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Original Article

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Modeling Forest Fire Susceptibility Based on Bioclimatic Environmental Variables in Ambon Island, Indonesia

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Abstract. Forest fires in small-island regions such as Ambon Island threaten ecosystem sustainability and community safety; however, precise geospatial risk mapping in these areas remains very limited. Therefore, this study aims to model forest fire vulnerability levels using the Maximum Entropy (MaxEnt) algorithm based on bioclimatic variables. The modeling integrated 58 MODIS hotspots as presence points with 11 bioclimatic predictor variables free from multicollinearity (BIO 2, BIO 3, BIO 4, BIO 7, BIO 8, BIO 9, BIO 10, BIO 12, BIO 14, BIO 15, and BIO 17), and its accuracy was evaluated using Receiver Operating Characteristic (ROC) curve analysis based on the testing Area Under the Curve (AUC) value. The results showed that the MaxEnt model had good spatial discrimination performance, with a mean testing AUC of 0.821. Fire vulnerability dynamics were predominantly controlled by the Mean Temperature of the Driest Quarter (BIO 9; contribution of 37.3%), Annual Precipitation (BIO 12; 21.4%), and Temperature Seasonality (BIO 4; 11.3%), which cumulatively contributed 70.0% to the modeling, with supporting contributions from BIO 14, BIO 2, BIO 3, BIO 17, BIO 10, BIO 7, BIO 15, and BIO 8. Spatially, high-vulnerability zones were clustered in wildland–urban interface (WUI) areas in the Nusaniwe (20.58 ha), Leihitu (16.82 ha), and Salahutu (16.77 ha) Districts. The synergy between extreme temperature stress and precipitation deficits was shown to accelerate vegetation fuel moisture depletion, which has strategic policy implications for transforming disaster management from reactive response to proactive prevention through the integration of vulnerability maps into Regional Spatial Planning and the Regional Disaster Management Agency, strengthening real-time early warning systems, preparing field monitoring posts, and actively involving local communities in community-based prevention management.

Keywords: Ambon Island; Bioclimatology; Forest Fire; MaxEnt; Spatial Vulnerability; Wildland Urban Interface

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INTRODUCTION

In recent decades, the increasing frequency, intensity, and unpredictability of forest fire events has become one of the most critical global environmental issues. The phenomenon of global climate change has significantly altered surface temperature patterns and precipitation regimes, ultimately triggering extreme fire weather conditions and threatening ecosystem integrity, human health, and the stability of the world's carbon reserves (Goltas et al., 2025; Tian et al., 2026). Conventional statistical analysis methods often have limitations in modeling the complexity of dynamic and non-linear multivariate environmental systems. This condition has driven a paradigm shift in environmental geography and disaster management studies toward the use of machine learning approaches to produce accurate and precise fire susceptibility mapping (Goltas et al., 2025).

As one of the countries with the largest tropical forests in the world, Indonesia occupies a highly vulnerable position with respect to forest and land fire disasters (Karurung et al., 2025). The complex interaction between anthropogenic pressures, such as agricultural expansion, deforestation, and land-use change, and interannual climate variability, including the El Niño–Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD), has been shown to be a major trigger of severe fires occurring periodically (Goltas et al., 2025; Karurung et al., 2025). Historical forest fire events, such as those in 2015 and 2019, not only destroyed millions of hectares of forest and peatland cover but also released massive greenhouse gas emissions, caused a transboundary haze crisis, and resulted in substantial economic losses and public health impacts (Purnomo et al., 2024). Although fire susceptibility studies in Indonesia have largely focused on large islands such as Kalimantan, Sumatra, and Papua, scientific attention to small island regions in eastern Indonesia remains very limited (Karurung et al., 2025)

Maluku Province, which is dominated by archipelagic characteristics, faces an increasing threat of forest fires in line with changes in regional microclimatic conditions. On several islands in Maluku, such as Buru Island, prolonged dry seasons, rising Land Surface Temperature (LST), and the presence of highly flammable vegetation, combined with conventional land-clearing practices, have triggered an increase in the number of hotspots and fire incidents (Muin & Rakuasa, 2023). Island ecosystems have a high level of ecological sensitivity to environmental disturbances; forest degradation caused by fires in island areas can accelerate land degradation, disrupt local hydrological systems, and drastically reduce environmental carrying capacity (Salakory & Rakuasa, 2022).

More specifically, Ambon Island, which serves as the center of socio-economic and governmental activity in Maluku, exhibits climatic dynamics and land-cover conditions that are highly sensitive to fire ignition. The tropical climate of Ambon Island is characterized by rainfall fluctuations, with dry periods reaching a minimum rainfall level of approximately 78 mm, as well as relatively high surface temperatures ranging from 30°C to more than 33.9°C (Herdian et al., 2021; Rakuasa, 2022). High air and surface temperatures accelerate evaporation and fuel drying in both primary and secondary dryland forest cover, thereby increasing the potential for rapid fire spread, as previously occurred in southern Leitimur Peninsula, precisely in Negari Rutong (Herdian et al., 2021). Nevertheless, Ambon Island does not yet have an integrated geospatial-based forest fire susceptibility model to anticipate future disaster risks. In geospatial-based forest fire susceptibility analysis, the use of bioclimatic data the 19 WorldClim bioclimatic variables (bio1–bio19) plays a fundamental role (Mupfiga et al., 2025; Goltas, 2026).

Bioclimatic variables derived from long-term mean temperature and precipitation data provide indicators that are far more ecologically meaningful than raw monthly weather data alone (Mupfiga et al., 2025). Parameters such as annual mean temperature (bio1), maximum temperature of the warmest month (bio5), annual precipitation (bio12), and precipitation of the driest or coldest quarter (bio17, bio19) directly control fuel moisture, vegetation structure, and the accumulation of dry biomass (Paudel et al., 2024; Goltas, 2026). Therefore, the integration of bioclimatic data enables the identification of moisture thresholds and spatial conditions that are most conducive to fire ignition and spread.

To model these complex multivariate interactions, the use of the Maximum Entropy (MaxEnt) machine learning-based algorithm has been proven to be a highly superior and reliable approach for mapping forest fire probability (Apostol et al., 2025; Chepashev et al., 2025). As a presence-only model, MaxEnt works by relating historical fire hotspot locations to bioclimatic and environmental predictors without requiring absence data, which are often uncertain or difficult to verify in fire disaster records (Phillips et al., 2006; Meraj et al., 2025). MaxEnt is capable of extracting complex non-linear relationships through various feature functions (linear, quadratic, hinge, and product), and it provides a high level of accuracy evaluation validated through the Area Under the Curve (AUC) of the ROC curve, the True Skill Statistic (TSS), and variable contribution assessment using the Jackknife test (Lorenț et al., 2025; Meraj et al., 2025).

Therefore, the spatial mapping and fire susceptibility zoning results generated by this study are expected to serve as a primary scientific reference for local governments, forestry agencies, and disaster management authorities in formulating adaptive mitigation strategies, developing risk-based early warning systems, and preparing sustainable spatial planning for small islands in the future.

MATERIALS AND METHODS

Study Area

Ambon Island is located in the Maluku Islands, eastern Indonesia. The area has the distinctive geophysical characteristics of a small island, with rolling to steep hilly topography and is surrounded by both shallow and deep marine waters. Administratively, Ambon Island comprises Ambon City and part of Central Maluku Regency (BPS, 2025). The climate of Ambon Island is classified as a wet tropical rainforest climate, influenced by the island monsoon system. The average air temperature on Ambon Island ranges from 25.1°C to 33.9°C, with dry monthly periods during which rainfall can decrease to 78 mm (Herdian et al., 2021). The combination of high surface temperatures, rapid evaporation, and the presence of primary and secondary dryland forest cover accelerates fuel drying, thereby triggering the potential for rapid forest fire ignition and spread during the dry season (Herdian et al., 2021). The study area can be seen in Figure 1.

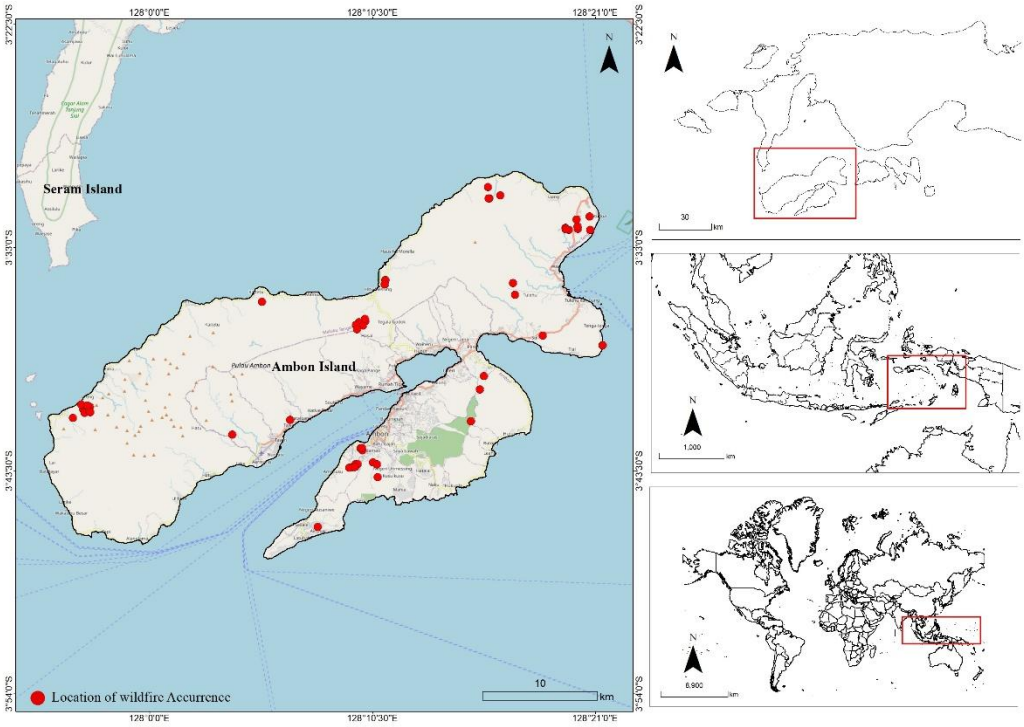


Figure 1. Research Location: Ambon Island, Indonesia.

Fire Occurrence Data (Dependent Variable)

Historical forest fire occurrence data (fire presence-only data) were obtained from the Active Fire Data product of the Moderate Resolution Imaging Spectroradiometer (MODIS) Collection 6.1, downloaded through the Fire Information for Resource Management System (FIRMS) platform of NASA (https://firms.modaps.eosdis.nasa.gov/). The hotspot records used cover a specific observation period from 1 October to 13 October in the Ambon Island area. During this period, a total of 58 verified hotspots were detected. To ensure data reliability and minimize commission errors, all hotspot points were filtered based on a confidence level of 70% and extracted specifically from vegetated land cover by eliminating non-forest static thermal anomalies. The spatial coordinates of these 58 fire occurrence points were stored in Comma-Separated Values (.csv) format for integration into the MaxEnt model.

Bioclimatic Predictor Variables (Independent Variables)

The independent predictor variables in this study focused on 11 bioclimatic environmental variables downloaded from the WorldClim V2.1 spatial database at their original spatial resolution of 30 arc-seconds (1 km²) (Fick & Hijmans, 2017). The bioclimatic variables were derived from long-term spatial data on mean temperature and precipitation, representing seasonal variability and extreme climatic conditions in ecological

terms (Table 1). To ensure spatial harmonization at the local scale of the Ambon Island analysis and to align the pixel matrix with other geospatial predictor variables, all bioclimatic raster layers were resampled from the original resolution of 30 arc-seconds (1 km²) to a spatial resolution of 30 meters (30 m × 30 m) using the bilinear interpolation technique. The bilinear interpolation method was selected because it calculates a weighted average of the nearest pixels, thereby maintaining the continuity of continuous climate data without producing sharp spatial distortions. Subsequently, all bioclimatic rasters were spatially aligned (raster matching), clipped according to the administrative boundary of Ambon Island, and converted into ASCII (.asc) format in the WGS84 geographic coordinate system for processing in the MaxEnt software.

Table 1. Description of bioclimatic environmental variables and fire hotspot data used in MaxEnt modeling on Ambon Island.

Data Category	Variable Code	Description of Bioclimatic / Fire Variable	Unit
Dependent	Hotspots	MODIS active fire hotspots (Oct 1–13, n = 58)	˚C
Temperature	BIO 2	Mean Diurnal Range (Mean of monthly [Tmax - Tmin])	˚C
Temperature	BIO 3	Isothermality (BIO2/BIO7) × 100	˚C
Temperature	BIO 4	Temperature Seasonality (Standard Deviation × 100)	˚C
Temperature	BIO 7	Temperature Annual Range (BIO5 - BIO6)	˚C
Temperature	BIO 8	Mean Temperature of Wettest Quarter	˚C
Temperature	BIO 9	Mean Temperature of Driest Quarter	˚C
Temperature	BIO 10	Mean Temperature of Warmest Quarter	˚C
Precipitation	BIO 12	Annual Precipitation	mm
Precipitation	BIO 14	Precipitation of Driest Month	mm
Precipitation	BIO 15	Precipitation Seasonality (Coefficient of Variation)	%
Precipitation	BIO 17	Precipitation of Driest Quarter	mm

Source: NASA FIRMS and WorldClim V2.1

Multicollinearity Analysis and Variable Selection

Bioclimatic datasets frequently exhibit high inter-correlation among variables. Severe multicollinearity among environmental predictors can cause overfitting, inflate parameter estimation uncertainty, and distort the interpretation of independent variable contributions to fire susceptibility. Therefore, prior to calibrating the MaxEnt model, a pairwise Pearson correlation analysis (r) and Variance Inflation Factor (VIF) test were conducted on all 11 independent bioclimatic variables. The VIF value is calculated using the following equation:

$$\mathrm{VIF}_j = \frac{1}{1-R_j^2}$$

where R_j^2 is the coefficient of determination from the regression of predictor variable j against all other predictor variables. Variable pairs displaying a Pearson correlation coefficient | r | > 0.80 and a VIF >10 were identified as collinear. Among highly correlated pairs, variables demonstrating greater ecological relevance to vegetation fuel dryness and higher training gain in preliminary Jackknife tests were retained for the final modeling dataset.

Maximum Entropy (MaxEnt) Modeling Setup

Forest fire susceptibility modeling was performed using the Maximum Entropy machine learning algorithm (MaxEnt v3.4.4). MaxEnt is a presence-only modeling technique that estimates the target probability distribution closest to uniform (*maximum entropy*) across the study area, subject to constraints derived from the environmental characteristics of observed occurrence points (Choi & Chae, 2025).
Mathematically, the probability distribution $P(x)$ at spatial location x is formulated as:

$$P(x) = \frac{1}{Z}\exp\left(\sum_{j=1}^{N}\lambda_j f_j(x)\right)$$

where Z is a normalization constant, λ_j represents the weight multiplier for feature j, and $f_j(x)$ represents feature functions associated with the bioclimatic predictor variables.

The model parameters for Ambon Island were configured as follows: (a) Data Partitioning: The 58 hotspot occurrence records were randomly split into 70% training data (n = 41) for model construction and 30% testing data (n = 17) for independent model validation. (b) Background Sampling: A total of 10,000 background points

(pseudo-absence points) were randomly sampled across the land surface of Ambon Island to represent background environmental conditions. (c) Feature Classes & Regularization: Feature classes included linear (L), quadratic (Q), hinge (H), and product (P) functions to capture complex non-linear responses between climate predictors and fire occurrence. The regularization multiplier was set to $\beta = 1.0$ to constrain model complexity and prevent overfitting. (d) Replication & Output Format: The model was executed using a 10-fold bootstrap replication approach to obtain stable mean susceptibility estimates. The output format selected was complementary log-log (cloglog), producing continuous fire susceptibility probability values ranging from 0 to 1 (Lorenț et al., 2025).

Model Validation and Performance Evaluation

The predictive performance and discrimination capability of the MaxEnt model were rigorously evaluated using a combination of standardized, threshold-independent statistical metrics. Model accuracy in distinguishing fire-susceptible areas from random background pseudo-absence points was evaluated via the Receiver Operating Characteristic (ROC) curve and the corresponding Area Under the Curve (AUC). Model performance levels were classified into five distinct reliability categories: fail (AUC < 0.60), poor (0.60 - 0.70), fair (0.70 - 0.80), good (0.80 - 0.90), and excellent (AUC ≥90) (Agustiyara et al., 2026). To complement the AUC metric, the True Skill Statistic (TSS) was calculated based on sensitivity and specificity ratios (TSS = Sensitivity + Specificity - 1) at the optimal decision threshold, where values approaching 1 reflect near-perfect classification accuracy independent of sample prevalence (Mupfiga et al., 2025).

In addition to overall spatial predictive accuracy, the relative importance and contribution of individual bioclimatic variables to the model setup were quantified using MaxEnt's internal Jackknife test, along with Percent Contribution and Permutation Importance analyses. The Jackknife test evaluated regularized training gain when each bioclimatic predictor was used in isolation as well as when it was excluded from the model, thereby identifying the predictors containing the most dominant explanatory power and unique information. Furthermore, marginal response curves were constructed to analyze the non-linear relationship between gradient changes in bioclimatic variables and fire occurrence probability. The response curve analysis was essential for determining quantitative ecological thresholds such as temperature lower bounds or precipitation upper bounds that trigger sharp increases in forest fire susceptibility across Ambon Island.

Forest Fire Susceptibility Mapping and Reclassification

The continuous probability output raster generated by the MaxEnt model (.asc format) was imported into a geographic information system (GIS) environment and reclassified to construct spatial zones of the Forest Fire Susceptibility Index. To produce operationally meaningful risk zoning for disaster management and spatial planning, the continuous spatial probability values (0.00–1.00) were categorized into four primary susceptibility classes Very Low (0.00–0.25), Low (0.25–0.50), High (0.50–0.75), and Very High (0.75–1.00) using equal interval and Jenks natural breaks classification methods. Subsequently, pixel-based spatial overlay analysis was conducted to quantify the total land area (in hectares and percentage) corresponding to each susceptibility tier, enabling a precise spatial evaluation of high-risk fire zones across Ambon Island.

RESULTS AND DISCUSSION

Hotspot distribution

Based on spatial distribution data of active fire hotspots detected by the MODIS sensor across Ambon Island from October 1 to 13, a total of 58 hotspots were identified, displaying a highly uneven spatial pattern across eight districts. The highest concentration of fire occurrences was predominantly localized in the northern and northeastern sectors of the island, specifically Leihitu District with 21 hotspots (36.2%) and Salahutu District with 19 hotspots (32.8%), cumulatively accounting for 69.0% of all recorded fire events on Ambon Island. The elevated hotspot frequency in Leihitu and Salahutu highlights a critical accumulation of dry vegetation fuel prone to ignition under the combined influence of climatic drivers (high surface temperatures and low moisture) and anthropogenic pressures, such as agricultural land clearing. Meanwhile, Nusaniwe District in the southwestern sector recorded 13 hotspots (22.4%), underscoring notable fire risks along the urban-forest interface. Conversely, the remaining districts Teluk Ambon (2 hotspots), Leitimur Selatan (2 hotspots), Sirimau (1 hotspot), as well as Teluk Ambon Baguala and Leihitu Barat (0 hotspots) exhibited minimal to zero fire activity, reflecting substantial spatial heterogeneity and ecological susceptibility gradients across Ambon Island (Figure 2).

Spatial variable selection

The multicollinearity evaluation demonstrated that all 11 bioclimatic predictor variables selected for forest fire susceptibility modeling on Ambon Island exhibited Variance Inflation Factor (VIF) values well below the standard critical threshold (VIF < 10.0), ranging between 1.85 (BIO 3) and 4.28 (BIO 8) (Table 2). Furthermore, none of the pairwise Pearson correlation coefficients exceeded the critical collinearity limit (|r| < 0.80). The highest VIF values were observed in the Mean Temperature of Wettest Quarter (BIO 8, VIF} = 4.28) and the Mean Temperature of Driest Quarter (BIO 9, = 4.15), which shared a moderate positive correlation (|r| = 0.52). Because no severe multicollinearity or excessive spatial information redundancy was detected across the predictor set, all 11 bioclimatic variables were retained to calibrate the MaxEnt algorithm without risking parameter instability or model variance inflation.

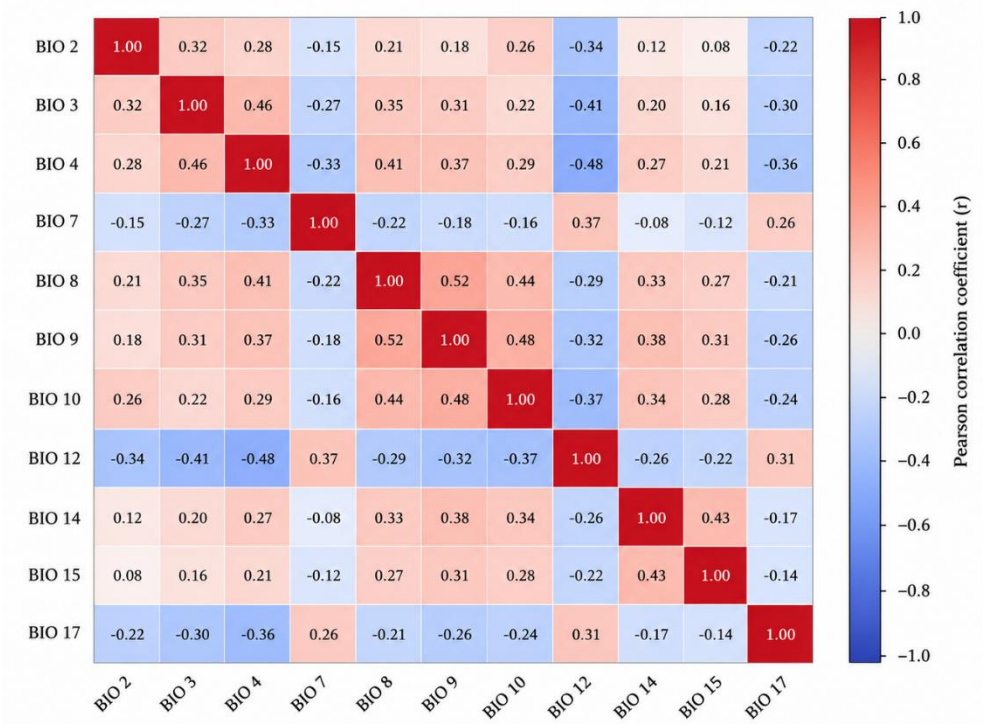


Figure 2. Pearson correlation coefficients among the selected predictor variables

Bioclimatic Variable Contributions and Importance Analysis

Based on the Percent Contribution metrics derived from the MaxEnt algorithm, the most dominant bioclimatic factor influencing forest fire susceptibility across Ambon Island was the Mean Temperature of Driest Quarter (BIO 9), accounting for a 37.3% contribution and a 33.4% Permutation Importance. The high values across both diagnostics confirm that thermal stress during the driest quarter serves as the primary environmental driver governing fire weather conditions. The second most influential predictor was Annual Precipitation (BIO 12), which exhibited a 21.4% Percent Contribution (with a 5.4% Permutation Importance), followed by Temperature Seasonality (BIO 4), contributing 11.3% with a 17.4% Permutation Importance. Cumulatively, these top three bioclimatic variables (BIO 9, BIO 12, and BIO 4) accounted for 70.0% of the total model contribution, highlighting the synergistic dominance of thermal regimes and precipitation deficits in shaping wildfire susceptibility across tropical island landscapes.

The remaining eight bioclimatic variables provided secondary contributions to model construction, including Precipitation of Driest Month (BIO 14; 5.2%), Mean Diurnal Range (BIO 2; 4.5%), Isothermality (BIO 3; 4.4%), Precipitation of Driest Quarter (BIO 17; 3.8%), Mean Temperature of Warmest Quarter (BIO 10; 3.7%), Temperature Annual Range (BIO 7; 3.5%), Precipitation Seasonality (BIO 15; 3.1%), and Mean Temperature of Wettest Quarter (BIO 8; 1.8%). Despite their lower initial contributions during model fitting, several secondary variables exhibited substantial Permutation Importance values, notably BIO 17 (8.7%), BIO 7 (8.2%), BIO 10 (7.9%), and BIO 14 (7.6%). This divergence between Percent Contribution and Permutation Importance arises because Percent Contribution is path-dependent during iterative model training, whereas Permutation Importance directly measures model performance degradation when predictor values are randomly permuted. A notable example is BIO 2, which yielded a 4.5% training contribution but a 0.0% Permutation Importance, indicating that its spatial predictive information was mostly redundant when evaluated in the presence of other covariates. All bioclimatic variables can be seen in Figure 3.

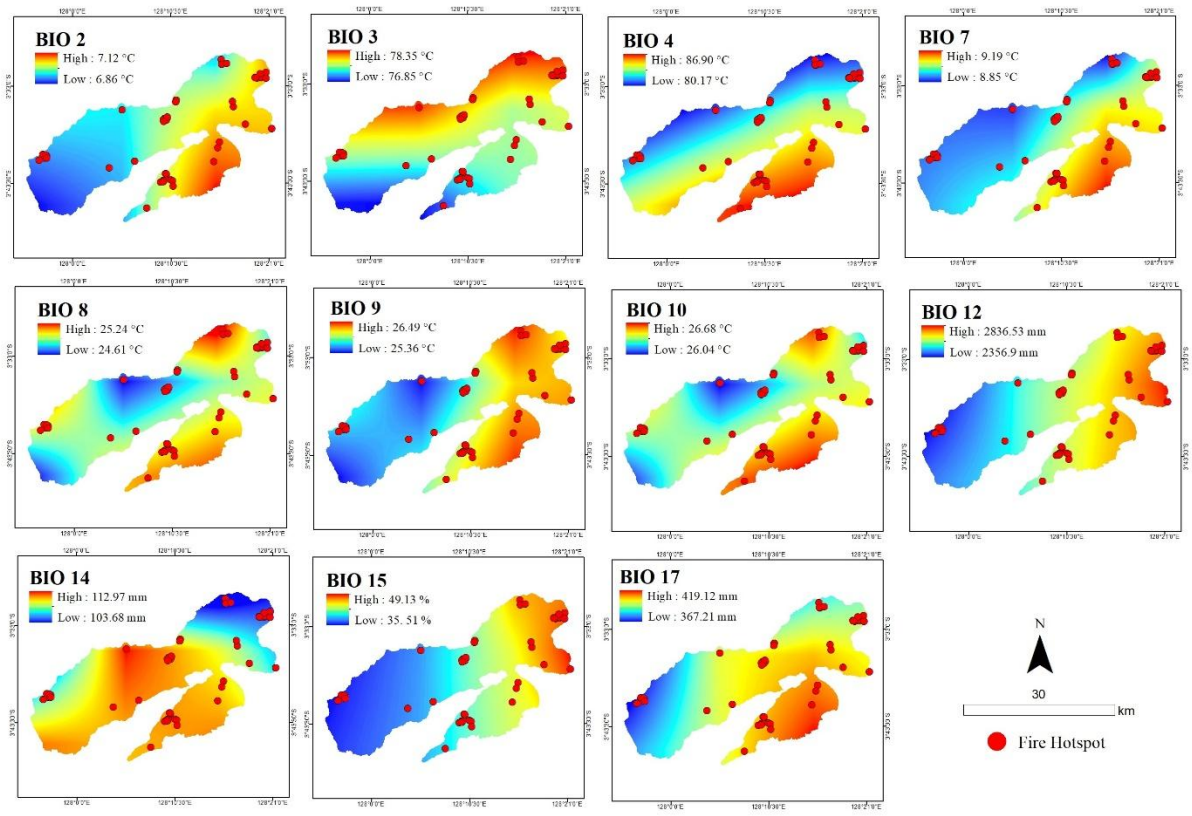


Figure 3. Bioclimatic variables

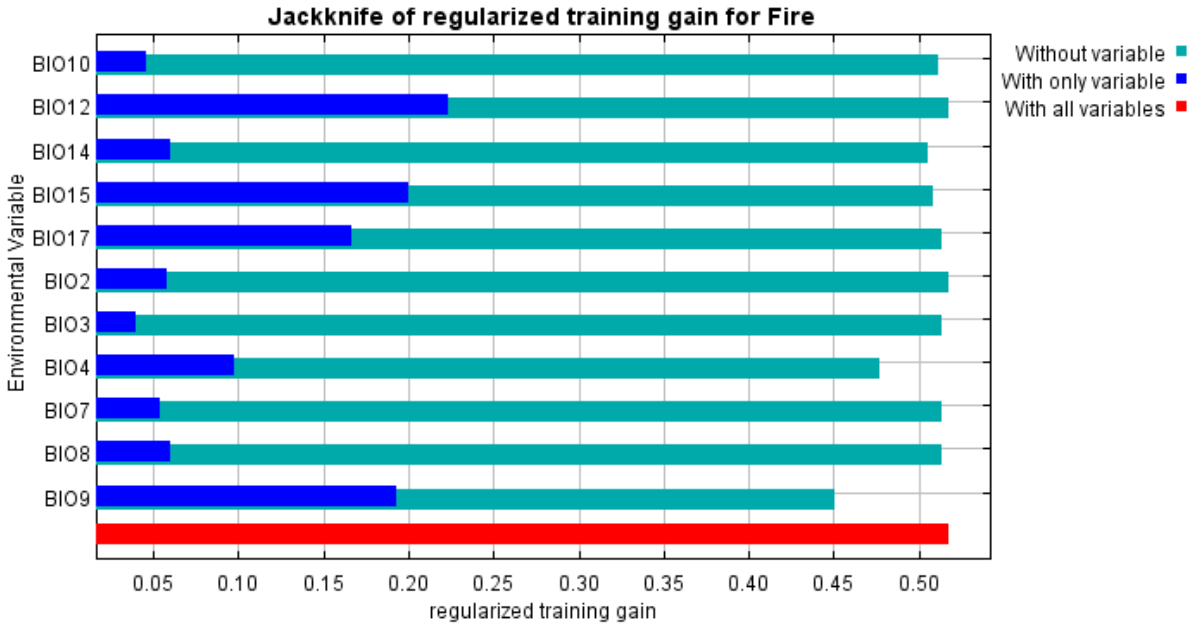


Figure 4. Jackknife plot of training gains for wildfires.

Ecologically, the primary influence of BIO 9 and BIO 12 underscores the biophysical mechanisms driving vegetation fuel drying in tropical ecosystems (Kamyo et al., 2025). Elevated thermal conditions during dry periods accelerate evapotranspiration and severely deplete fuel moisture levels, while low annual rainfall extends the window of fuel flammability (Usmadi, 2023). However, statistical contribution percentages and permutation importance rankings do not inherently imply direct causality or indicate the directionality of variable influences (Lorenț et al., 2025). Consequently, a complete interpretation of forest fire susceptibility on Ambon Island necessitates further examination using marginal response curves, spatial interactions with land cover, and local anthropogenic disturbance patterns.

Response Curve Analysis and Ecological Thresholds

The analysis of marginal response curves generated by the MaxEnt model depicts complex, non-linear spatial relationships between bioclimatic predictor variables and the environmental suitability index for forest fire occurrence on Ambon Island. Among the primary predictors, the Mean Temperature of Driest Quarter (BIO 9) exhibits a non-linear unimodal response trajectory, wherein environmental suitability increases sharply from low initial values to a peak output of approximately 0.50 (*cloglog output*) before declining gradually at higher thermal ranges, signaling the presence of a critical thermal threshold that triggers severe vegetation fuel desiccation. Conversely, Annual Precipitation (BIO 12) and Precipitation of Driest Month (BIO 14) display a steep, monotonically negative downward trend, with environmental suitability peaking near 1.00 under extremely low rainfall regimes and dropping before stabilizing around a probability baseline of 0.50 as precipitation increases. This pattern confirms that moisture deficits during dry periods act as the primary ecological limiter, significantly expanding the fire ignition window across Ambon Island.

Meanwhile, secondary bioclimatic predictors demonstrate varied yet complementary response curves that capture seasonal climate dynamics and local microclimatic variations. Temperature Seasonality (BIO 4) and Precipitation Seasonality (BIO 15) indicate that heightened seasonal climatic variability correlates positively with increases in environmental fire suitability, whereas Precipitation of Driest Quarter (BIO 17) yields peak suitability under the lowest rainfall levels during the driest quarter. Furthermore, the Mean Temperature of Warmest Quarter (BIO 10) and Isothermality (BIO 3) show non-linear positive trends, reinforcing fire susceptibility as temperatures rise during the warmest period and as diurnal-to-annual temperature fluctuations remain stable. In contrast, Temperature Annual Range (BIO 7), Mean Temperature of Wettest Quarter (BIO 8), and Mean Diurnal Range (BIO 2) exhibit declining or constant probability responses around 0.50, indicating that isolated diurnal temperature variations do not function as primary limiting constraints unless accompanied by significant moisture deficits. The response curves of the bioclimatic variables can be seen in Figure 5.

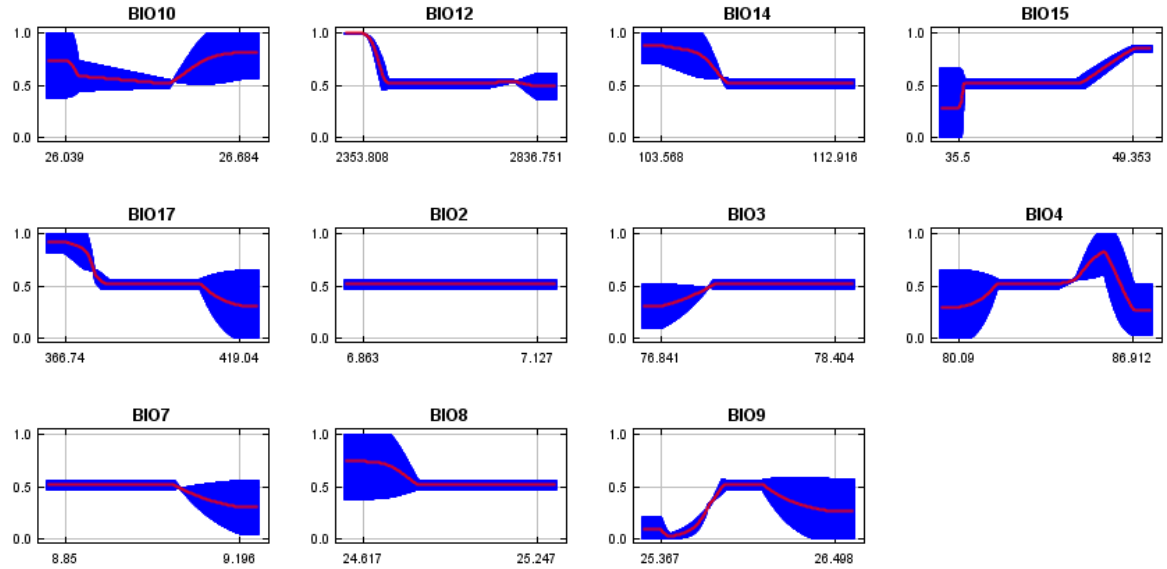


Figure 5. Response curves of bioclimatic variables.

Ecologically, the synthesis of these response curves underscores that forest fire susceptibility on Ambon Island is governed by synergistic interactions between extreme thermal stress and rainfall deficits, which jointly accelerate vegetation fuel moisture depletion. Nevertheless, interpreting these response curves warrants careful consideration, as MaxEnt cloglog outputs represent relative environmental suitability based on observed fire occurrence points (*hotspots*) and background samples, rather than absolute calibrated occurrence probabilities. Consequently, the quantitative ecological thresholds derived from these curves must be comprehensively integrated with Percent Contribution, Permutation Importance, land cover conditions, and human activity zones to formulate targeted mitigation priorities and adaptive early warning systems for forest fire management on Ambon Island.

Forest Fire Susceptibility Levels on Ambon Island

The distribution of wildfire risk levels across districts on Ambon Island reveals considerable spatial variation among the not vulnerable, low, medium, and high-risk categories. The total mapped areas are

2,553.10 km² for low risk, 232.89 km² for areas classified as not vulnerable, 212.14 km² for medium risk, and 56.76 km² for high risk. Leitimur Selatan District has the largest reported low-risk area, at 2,312.98 km², substantially exceeding the values recorded in other districts. However, this value should be verified because it represents approximately 90.6% of the total low-risk area reported for all districts and may indicate a data-entry error or an issue with spatial aggregation. Leihitu District exhibits mapped areas across all four risk categories, including 16.82 km² classified as high risk. Salahutu District also records substantial medium-risk and high-risk areas of 63.36 km² and 16.77 km², respectively. These findings indicate that the spatial distribution of wildfire risk varies considerably across the island. The area of forest fire vulnerability levels on Ambon Island can be seen in Table 2.

Table 2. Area of forest fire vulnerability levels on Ambon Island (km²).

District	Not vulnerable	Low	Medium	High
Leihitu	78.41	55.68	39.39	16.82
Teluk Ambon Baguala	0	42.94	17.48	0
Teluk Ambon	50.12	26.81	56.41	0
Leitimur Selatan	23.80	2312.98	0	0
Nusaniwe	1.71	4.63	19.28	20.58
Serimau	4.13	14.81	15.46	2.58
Salahutu	0	66.68	63.36	16.77
Leihitu Barat	74.71872	28.56867	0.75459	0
Total area	232.89	2553.10	212.14	56.76

In the medium-risk category, Salahutu records the highest value (63.36), followed by Teluk Ambon (56.41). For the high-risk category, Nusaniwe has the highest reported value (20.58), followed by Leihitu (16.82) and Salahutu (16.77). Serimau has a relatively small high-risk value of 2.58. In contrast, Teluk Ambon Baguala, Teluk Ambon, Leitimur Selatan, and Leihitu Barat have no areas classified as high risk in the model output. However, a value of zero does not mean that wildfires cannot occur in these districts; rather, it indicates that no areas were classified as highly vulnerable by the model. Differences in wildfire risk among districts may be associated with vegetation conditions, land-cover characteristics, climatic conditions, topography, and human activities (Jaouani et al., 2027). Nevertheless, these relationships require further spatial analysis to be confirmed. The fire vulnerability map can be seen in Figure 6.

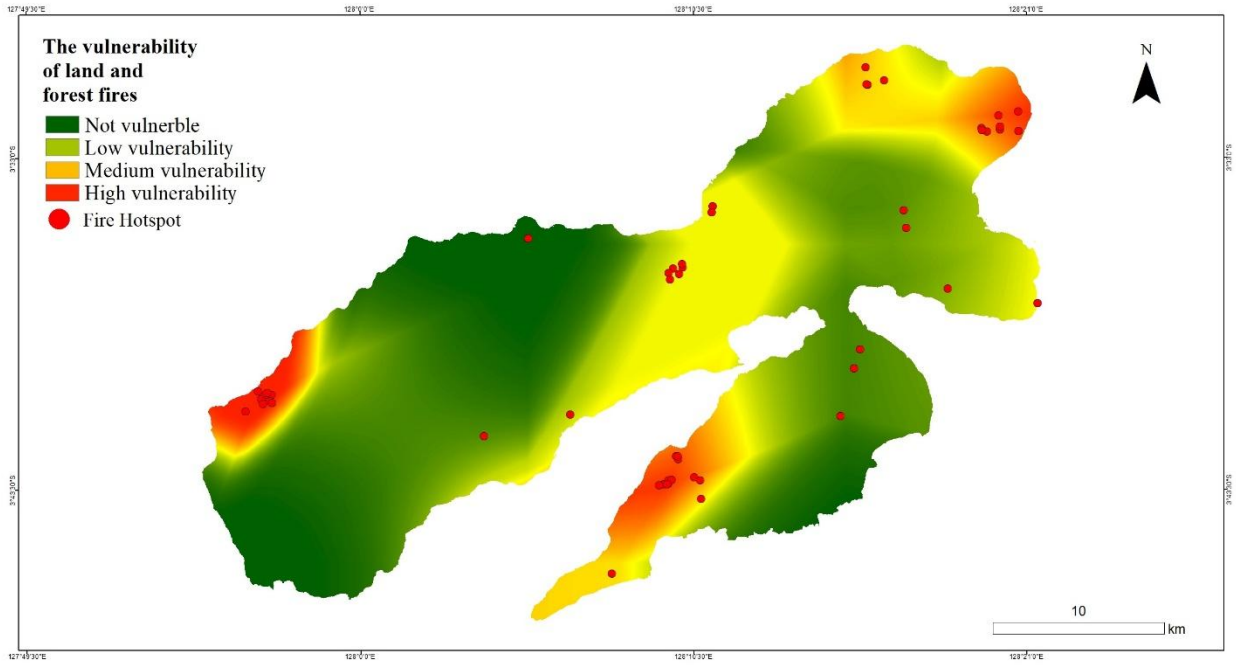


Figure 6. Visualization of wildfire risk levels in Ambon Island

Overall, the modeling results indicate that Nusaniwe, Leihitu, and Salahutu districts should receive particular attention in wildfire mitigation efforts, given their relatively high reported values in the high-risk category. Monitoring should also be maintained in medium-risk areas, particularly Salahutu and Teluk Ambon, as well as in extensive low-risk areas, especially Leitimur Selatan. Recommended mitigation strategies include monitoring vegetation conditions and fuel loads, strengthening early-warning systems during the dry season,

raising community awareness about wildfire prevention, and controlling uncontrolled land burning. Before these results are used in a scientific publication, the reported area values and measurement units should be rechecked, particularly the value of 2,312.98 for Leitimur Selatan, along with the consistency between the district-level values and the overall totals.

Model accuracy assessment

MaxEnt model accuracy assessment begins with evaluating the relationship between the test omission rate and the fractional predicted area as a function of the cumulative threshold, averaged across all replicate model runs (Astuti & Fatimah, 2024). Based on the theoretical formulation of the cumulative threshold in MaxEnt, the test omission rate should closely align with the predicted omission curve (Butar Butar et al., 2026). This strong agreement between the observed test omission rate and the theoretical expectation confirms that the model is well-calibrated, shows minimal evidence of overfitting, and maintains robust predictive consistency across varying threshold levels. The MaxEnt model performance can be seen in Figure 7.

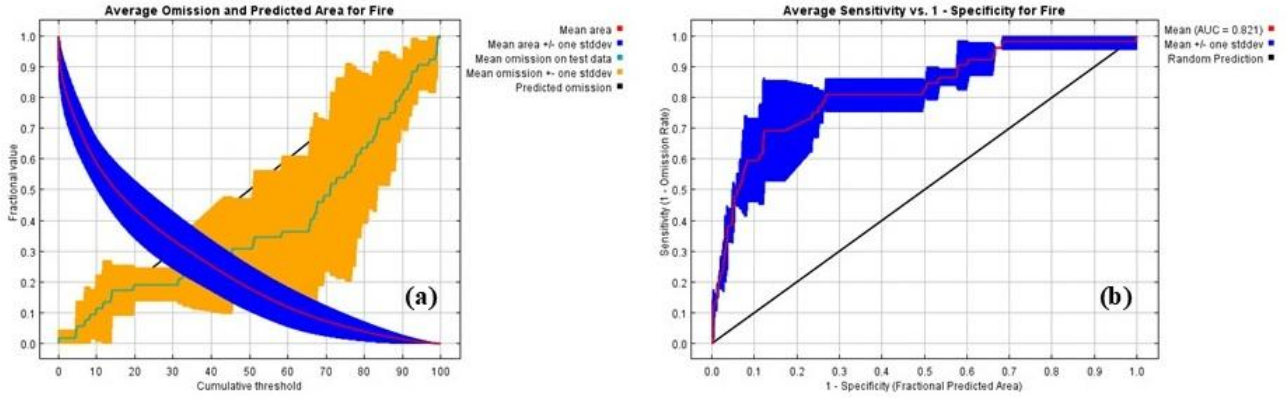


Figure 7. MaxEnt model performance: (a) omission rate and predicted area in relation to the cumulative threshold; (b) receiver operating characteristic (ROC) curve

Subsequently, the spatial discrimination capability of the model was evaluated using the Receiver Operating Characteristic (ROC) curve, in which specificity is calculated using the fractional predicted area rather than the true commission rate, following the presence-only modeling methodology formulated by Phillips et al., (2006). The model achieved an average test AUC of 0.821 with a standard deviation of 0.059. An average AUC value within the 0.80–0.90 interval indicates good predictive performance, demonstrating that the MaxEnt model possesses high accuracy and stability in differentiating fire-susceptible forest areas from background pseudo absence points on Ambon Island (Kamyo et al., 2025).

Policy recommendations

The results of the MaxEnt-based forest fire susceptibility modeling need to be formally integrated into regional spatial planning and disaster management frameworks, such as the Regional Spatial Plan and the Regional Disaster Management Agency of Ambon City and Central Maluku Regency. This integration enables more precise allocation of monitoring resources by shifting from a reactive approach to proactive prevention, particularly through the deployment of field monitoring teams and disaster preparedness posts in high-risk districts, namely Nusaniwe, Leihitu, and Salahutu, as well as buffer zones in Teluk Ambon. Given that the Mean Temperature of the Driest Quarter and Annual Precipitation are the dominant predictors, the Regional Disaster Management Agency, in collaboration with the Meteorology, Climatology, and Geophysics Agency, needs to strengthen real-time early warning systems and hotspot monitoring to anticipate risk surges during prolonged droughts and El Niño climate anomalies (Chepashev et al., 2025).

Prevention efforts also need to focus on monitoring anthropogenic activities along the forest and settlement interface through regulatory enforcement and community empowerment. Local governments need to establish and strictly enforce Regional Regulations on Forest and Land Fire Control, which regulate the prohibition of unsupervised land burning, mechanisms for land-clearing permits, and firm legal sanctions for violators. These law enforcement efforts need to be aligned with the empowerment of community groups and local farming communities through education on fire-free land preparation techniques, the provision of alternative land management equipment, and adaptive risk communication to minimize the risk of fire ignition

caused by human activities throughout Ambon Island. Assessing and mapping forest fire vulnerability in romania using maximum entropy and extreme gradient boosting

CONCLUSION

The results of this study demonstrate good reliability and predictive accuracy, with an excellent mean testing AUC value. The dynamics of fire vulnerability in this region are predominantly controlled by bioclimatic factors, in which the interaction among the Mean Temperature of the Driest Quarter (BIO 9; contribution of 37.3%), Annual Precipitation (BIO 12; 21.4%), and Temperature Seasonality (BIO 4; 11.3%) cumulatively contributed 70.0% to model formation, confirming that extreme temperature stress and precipitation deficits during dry periods are the main drivers of vegetation fuel drying. Spatially, high-vulnerability zones are concentrated in the Nusaniwe, Leihitu, and Salahutu Districts, which strongly correlate with the distribution of 58 detected hotspots and the presence of forest–settlement boundary areas (wildland–urban interface). These findings provide a strategic basis for local governments to formally integrate MaxEnt risk maps into Regional Spatial Planning documents and the Regional Disaster Management Agency's frameworks, strengthened through a real-time early warning system, regulatory enforcement, the readiness of field monitoring teams, and the empowerment of local communities to achieve proactive forest fire mitigation governance on Ambon Island.

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CONFLICT OF INTEREST

The authors declare no conflict of interest and take full responsibility for the content of the article, including the implications of AI-generated content.

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