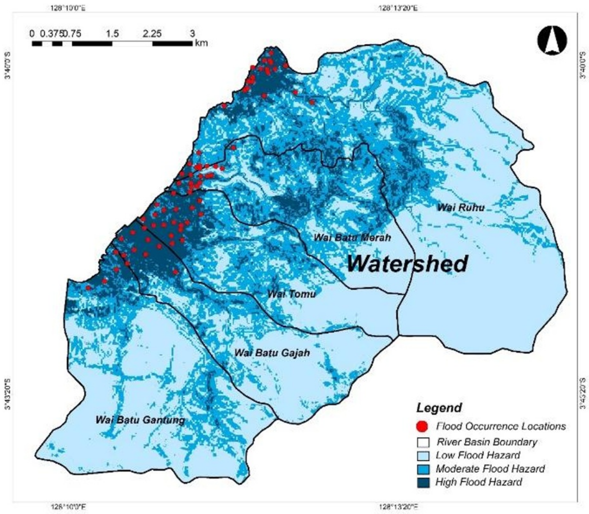


**Figure 4.** Flood Model.

The flood susceptibility distribution across the five watersheds in the center of Ambon City indicates that most areas still fall into the low susceptibility class, yet several watersheds have a relatively large proportion of medium–high susceptibility. Wae Batu Gantung and Wai Batu Gajah are dominated by low susceptibility (67.94% and 59.12%, respectively), whereas Wai Batu Merah has a higher proportion of medium susceptibility (46%), and Wai Tomu has 37.07% in the medium class, making these two watersheds more prone to flooding. Elevation, land cover change, and settlement planning along rivers are the main factors increasing the extent of high susceptibility areas, underscoring the need for better handling and watershed management in the future. The complete presentation of flood susceptibility areas can be seen in Figure 3.

### 3.3 Flood-Affected Settlement Prediction

The overlay between the flood model and built up land in 2026 shows that a large portion of settlements and infrastructure in the Ambon City watersheds still lies within low susceptibility areas, covering 280 ha or about 16% of the total built up area. This indicates that roughly six out of ten developed areas in the Ambon watersheds are located in relatively safer flood zones, so the direct risk to lives and building damage remains comparatively limited in the low susceptibility class.

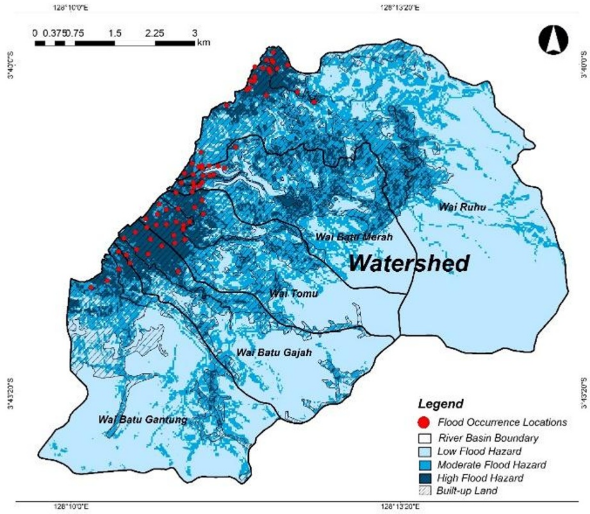


**Figure 5.** Prediction of Flood-Affected Built-Up Land.

However, the analysis also reveals that 918 ha (52%) of built up land are situated in medium susceptibility areas, while 557 ha (32%) fall within high susceptibility zones, meaning nearly one third of all built up land lies in the most flood prone areas. This highlights that expansion of settlements and physical development in the Ambon City watersheds has not fully followed the flood susceptibility pattern, underscoring the need for spatial planning corrections, restrictions on construction in high risk zones, and strengthened drainage infrastructure and GIS based mitigation measures to reduce future losses [1]. Spatially, the built up areas predicted to be affected by flooding can be seen in Figure 5.

### 3.4 Model Validation Test

The validation results of the flood model using MaxEnt are presented through a validation curve consisting of the omission–predicted area graph and the AUC graph. Panel (Fig. 6a) shows how omission rates for both training and test data change along the cumulative threshold, together with the proportion of area predicted as flood prone. When the omission curves are close to the predicted omission line, the model is considered to represent the spatial pattern of flood occurrences consistently with the cumulative MaxEnt output, so the resulting flood susceptibility map can be regarded as reliable for spatial flood analysis [8].

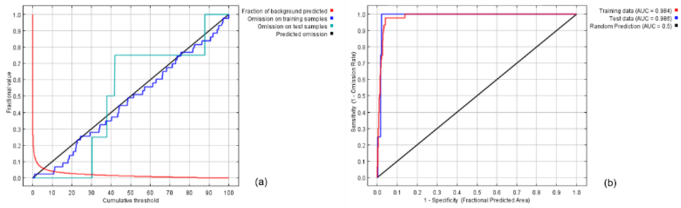


**Figure 6.** Validation curve; (a) Curve graph omission predicted area, (b) AUC graph on flood event modelling.

The validation results of the flood model using MaxEnt are also reflected in panel (Fig. 6b) through the ROC curve and the AUC value, which describe the model's ability to distinguish between flood prone and non-flood prone areas. In MaxEnt's ROC calculation, specificity is defined based on the fraction of predicted area, so the theoretical maximum AUC is slightly below 1, yet it remains a strong indicator of model performance [11]. The AUC value in this study is 0.986, which means that the model performs very well and can be used for further analysis. The high AUC obtained in this flood modelling is consistent with many flood susceptibility and hydrometeorological hazard studies that use AUC as a primary measure of predictive quality, indicating that the model outputs are suitable to support mitigation planning and spatial management in the study area [13].

### 3.5 Discussion

This MaxEnt based flood modelling approach uses historical flood occurrences as presence points and relates them to a set of environmental variables, including elevation, slope, soil type, rainfall, distance from river, land cover, drainage density, and the Topographic Wetness Index (TWI), so that low lying areas with these characteristics tend to be highlighted as high probability zones on the susceptibility map. Even so, the framework still focuses mainly on environmental controls and point based event representation, meaning that socio economic conditions and the inherently spatial extent of floods are only partially captured; areas without recorded flood points are not necessarily safe, as they may be uninhabited or simply lack reporting. For that reason, the model outputs are best treated as an initial screening tool that should be refined through field verification, continuous updating of the flood inventory, and repeated model iterations before serving as a primary reference for disaster risk reduction planning.

## 4 Conclusion

The MaxEnt method is a machine learning–based approach that has proven highly effective for flood modeling because it can produce accurate flood models using historical flood occurrence data and contributing environmental variables. When this model is applied in different regions, the resulting flood susceptibility patterns will vary, as they are strongly influenced by local physical and environmental conditions as well as the spatial distribution of past flood events. In the five river basins located in the central area of Ambon City, the modeling results indicate that elevation and land cover are the most influential environmental variables, with 590 ha, or 12%, of the study area classified as high susceptibility zones; the Wae Ruhu watershed has the largest high susceptibility extent, reaching 177 ha. When overlaid with built up land data, 557 ha of built-up areas fall within the high susceptibility class, showing that a substantial portion of existing settlements are exposed to significant flood risk. These results demonstrate that MaxEnt can provide sufficiently accurate information at relatively low cost, making it an important tool to guide river basin spatial planning and flood mitigation oriented land use policies.

We would like to thank the head of the GIS laboratory, Department of Geography, Tomsk State University, for facilitating us during the data processing and analysis.

## References

1. H. Rakuasa, V.V. Khromykh, Utilization of GIS Technology for Mapping Flood-Prone Areas in Ambon Island, Indonesia KnE Soc. Sci. **10,** 296 (2025)
2. W. Handayani, U.E. Chigbu, I Rudiarto, I.H.S. Putri, Urbanization and Increasing Flood Risk in the Northern Coast of Central Java—Indonesia: An Assessment towards Better Land Use Policy and Flood Management Land. **9,** 343 (2020)
3. M. Salakory, H. Rakuasa, Modeling of Cellular Automata Markov Chain for predicting the carrying capacity of Ambon City J. Pengelolaan Sumberd. Alam dan Lingkung. **12**, 372 (2022)
4. H. Mushwani, A. Arabzai, L. Safi, H. Ullah, A. Afghan, A Parven, Evaluation of flood hazard vulnerabilities and innovative management strategies in Afghanistan's central region Nat. Hazards. **121**, 4639 (2025)
5. F. Vujović, G. Grozdanić, R. Đurović, A. Valjarević, I. Milevski, Comparative assessment of GIS-based multi-criteria decision analysis (AHP) and machine learning (MaxEnt) approaches for wildfire susceptibility modeling in Montenegro Egypt. J. Remote Sens. Sp. Sci. **28**, 724 (2025)
6. M Norallahi, H.S. Kaboli, Urban flood hazard mapping using machine learning models: GARP, RF, MaxEnt and NB Nat. Hazards. **106**, 119 (2021)
7. N. Kalita, N. Bhattacharjee, N. Sarmah, M.J. Nath, Estimation of Flood Hazard Zones of Noa River Basin Using Maximum Entropy Model in GIS Nat. Environ. Pollut. Technol. **24**, B4216 2025
8. S.J. Phillips, R.P. Anderson, R.E. Schapire R E, Maximum entropy modeling of species geographic distributions Ecol. Modell. **190**, 231 (2006)
9. J. Elith, S.J. Phillips, T. Hastie, M. Dudík, Y.E. Chee and C.J. Yates, A statistical explanation of MaxEnt for ecologists Divers. Distrib. **17**, 43 (2011)
10. N. Javidan, A. Kavian, H.R. Pourghasemi, C. Conoscenti, Z. Jafarian, J. Rodrigo-Comino, Evaluation of multi-hazard map produced using MaxEnt machine learning technique Sci. Rep. **11**, 6496 (2021)
11. A.B. Qasimi, V. Isazade, R. Berndtsson R, Flood susceptibility prediction using MaxEnt and frequency ratio modeling for Kokcha River in Afghanistan Nat. Hazards. **120**, 1367 (2024)