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PREDICTING EDELWEISS (*Anaphalis javanica*) HABITAT SUITABILITY UNDER CLIMATE SCENARIOS: MACHINE LEARNING APPROACHES

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ABSTRACT

Climate change threatens species distribution by altering environmental conditions, posing severe risks to high-elevation endemic plants like Anaphalis javanica (Javan Edelweiss). Research on the performance of machine learning models in predicting the habitat suitability of Anaphalis javanica under various climate scenarios is crucial for generating accurate scientific information to support conservation efforts, given that climate change has the potential to affect the future distribution and mortality of this species. This study evaluated current and future habitat suitability for A. javanica across Java, Bali, and Nusa Tenggara using Decision Tree (DT), Random Forest (RF), and Maximum Entropy (MaxEnt) models. Species occurrence records were compiled from GBIF and published literature, while topographic, edaphic, climatic, and bioclimatic predictors. Model evaluation relied on Accuracy, Precision, Recall, F1-score, Cohen's Kappa, and AUC. All models demonstrated outstanding predictive performance (accuracy: 0.953–0.974; AUC: 0.976–0.999), with Random Forest achieving the highest performance (accuracy: 0.974; Kappa: 0.947; AUC: 0.999). Soil type, elevation, temperature, and precipitation emerged as primary determinants. Currently, highly suitable habitats are concentrated in montane regions. However, projections for 2080 under RCP 2.6 and RCP 8.5 scenarios indicate a progressive decline in habitat suitability, most severely under RCP 8.5. These findings highlight that climate change will shrink suitable habitats and confine A. javanica to high-elevation climate refugia, underscoring the urgency of targeted conservation strategies.

Keywords: *Climate Change; Machine Learning; Montane Ecosystem; Random Forest; MaxEnt*

INTRODUCTION

Climate change and habitat degradation are among the primary drivers of biodiversity loss worldwide, influencing species distributions, ecosystem functions, and habitat availability (Cheng et al., 2025). Mountain ecosystems are particularly vulnerable because they harbor numerous endemic species that are strongly dependent on specific environmental conditions and elevation gradients (Novenda et al., 2026). Consequently, understanding how species respond to environmental change is essential for developing effective conservation strategies.

Habitat suitability modelling has become an important tool for predicting species distributions and identifying environmentally suitable areas for conservation and management (Boogar et al., 2019; Rendana et al., 2023). These models integrate species occurrence records with environmental variables to evaluate habitat conditions and forecast potential distribution changes under future scenarios (Dastres et al., 2025). Recent advances in machine learning have improved predictive accuracy by enabling the analysis of complex and nonlinear relationships between species occurrence and environmental factors (Boogar et al., 2019; Çoban et al., 2020; Dastres et al., 2025; Garzón et al., 2006; Purnama et al., 2026). Among the most widely applied approaches are Decision Tree (DT), Random Forest (RF), and Maximum Entropy (MaxEnt), which have shown strong performance in ecological and habitat suitability studies (Boogar et al., 2019; Çoban et al., 2020; Purnama et al., 2026).

Anaphalis javanica (Javan Edelweiss) is a protected endemic species that represents one of the most iconic plants of Indonesian mountain ecosystems (Susanto et al., 2024). The species commonly occurs in volcanic highland environments and plays an important ecological role as a pioneer species in disturbed habitats and early successional stages (Novenda et al., 2026). Previous studies have shown that the distribution of *A. javanica* is closely associated with environmental factors such as elevation, temperature, humidity, and habitat characteristics (Cui et al., 2021; Novenda et al., 2026). In addition to its ecological importance, the species possesses considerable cultural and conservation value in Indonesia(Susanto et al., 2024).

Despite its significance, *A. javanica* faces increasing threats from tourism activities, habitat disturbance, illegal harvesting, and environmental change (Novenda et al., 2026). Local ecological assessments have reported declining population trends and increasing rarity of the species in several mountain areas, raising concerns regarding its long-term conservation status (Susanto et al., 2024; Wahyudi, 2010). Furthermore, future climate change may alter the environmental conditions that determine habitat suitability, potentially affecting the distribution and persistence of *A. javanica* populations (Cheng et al., 2025).

Although previous studies have examined the habitat characteristics, ecological importance, and conservation status of *A. javanica* (Ade et al., 2019; Novenda et al., 2026; Oo et al., 2022; Sadili et al., 2009; Susanto et al., 2024), information regarding its potential habitat suitability under future climate scenarios remains limited. In addition, comparative assessments of different machine-learning algorithms for predicting the current and future distribution of this species are still scarce. Therefore, this study evaluates the habitat suitability of *A. javanica* under current and future climate scenarios using Decision Tree, Random Forest, and Maximum Entropy models. The study further compares model performance and identifies key environmental drivers influencing species distribution to support evidence-based conservation planning.

METHOD

Study Area

This study was conducted across Java, Bali, and Nusa Tenggara Islands, Indonesia, which represent the major distribution range of *A. javanica* as shown in Figure 1. The region encompasses diverse environmental gradients, ranging from coastal lowlands to volcanic mountain ecosystems exceeding 3,000 m above sea level(Sun et al., 2024). The study area includes several important montane and subalpine ecosystems where *A. javanica* is commonly found, particularly in volcanic landscapes and high-elevation grasslands(Susanto et al., 2024).

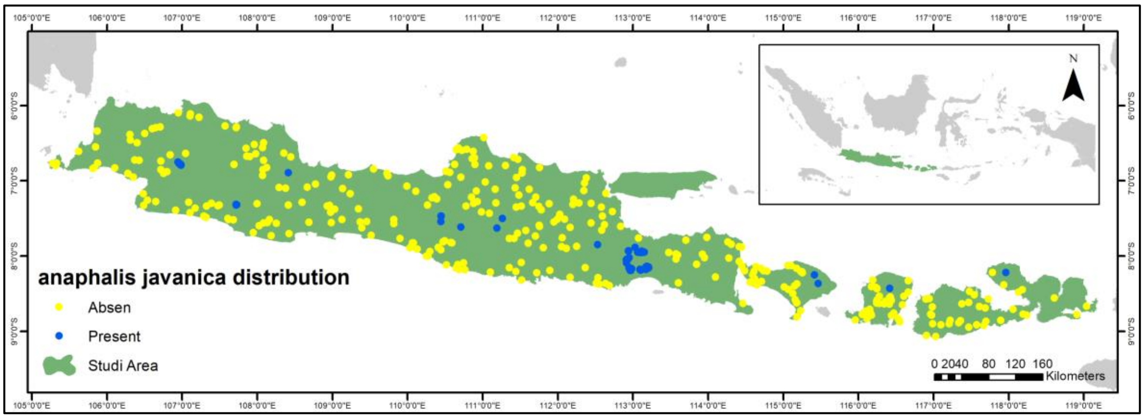


Figure 1. Study Area

Species Occurrence Data

Occurrence records of *A. javanica* were compiled from multiple sources, including the Global Biodiversity Information Facility (GBIF) database (GBIF.org, 2022) and published studies documenting the species distribution in Indonesia (Ade et al., 2019; Wahyudi, 2010). Duplicate records, spatial outliers, and records with incomplete geographic coordinates were removed during preprocessing. The final dataset consisted of presence and absence points represented by geographic coordinates and associated environmental variables.

Environmental Variables

Environmental predictors were selected based on their ecological relevance to plant distribution and habitat suitability(Carlson et al., 2013; Lannuzel et al., 2021). The variables consisted of topographic, edaphic, climatic, and bioclimatic factors.Topographic information was derived from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM), whereas climatic and bioclimatic variables were obtained from the KGClim Future dataset developed by (Cui et al., 2021).

Table 1. Environmental Variables Used in the Analysis

Variable	Description	Unit	Data Source	Spatial Resolution
Elevation	Elevation above sea level	meter	SRTM DEM	30 m (resampled to 1 km)
Slope	Terrain slope	percent	Derived from SRTM DEM	30 m (resampled to 1 km)
Soil	Soil type classification	class	FAO Digital Soil Map of the World	1 km
KC	Köppen-Geiger climate classification	class	KGClim Future	1 km
PDM	Precipitation of driest month	mm	KGClim Future	1 km
PDMSumm	Precipitation of driest month during summer	mm	KGClim Future	1 km
PDMWint	Precipitation of driest month during winter	mm	KGClim Future	1 km
PSumm	Total summer precipitation	mm	KGClim Future	1 km
PTot	Total annual precipitation	mm $year^{-1}$	KGClim Future	1 km
PWint	Total winter precipitation	mm	KGClim Future	1 km
PWM	Mean monthly precipitation	mm	KGClim Future	1 km
PWMSumm	Mean monthly precipitation during summer	mm	KGClim Future	1 km
PWMWint	Mean monthly precipitation during winter	mm	KGClim Future	1 km
Tavg	Mean annual temperature	°C	KGClim Future	1 km
TCM	Temperature of coldest month	°C	KGClim Future	1 km
TWM	Temperature of warmest month	°C	KGClim Future	1 km

More detail, for soil information was obtained from the FAO Digital Soil Map of the World (FAO, 2003) and represented 23 soil classes occurring within the study area, including Ferric Acrisol (Af), Gleyic Acrisol (Ag), Orthic Acrisol (Ao), Eutric Cambisol (Be), Gleyic Cambisol (Bg), Vertic

Cambisol (Bv), Eutric Gleysol (Ge), Lithosol (I), Dystric Andosol (Jd), Eutric Andosol (Je), Chromic Ferralsol (Lc), Orthic Ferralsol (Lo), Ferric Ferralsol (Lv), Dystric Nitisol (Nd), Eutric Nitisol (Ne), Eutric Histosol (Oe), Eutric Regosol (Re), Humic Andosol (Th), Mollic Andosol (Tm), Ochric Andosol (To), Vitric Andosol (Tv), Chromic Vertisol (Vc), and Pellic Vertisol (Vp). Climatic conditions were represented using the Köppen–Geiger climate classification derived from the KGClim Future dataset (Cui et al., 2021). Eight climate classes were identified within the study area, namely Af (110; tropical rainforest), Aw (120; tropical savannah), Am (130; tropical monsoon), BSh (221; hot semi-arid steppe), Cwb (322; temperate climate with dry winter and warm summer), Cwc (323; temperate climate with dry winter and cold summer), Cfb (332; temperate climate without dry season and warm summer), and ET (510; tundra climate).

Data Processing and Preparation

Environmental and species occurrence datasets were preprocessed prior to habitat suitability modelling. All spatial data were projected to the World Geodetic System 1984 (WGS84; EPSG:4326) and harmonized to a common spatial resolution of approximately 1 km (30 arc-seconds) (Franklin & Miller, 2010). Environmental variables derived from different sources were resampled and aligned to ensure consistent spatial extent, pixel size, and coordinate reference system across all raster layers (Elith et al., 2006). Raster preprocessing, resampling, and spatial alignment were performed using ArcGIS.

Occurrence records of *A. javanica* obtained from GBIF and published literature were converted into spatial point datasets. To facilitate binary classification modelling, presence points were assigned a value of 1, while absence points were generated within the study area and assigned a value of 0. The final dataset consisted of 330 presence points and 327 absence points, resulting in a total of 657 observations used for habitat suitability modelling.The resulting presence–absence dataset was subsequently used as the response variable for habitat suitability modelling.

Environmental attributes corresponding to each occurrence point were extracted from the raster layers using the Extract Multi Values to Points tool in ArcGIS (Purnama et al., 2024, 2026; Purnama & Çoban, 2025). This process assigned values of elevation, slope, soil type, climate classification, temperature variables, and precipitation variables to each species occurrence record. The extracted dataset was exported as a comma-separated values (CSV) file and used as the input dataset for machine learning analyses.

Subsequently, habitat suitability modelling was conducted in Google Colab using Python. Several libraries were employed, including Pandas for tabular data manipulation, NumPy for numerical computation, Rasterio for raster processing, Matplotlib and Seaborn for visualization, and Scikit-learn for machine learning model development and evaluation. Species distribution models were developed using Decision Tree (DT), Random Forest (RF), and Maximum Entropy (MaxEnt) algorithms (Purnama et al., 2026). The trained models were then applied to environmental raster datasets to generate habitat suitability maps under current climate conditions and future climate scenarios (RCP 2.6 and RCP 8.5 for 2080)(Çoban et al., 2020; Purnama et al., 2026).

Climate Change Scenarios

Future habitat suitability was projected under two Representative Concentration Pathway (RCP) scenarios, namely RCP 2.6 and RCP 8.5, representing low- and high-greenhouse gas emission trajectories, respectively. RCP 2.6 assumes that global greenhouse gas emissions peak early and decline substantially through strong climate mitigation efforts, resulting in relatively limited increases in global temperature. In contrast, RCP 8.5 represents a high-emission scenario characterized by continuously increasing greenhouse gas concentrations, leading to higher temperatures, altered precipitation patterns, and more pronounced climate change impacts by the end of the century (IPCC, 2014). Future climatic variables for the year

2080 were obtained from the KGClim Future dataset (Cui et al., 2021). In generating future habitat suitability projections, topographic variables (elevation and slope) and soil characteristics were assumed to remain constant over time, while climatic and bioclimatic variables were updated according to each climate scenario. These future environmental datasets were subsequently used to evaluate the potential impacts of climate change on the spatial distribution and habitat suitability of *A. javanica* across Java, Bali, and Nusa Tenggara Islands.

Habitat Suitability Modelling

Decision Tree (DT), Random Forest (RF) (Purnama et al., 2026), and Maximum Entropy (MaxEnt) (Çoban et al., 2020), were employed to model the habitat suitability of *Anaphalis javanica*. The Decision Tree model was implemented using the entropy criterion to recursively partition environmental space into suitable and unsuitable habitat classes, producing habitat suitability probabilities ranging from 0 to 1. The Random Forest model was developed using an ensemble of 500 decision trees and employed bootstrap aggregation and random feature selection to improve predictive performance and reduce overfitting (Breiman, 2001; Breiman et al., 2017). Meanwhile, the Maximum Entropy (MaxEnt) model was implemented using logistic regression with an L2 regularization penalty (ridge regularization) and the LBFGS optimization algorithm. The L2 penalty constrains coefficient magnitudes to reduce model overfitting while estimating habitat suitability by maximizing entropy based on species occurrence records (Phillips et al., 2006). All models generated continuous habitat suitability outputs ranging from 0 (unsuitable habitat) to 1 (highly suitable habitat) (Purnama et al., 2026).

Model Training and Validation

The occurrence dataset was randomly divided into training (70%) and testing (30%) subsets to develop and validate the habitat suitability models(Purnama et al., 2024, 2026). Model performance was evaluated using an independent testing dataset to assess the predictive capability and generalization of each algorithm. Several classification metrics were employed, including Overall Accuracy, Precision, Recall, F1-score, Cohen's Kappa coefficient (Miller et al., 2024), and the Area Under the Receiver Operating Characteristic Curve (AUC)(Lazagabaster et al., 2024).

Variable Importance Analysis

The contribution of environmental variables was evaluated for each modelling approach.For Decision Tree and Random Forest models, variable importance scores were extracted directly from the trained models(YILDIRIM, 2021). For MaxEnt, variable contributions were assessed using standardized regression coefficients(Liang et al., 2025). These analyses were used to identify the primary environmental drivers influencing the distribution of *A. javanica*.

Habitat Suitability Projection

The calibrated models were applied to current and future environmental raster datasets to generate continuous habitat suitability maps. Suitability values ranged from 0 (unsuitable habitat) to 1 (highly suitable habitat). Habitat suitability maps were produced for current climate conditions, RCP 2.6 (2080), and RCP 8.5 (2080)(Cui et al., 2021). Environmental raster layers were processed and analyzed in Google Colab using Python-based machine learning workflows. Model outputs were generated as GeoTIFF raster files and visualized directly within the Python environment to evaluate the spatial distribution of habitat suitability under current and future climate scenarios(Elith & Leathwick, 2009; Estopinan et al., 2024).

RESULTS AND DISCUSSION

Model Performance Evaluation

The predictive performance of the DT, RF, and MaxEnt models was evaluated using accuracy, precision, recall, F1-score, Cohen's Kappa coefficient, and Area Under the Receiver Operating Characteristic Curve (AUC). The results are presented in Table 2.

Table 2. Performance metrics of habitat suitability models for Anaphalis javanica

Model	Accuracy	Precision	Recall	F1-score	Kappa	AUC
DT	0.953	0.95	0.96	0.95	0.906	0.979
RF	0.974	0.95	1.00	0.98	0.947	0.999
MaxEnt	0.958	0.93	1.00	0.96	0.916	0.976

All three models demonstrated excellent predictive performance, with accuracy values exceeding 95% and AUC values greater than 0.97. Among the evaluated algorithms, Random Forest achieved the highest overall performance, producing an accuracy of 97.4%, a Kappa coefficient of 0.947, and an AUC value of 0.999, indicating near-perfect discrimination between suitable and unsuitable habitats. MaxEnt and Decision Tree also produced strong predictive results, with accuracies of 95.8% and 95.3%, respectively. The high recall values observed in RF and MaxEnt indicate that both models successfully identified nearly all presence records of *A. javanica*. The exceptionally high predictive performance, particularly for the Random Forest model, may be attributed to the strong environmental contrast between suitable and unsuitable habitats in the study area. The selected environmental predictors, including elevation, temperature, precipitation, soil type, and climate classification, exhibited distinct value ranges between presence and absence locations, enabling the machine learning algorithms to identify clear decision boundaries. Consequently, the models were able to learn the relationship between environmental conditions and species occurrence with high accuracy. Although such high performance indicates excellent discrimination, it may also reflect the relatively well-separated environmental characteristics of the dataset rather than model complexity alone, suggesting that the risk of overfitting is reduced but cannot be completely excluded.

a. Receiver Operating Characteristic (ROC) and Area Under the Curve (AUC)

The Receiver Operating Characteristic (ROC) curve was used to evaluate the discriminatory ability of each habitat suitability model. The Area Under the Curve (AUC) provides a threshold-independent measure of model performance, with values approaching 1 indicating excellent predictive accuracy and values close to 0.5 indicating random classification performance.

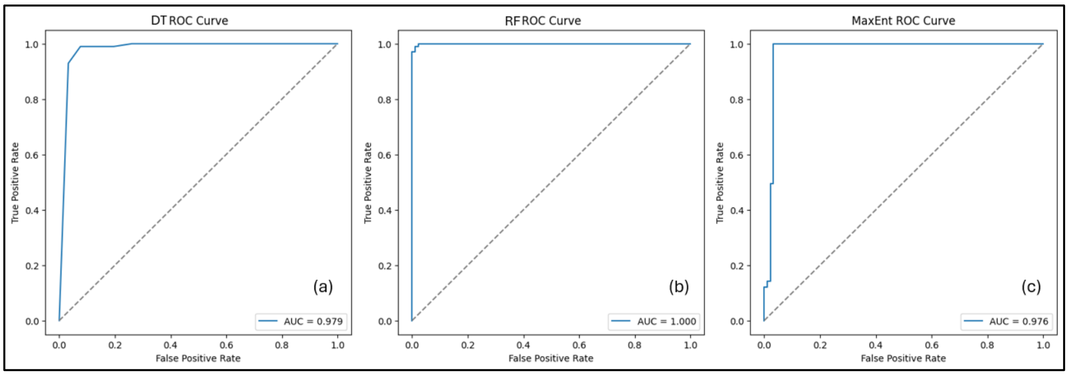


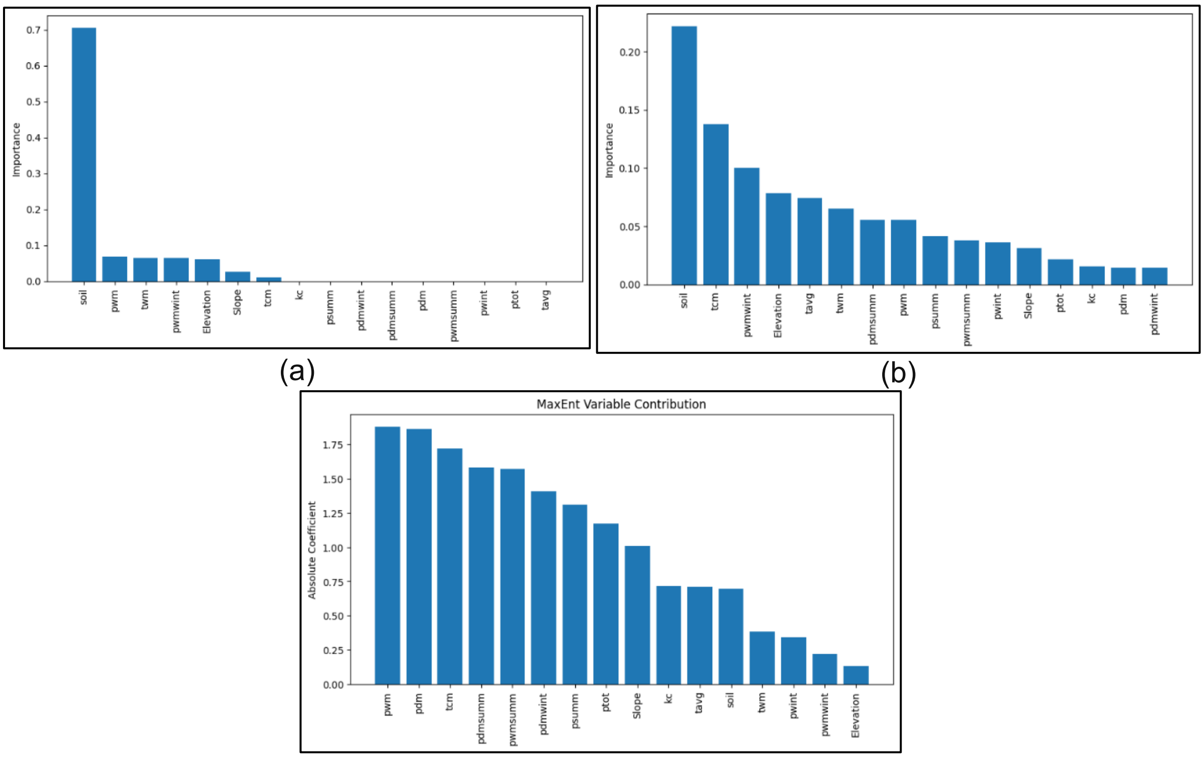
Figure 2. ROC/ AUC of the Habitat Suitability Model: (a) DT, (b) RF, (c) MaxEnt.

The ROC analysis in Figure 2 demonstrated excellent predictive performance for all three modelling approaches, with AUC values exceeding 0.97. The Random Forest model produced the highest AUC value (0.999), indicating an almost perfect ability to distinguish suitable from unsuitable habitats. Decision Tree and MaxEnt models also achieved very high AUC values of 0.979 and 0.976, respectively, suggesting strong predictive reliability.

Recent studies have highlighted AUC as one of the most robust threshold-independent metrics for evaluating binary classification models because it measures the ranking ability of a model across all classification thresholds (Li, 2024). The consistently high AUC values (> 0.97) suggest that all models were highly effective in predicting the potential distribution of *A. javanica*. The superior performance of the Random Forest model is likely attributable to its ensemble-learning framework, which combines multiple decision trees and effectively captures complex nonlinear relationships among environmental predictors while reducing overfitting and improving prediction stability (Lee et al., 2025).

Environmental Variable Importance

The Decision Tree (DT) model identified soil type as the most influential environmental predictor, contributing 70.5% of the total variable importance. The analysis controlled for other influential variables, including precipitation of the wettest month (PWM), temperature of the warmest month (TWM), precipitation of the wettest winter month (PWMWint), elevation, slope, and temperature of the coldest month (TCM) (Figure 3). The preponderant contribution of soil type signifies that edaphic conditions are the primary determinant of *A. javanica* distribution and habitat suitability. As a pioneering species inhabiting alpine and sub-alpine volcanic ecosystems, *A. javanica* is well adapted to the distinctive physical and chemical properties of volcanic soils, which are characterized by high porosity, abundant mineral content, and limited organic matter during the early stages of soil development (Ahmad et al., 2019). These edaphic characteristics engender harsh environmental conditions that restrict the establishment of many competing plant species while favoring pioneer species capable of colonizing newly formed volcanic substrates. Consequently, *A. javanica* gains a competitive advantage in these habitats, enabling it to establish and persist in areas where few other species can survive (Susanto et al., 2024).



(a) (b)

(c)

Figure 3. Environmental Variable Importance/contribution for Habitat Suitability of Anaphalis javanica: (a) DT, (b) RF, (c) MaxEnt.

Conversely, the presence of climatic factors such as PWM, TWM and TCM as secondary predictors suggests multiscale interactions between macroclimate and micro-edaphic conditions. Climatic and topographic factors play a role in regulating geographic and thermal boundaries at the macro level, while soil type acts as the final determinant of whether *A. javanica* seeds can become established and form colonies in a given habitat. This pattern confirms that the suitability of the natural habitat of *A. javanica* is not solely driven by mountain weather factors, but rather by its specific volcanic substrate characteristics (Siki et al., 2025)

The Random Forest model distributed variable importance more evenly among predictors. Soil remained the most influential variable (22.2%), followed by temperature of the coldest month (TCM), mean monthly winter precipitation (PWMWint), elevation, mean annual temperature (Tavg), and temperature of the warmest month (TWM).These results indicate that habitat suitability is jointly controlled by climatic, topographic, and edaphic factors rather than by a single environmental variable (Sutomo et al., 2025)

Variable contribution analysis from the MaxEnt model revealed a stronger influence of precipitation-related variables than observed in the tree-based algorithms.The high contribution of precipitation variables suggests that seasonal water availability is a critical determinant of habitat suitability for *A. javanica*. Temperature variables, particularly TCM, also contributed substantially, highlighting the importance of cool montane environments.

Comparison of Habitat Suitability Among Climate Scenarios

a. Present

As illustrated in Figures 4–6, the predicted habitat suitability of *A. javanica* under present climatic conditions was determined using the Decision Tree (DT), Random Forest (RF), and Maximum Entropy (MaxEnt) models. The present climate represents historical climatic conditions derived from the KGClim dataset, which is based on observations for the period 1979–2017 (Cui et al., 2021). Despite minor discrepancies in the spatial patterns exhibited by these three approaches, there is a notable consistency in the identification of suitable habitats, which are concentrated in high-elevation mountainous regions characterized by relatively low temperatures, adequate precipitation, and favorable soil conditions. The Decision Tree model produces more discrete habitat boundaries, reflecting its rule-based classification approach, whereas the Random Forest model generates smoother and more spatially continuous predictions by integrating multiple decision trees. Conversely, the Maximum Entropy model identifies broader areas of moderate habitat suitability, thereby demonstrating its capacity to capture complex nonlinear relationships between species occurrences and environmental predictors.

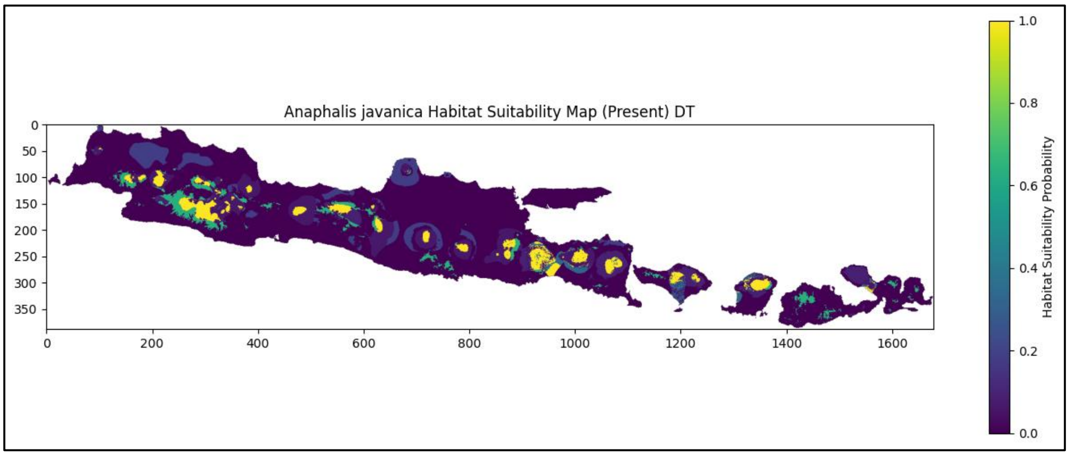


Figure 4. *Anaphalis javanica* Habitat Suitability under Present Climate Conditions Using Decision Tree.

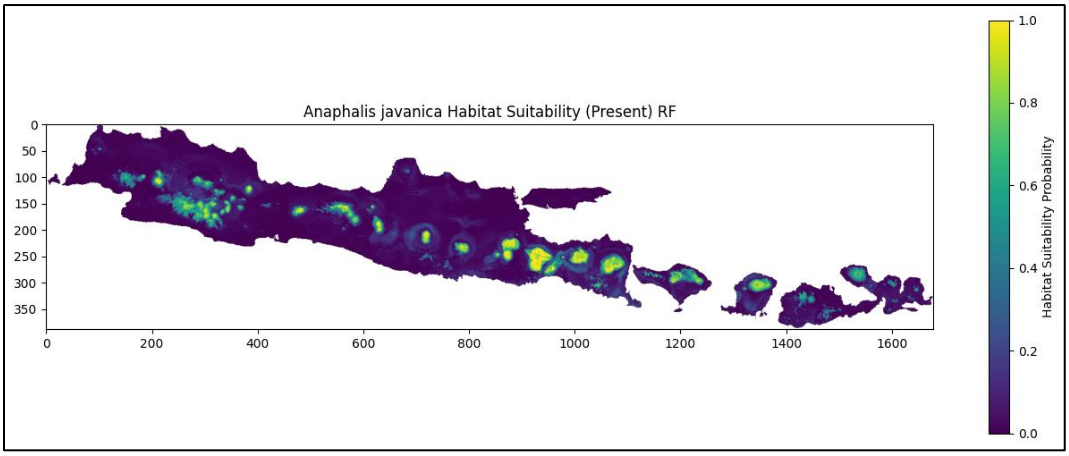


Figure 5. Anaphalis javanica Habitat Suitability Map under Present Climate Conditions Using Random Forest.

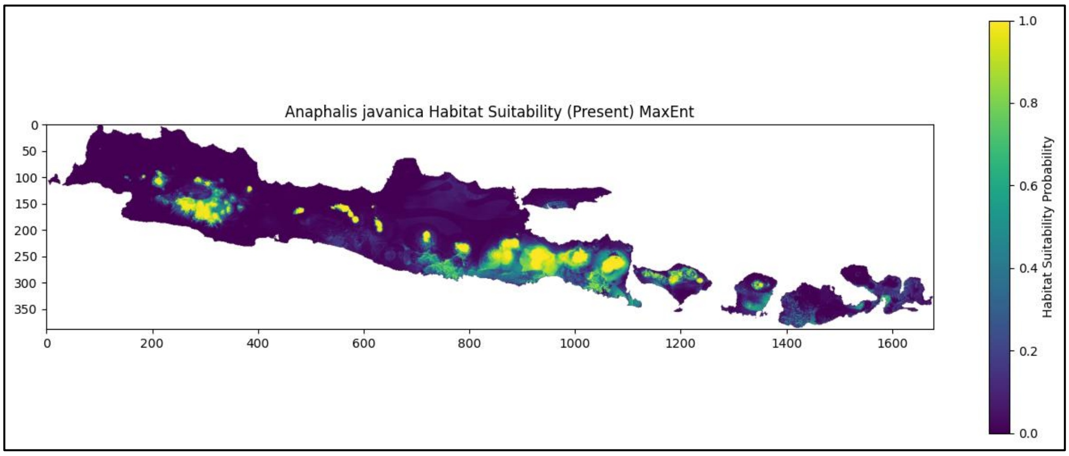


Figure 6. Anaphalis javanica Habitat Suitability Map under Present Climate Conditions Using Maximum Entropy.

As has been extensively documented in the extant literature, notable disparities among machine-learning algorithms have been reported in the context of species distribution modeling studies. In this setting, algorithms such as MaxEnt, Random Forest, and Decision Tree have been observed to manifest distinct predictive behaviors. However, these algorithms have demonstrated a consistent ability to identify ecologically suitable habitats for mountain species (Ahmadi et al., 2023; Safdar et al., 2025). Furthermore, the suitability of a habitat in montane ecosystems is strongly influenced by the interplay of climatic, topographic, and edaphic variables. The integration of these predictors significantly enhances the reliability of habitat suitability projections under both current and future climate conditions (Smith & Levine, 2025). In general, the three models consistently identify montane ecosystems as the predominant habitat for *A. javanica*. This provides a solid foundation for assessing the potential shifts in habitat under future climate change scenarios.

b. RCP 2.6- 2080

Figures 7–9 present the projected habitat suitability of *A. javanica* under the RCP 2.6 climate scenario for 2080 using the DT, RF, and MaxEnt models. In accordance with the low-emission scenario, the three models indicate that suitable habitats persist in high-elevation regions; however, the total extent of such habitats is diminished relative to present climatic conditions. The Decision Tree model identifies more fragmented patches of highly suitable habitat, whereas the Random Forest model predicts relatively continuous habitat connectivity. Conversely, the MaxEnt model projects a wider range of moderate suitability, albeit with a gradual decline toward higher elevations.

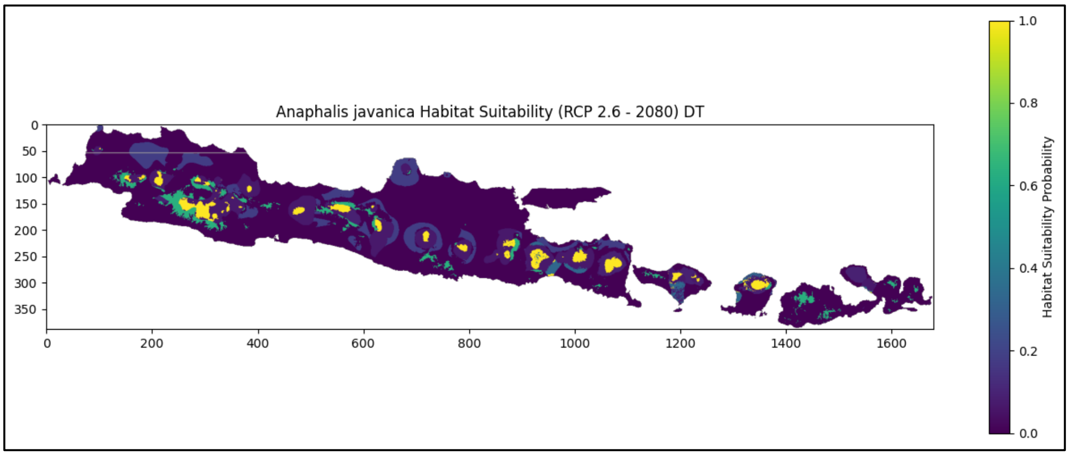


Figure 7. Projected Habitat Suitability Map for Anaphalis javanica (RCP 2.6 - 2080) Using Decision Tree.

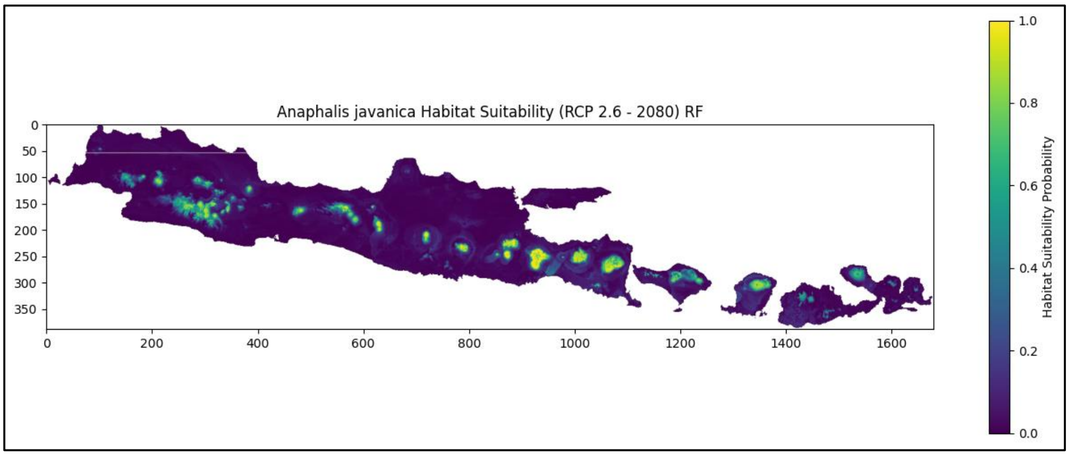


Figure 8. Projected Habitat Suitability Map for Anaphalis javanica (RCP 2.6 - 2080) Using Random Forest.

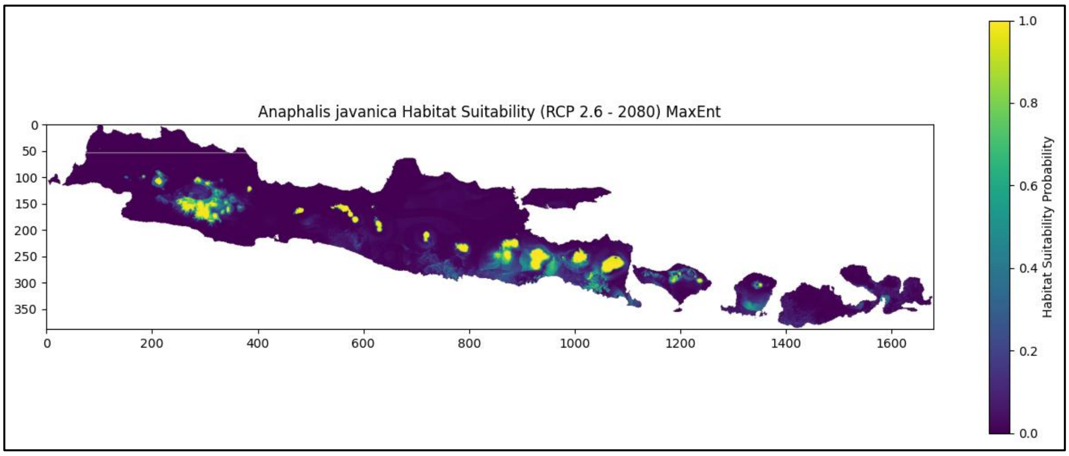


Figure 9. Projected Habitat Suitability Map for Anaphalis javanica (RCP 2.6 - 2080) Using Maximum Entropy.

These projections suggest that even under a low greenhouse gas emission pathway, moderate increases in temperature and shifts in precipitation regimes may reduce habitat availability for *A. javanica*, forcing the species to persist in cooler mountain refugia. Similar upward shifts and habitat contractions have been reported for montane plant species worldwide, where climate warming disproportionately affects species with narrow elevational ranges (Maharjan et al., 2022; Safdar et al., 2025). Recent studies have demonstrated the efficacy of machine-learning-based species distribution models in predicting future habitat change. These models consistently indicate that climate change will reduce the extent of suitable habitats and increase fragmentation in mountainous ecosystems (Susilo et al., 2026). Consequently, the conservation of high-elevation habitats will be essential for maintaining the long-term persistence of *A. javanica* under future climate conditions.

c. RCP 8.5 - 2080

As illustrated in Figures 10–12, the projected habitat suitability of *Anaphalis javanica* under the RCP 8.5 climate scenario for 2080 was determined using the DT, MaxEnt, and RF models. A comparison of the present climate and the RCP 2.6 scenario with the models' predictions reveals a marked decline in suitable habitat, with remaining suitable areas becoming increasingly restricted to the highest mountain elevations. The DT model identifies highly fragmented habitat patches, whereas the RF model predicts a limited number of climatically stable refugia with relatively higher suitability. Conversely, the MaxEnt model projects the most significant contraction of suitable habitat, indicating that only isolated high-elevation areas are likely to remain environmentally suitable under severe climate warming.

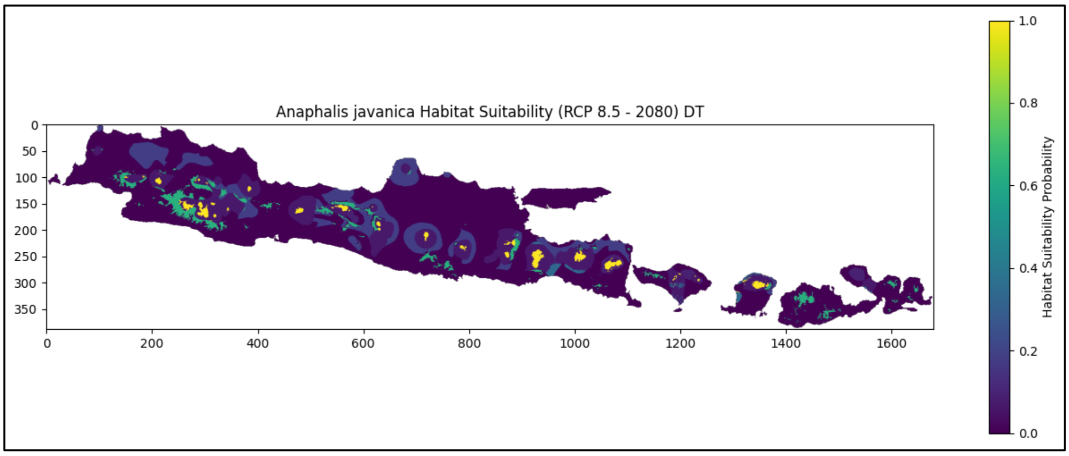


Figure 10. Projected Habitat Suitability Map for *Anaphalis javanica* (RCP 8.5 - 2080) Using Decision Tree.

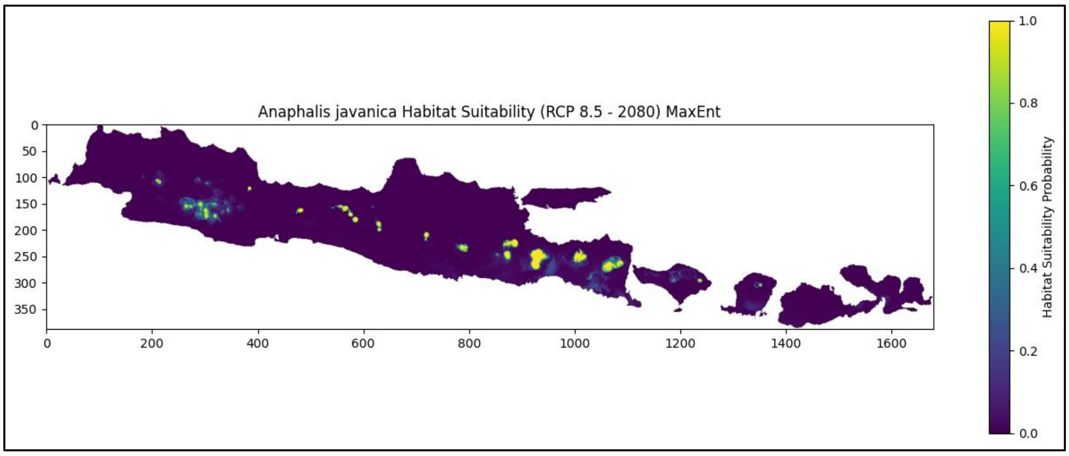


Figure 11. Projected Habitat Suitability Map for Anaphalis javanica (RCP 8.5 - 2080) Using Maximum Entropy.

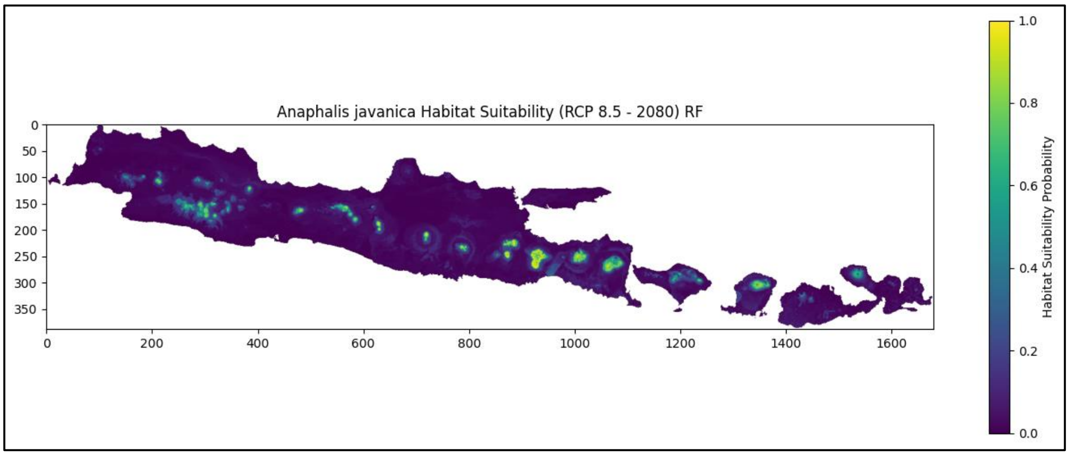


Figure 12. Projected Habitat Suitability Map for Anaphalis javanica (RCP 8.5 - 2080) Using Random Forest.

These projections suggest that rising temperatures and altered precipitation patterns under the high-emission scenario will substantially increase habitat fragmentation and reduce landscape connectivity. This, in turn, will elevate the extinction risk for high-altitude endemic species such as *A. javanica*. As indicated by (Liang et al., 2025; Sękiewicz et al., 2024), analogous patterns have been documented for endemic woody species and alpine flora. These findings demonstrate that high-emission climate scenarios invariably result in substantial habitat contraction and upward shifts toward mountain refugia. Recent studies in Indonesia provide further evidence that endemic montane plant species are expected to experience considerable losses of climatically suitable habitat under future high-emission scenarios. This underscores the importance of protecting climate refugia and maintaining ecological connectivity to enhance species persistence (Risna et al., 2026).

All models projected a progressive reduction in habitat suitability from current climatic conditions toward future climate scenarios. The strongest decline was predicted by MaxEnt, where mean suitability decreased from 0.149 under current conditions to 0.031 under RCP 8.5, representing a reduction of approximately 79%. Similar declining trends were observed in DT and RF, indicating that future climate change may substantially reduce suitable habitats for *A. javanica*.

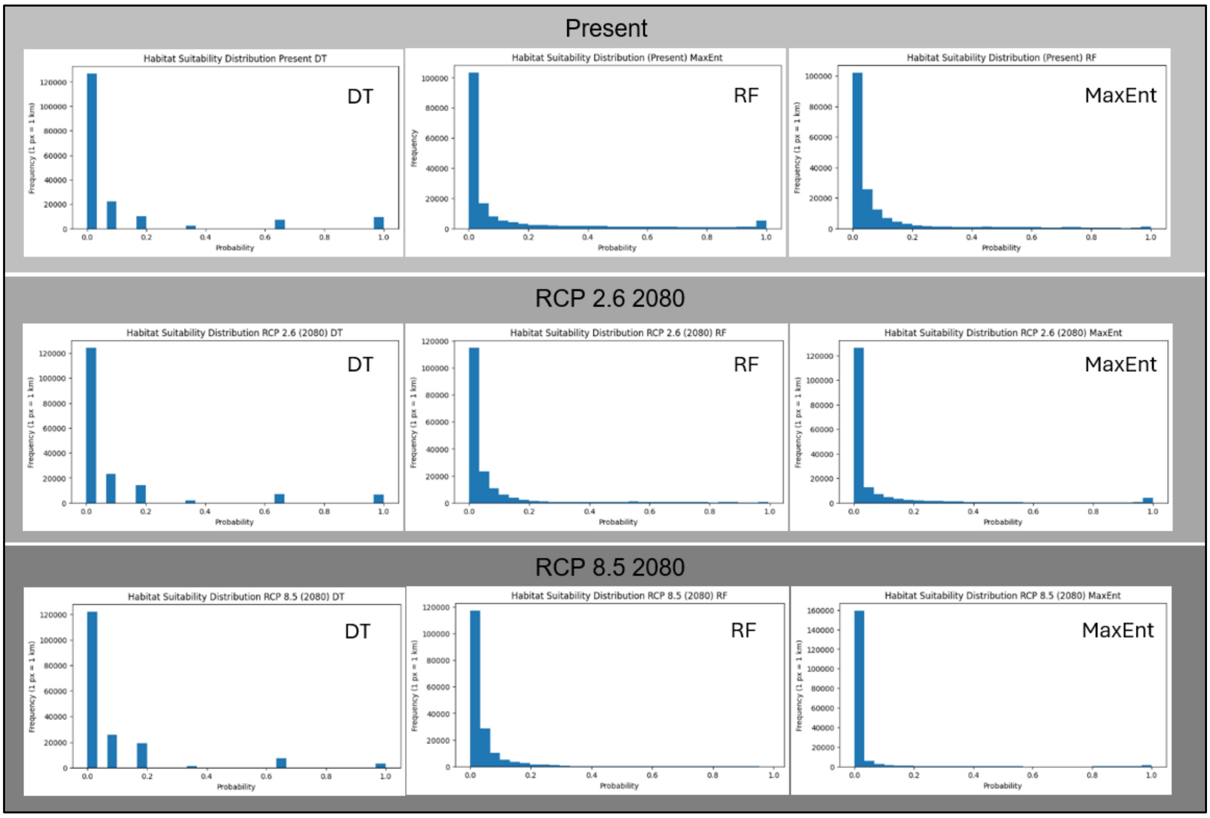


Figure13. Pixel Distribution of Habitat Suitability of A. javanica under Current and Future Climate Scenarios Predicted by Different ML Models (1 px approximately 1 km^2)

The consistency among the three modelling approaches suggests that *A. javanica* is vulnerable to projected climate change, particularly under high-emission scenarios. Across all models, the estimated extent of suitable habitat is projected to decline substantially from the present distribution under both future climate scenarios, with a greater reduction occurring under RCP 8.5 than under RCP 2.6. This decrease in habitat area indicates that a considerable proportion of currently suitable environments may become unsuitable by 2080 Mountain ecosystems that retain high suitability under both RCP scenarios may function as climate refugia and should therefore be prioritized for conservation and long-term monitoring. Maintaining habitat connectivity among montane regions may further enhance the species' capacity to respond to future environmental change (Barrows et al., 2020).

CONCLUSION AND RECOMMENDATION

This study demonstrated that Decision Tree (DT), Random Forest (RF), and Maximum Entropy (MaxEnt) models are effective approaches for predicting the habitat suitability of *Anaphalis javanica* across Java, Bali, and the Nusa Tenggara Islands. The consistent predictions produced by the three models indicate that elevation, temperature, precipitation, soil type, and climate classification are key environmental factors influencing the species' distribution. Future climate projections consistently suggest a contraction of suitable habitats by 2080, particularly under the high-emission RCP 8.5 scenario, indicating that *A. javanica* is likely to become increasingly restricted to high-elevation mountain ecosystems. Although the models achieved high predictive performance, these results should be interpreted with caution because high AUC values may partly reflect the clear environmental separation between suitable and unsuitable habitats rather than model generalizability alone. Therefore, the possibility of model overfitting cannot be completely excluded, and future studies should evaluate model transferability using independent datasets or additional validation approaches.

This study also has several limitations. The modelling relied on historical occurrence records and environmental variables at a spatial resolution of approximately 1 km², and future projections assumed that topographic and soil variables remain unchanged over time. In addition, other ecological factors, such as species interactions, dispersal limitations, and human disturbances, were not explicitly incorporated into the modelling framework.

From a conservation perspective, high-elevation areas projected to remain suitable under both climate scenarios should be prioritized as climate refugia through strengthened habitat protection, long-term ecological monitoring, and landscape-scale connectivity management. Active human interventions, including habitat restoration, reduction of anthropogenic disturbances, and ex situ conservation programs where necessary, may also be required to enhance the long-term persistence of *A. javanica* populations under future climate change.

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