IJTB VOLUME 2 (1) 2026
Indonesian Journal of Tropical Biology
https://journals.widhatulfaeha.id/index.php/ijtb

Original Research Paper

Modelling Current and Future Mangrove Distribution under RCP 8.5 Climate Scenario: A Machine Learning Approach on Lombok Island, Indonesia

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Article Info

Recived: February 25, 2026
Revised: March 3, 2026
Accepted: April 27, 2026
Published: April 30, 2026

ISSN: **3108-9801**
ESSN: **3109-0842**
DOI: **10.65622/ijtb.v2i1.235**

Abstract

Mangrove ecosystems are essential for coastal protection and biodiversity, yet their distribution is highly influenced by climate variability. This study aims to predict current and future distribution of mangrove habitats on Lombok Island-Indonesia, using environmental predictor variables derived from topographic data and Köppen–Geiger climate classification. Mangrove distribution data were classified into presence and absence categories and integrated with climatic and terrain variables to develop habitat suitability models using five machine learning algorithms: Random Forest (RF), Decision Tree (DT), Naïve Bayes (NB), Artificial Neural Network (ANN), and Support Vector Machine (SVM). Model performance was evaluated using accuracy metrics, and the best-performing model was selected for spatial projection under the Representative Concentration Pathway (RCP) 8.5 scenario for 2050 and 2080. The RF model showed the highest predictive performance. The results indicate a substantial decline in suitable mangrove habitats, decreasing from 12,443 ha under current conditions to 7,255 ha in 2050 and 6,336 ha in 2080, representing a reduction of nearly 50%. This decline is associated with changes in precipitation and temperature regimes that influence hydrological conditions and habitat suitability. The application of machine learning provides a robust spatial approach for predicting mangrove distribution and supports conservation planning and climate-adaptive coastal management.

Keywords: Climate change; Habitat suitability; Machine learning; Mangrove distribution; Random Forest

INTRODUCTION

Mangrove ecosystems, which offer essential services where land meets sea, are among the most productive coastal environments (B. Zhang et al., 2024). These forests support biodiversity, provide natural defense against storms and coastal erosion, and play a crucial role in carbon storage and nutrient cycling (Lovelock et al., 2025). As highlighted by Sippo et al. (2018), Mangroves provide highly valued ecosystem services like nutrient processing, carbon sequestration, coastal protection, and biodiversity support. However, the efficacy of these benefits depends on the ecological health and spatial distribution of mangrove habitats, which are increasingly threatened by human activity and environmental disturbances. The ecological functioning and spatial distribution of mangrove ecosystems are greatly influenced by environmental conditions, especially climatic factors like temperature, precipitation, and sea-level dynamics. (Friess et al., 2023). Climate change further affects these ecosystems through rising sea levels, increased storm frequency, temperature fluctuations, and altered precipitation patterns, which in turn modify hydrological and environmental conditions and shape mangrove distribution at regional scales (Ward et al., 2016). As a result, these changes impact mangrove productivity, ecological resilience, and spatial distribution across coastal landscapes. Moreover, due to their intertidal position and high sensitivity to environmental changes, mangroves are especially vulnerable to climate-related stressors and are expected to be among the ecosystems most affected by climate change (Friess et al., 2022).

RCP 8.5 scenario, when combined with Machine Learning algorithms, offers advantages in utilizing large datasets without requiring non-parametric statistical tests, as the models can automatically identify complex patterns in environmental data (Bindajam et al., 2023; Al-Huqail et al., 2024). Recent research shows that machine learning techniques like ensemble models, Random Forest, and Support Vector Machine can map and predict mangrove distribution and changes with high accuracy (Putra et al., 2025; Niceline et al., 2025). Additionally, machine learning frameworks that integrate various environmental variables, such as climatic, topographic, and hydrological factors, have been successfully used to evaluate mangrove ecosystem dynamics and global restoration potential under current and future climate scenarios (Peng et al., 2025; Zhang et al., 2026).

Citacion: Purnama, M. I., Azizah, L., Grendis, N. W. B., Zulkurniawan, M., & Çoban, H. O. (2026). Modelling current and future mangrove distribution under RCP 8.5 climate scenario: A machine learning approach on Lombok Island, Indonesia. *Indonesian Journal of Tropical Biology*, 2(1), 1-8. http://doi.org/10.65622/ijtb.v2i1.235

These methods are useful tools for forecasting future habitat changes because they yield dependable and highly accurate results, especially when considering environmental dynamics impacted by extreme climate change scenarios.

With the advantages of the RCP 8.5 scenario combined with Machine Learning algorithms, mangrove management and conservation efforts can be optimized, as they are able to predict changes in land cover and habitat conditions more accurately. This supports data-driven planning in addressing the impacts of climate change, identifying vulnerable areas, and formulating more effective adaptation and mitigation strategies to maintain the sustainability of mangrove ecosystems on Lombok Island (Abijith, Saravanan, Parthasarathy, S. S., Prasanna, Venkatesan, & Mohanraj, 2025; Aldea Noor, Jaelani, Hayati, & Syariz, 2024; Marfi, Prasetyo, Dharmawan, & Kusmana, 2025).

RESEARCH METHODS

Study Area

Mangrove habitats on Lombok Island-West Nusa Tenggara Province are found along coastal areas such as Sekotong and Gerupuk Bay (Figure 1). These ecosystems are made up of dominant genera like Rhizophora, Avicennia, and Sonneratia and are impacted by salinity gradients, substrate, and tidal inundation. At least eight mangrove species were found in Sekotong during a field investigation; Rhizophora apiculata was found on every transect, demonstrating its tolerance to different coastal conditions (Japa & Santoso, 2019). Lombok represents a suitable case study for evaluating climate-driven mangrove distribution patterns using spatial modeling approaches, as these ecosystems not only experience increasing degradation trends but also provide important ecological and economic benefits for local communities through fisheries, coastal protection, and livelihood support. This study was conducted on Lombok Island, West Nusa Tenggara, Indonesia, utilizing geographical datasets that illustrate the state of the environment at present and anticipated climate scenarios for 2050 and 2080.

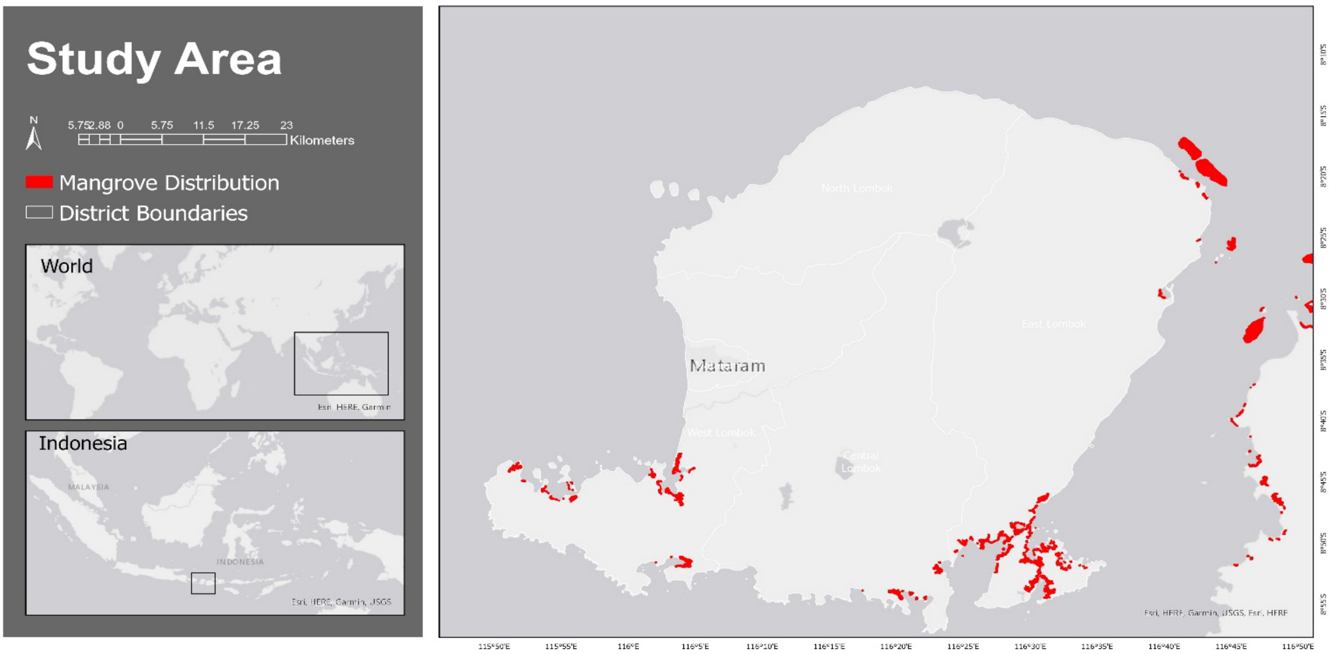

Figure 1. Study Area

Research Design, Population, and Sample

This study used environmental factors and machine learning algorithms in a quantitative spatial modeling approach to forecast the suitability of mangrove habitats.. The research population consisted of spatial units representing mangrove and non-mangrove areas across Lombok Island derived from the national mangrove distribution dataset. A total of 1,359 spatial samples were generated from the study area, consisting of presence and absence points extracted from the mangrove distribution layer. In order to minimize spatial bias and guarantee representative environmental coverage, the sampling procedure used a random spatial sampling approach, which is frequently used in species distribution modeling (Samal et al., 2022; Sulova & Arsanjani, 2020).

Data Variable and Data Collection

The spatial presence of mangrove ecosystems throughout the study area was represented by the response variable in this study, which was mangrove distribution. The mangrove data were obtained from the Indonesian Mangrove Distribution Dataset in shapefile (*.shp*) format derived from national-scale mapping conducted in 2014-2015. The original dataset includes mangrove density classifications categorized into five classes, namely very sparse, sparse, moderate, dense, and very dense. For modeling purposes, the mangrove distribution was reclassified into two classes, namely presence and absence, where mangrove areas were assigned as presence and non-mangrove areas as absence. This binary classification was used to extract occurrence data for habitat suitability modeling using Machine Learning (Aparicio & Viodor, 2025).

Environmental predictor variables were selected to represent climatic and topographic conditions influencing mangrove habitat suitability. The Shuttle Radar Topography Mission (SRTM) dataset (pixel resolution: 30 m) was used to obtain topographic variables such as elevation, slope, and aspect., while climatic predictors were obtained from the

Köppen-Geiger Climate (KGClim) dataset (pixel resolution: 1 km) (Cui et al., 2021). To ensure uniformity in pixel size throughout the modeling process, all datasets were then resampled to a spatial resolution of 30 m. In addition to precipitation-related variables like annual precipitation, precipitation of the driest month, precipitation of the wettest month, and seasonal precipitation indices, the chosen climatic variables include temperature indicators like annual mean temperature, temperature of the warmest month, and temperature of the coldest month. Ecological niche modeling frequently uses these variables to simulate possible species distributions under various environmental circumstances. (Chen et al., 2025). The environmental predictor variables used in this study are summarized in Table 1.

Table 1. Variable

PredictorszVariable Type	Original Variable Name	Description	Data Source
Topographic	Elevation	Elevation above sea level	SRTM
Topographic	Aspect	Terrain aspect	SRTM
Topographic	Slope	Terrain slope	SRTM
Climate	kccon	Köppen–Geiger Climate Classification Confidence	KGClim
Climate	kc	Köppen–Geiger Climate Class	KGClim
Climate	pdm	Precipitation of Driest Month	KGClim
Climate	pdmsumm	Precipitation of Driest Month (Warm Season)	KGClim
Climate	pdmwint	Precipitation of Driest Month (Cold Season)	KGClim
Climate	psumm	Precipitation of Warm Season	KGClim
Climate	ptot	Annual Precipitation	KGClim
Climate	pwint	Precipitation of Wettest Month	KGClim
Climate	pwm	Precipitation of Warmest Quarter	KGClim
Climate	pwmsumm	Precipitation of Wettest Month (Warm Season)	KGClim
Climate	pwmwint	Precipitation of Wettest Month (Cold Season)	KGClim
Climate	tavg	Annual Mean Temperature	KGClim
Climate	tcm	Temperature of Coldest Month	KGClim
Climate	twm	Temperature of Warmest Month	KGClim

Research data analysis

Following the preparation of the mangrove distribution dataset classified into presence and absence classes, the data were integrated with environmental predictor variables to develop habitat suitability models. The modeling process was conducted using multiple machine learning algorithms, including RF, DT, NB, ANN, and SVM, because these algorithms can capture intricate and nonlinear relationships between environmental predictors and species occurrence, they are frequently used in species distribution modelling (de Luna et al., 2019; Mitra & Basu, 2023; Rodrigues & De la Riva, 2014; Shmuel & Heifetz, 2023; Singh et al., 2023; Wang et al., 2022).

The Python programming language was used to carry out the modeling analysis in the Google Colab environment, which offers a cloud-based platform for machine learning computation. A number of Python libraries were used, such as GeoPandas and Rasterio for managing spatial datasets and extracting environmental variables from raster layers, Pandas and NumPy for data processing and numerical operations, and Scikit-learn (sklearn) for implementing machine learning algorithms and model evaluation. The Scikit-learn metrics module's functions were used to calculate model performance evaluation metrics like accuracy, precision, recall, F1-score, and Cohen's kappa. Matplotlib and Seaborn libraries were used to visualize model outputs and validation results (Purnama et al., 2024; Purnama & Çoban, 2025).

To assess model performance, the dataset was split into training and testing subsets at random using a conventional partitioning technique (Purnama et al., 2024; Sulova & Arsanjani, 2020). Predictive models were constructed using the training dataset, and their capacity for generalization was evaluated using the testing dataset. Several accuracy metrics, such as overall accuracy (ACC), precision, recall, F1-score, and Cohen's kappa coefficient, were used to assess the model's performance. Additionally, k-fold cross-validation was used to improve the robustness of prediction results and lessen model overfitting (Chen et al., 2025; Darapureddy et al., 2019; Purnama et al., 2024; Purnama & Çoban, 2025).

Overall accuracy represents the proportion of correctly classified samples and is calculated as (Visa et al., 2011):

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

where TP stands for true positives, TN for true negatives, FP for false positives, and FN for false negatives. Precision is computed as the percentage of correctly predicted positive observations (Yunial, 2020):

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

Recall (sensitivity) is the percentage of real positives that are accurately predicted (Yunial, 2020):

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

The F1-score offers a fair assessment metric by combining precision and recall (Rijsbergen, 1979):

$$F1 = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad (4)$$

Furthermore, the agreement between predicted and observed classifications beyond chance was assessed using Cohen's kappa coefficient (Cohen, 1960):

$$Kappa = \frac{P_o - P_e}{1 - P_e} \quad (5)$$

where Po represents the observed agreement and Pe represents the chance-based expected agreement. Additionally, k-fold cross-validation was used to improve the robustness of prediction results and lessen model overfitting.

Feature importance analysis was used to determine the most significant factors influencing habitat suitability in order to further evaluate the contribution of environmental predictors to mangrove distribution (Huang et al., 2023; Zhang et al., 2023). This analysis enables the interpretation of model outputs by quantifying the relative importance of each predictor variable in determining mangrove presence across the study area (Samal et al., 2022)

Spatial Climate Scenario Projection

For the spatial projection of mangrove distribution under future climate scenarios, the top-performing machine learning algorithm was chosen based on the highest accuracy metrics. Using bioclimatic variables obtained from the KGClim dataset under Representative Concentration Pathways RCP 8.5 for the mid-century (2050) and late-century (2080) periods, the chosen model was used to simulate potential mangrove habitat suitability. RCP 8.5 is a high greenhouse gas emission scenario that reflects a future pathway with limited mitigation efforts and continued reliance on fossil fuels. It is characterized by increasing radiative forcing that will reach 8.5 W/m² by the end of the twenty-first century. The quantification of changes in habitat suitability linked to variations in temperature and precipitation regimes, which impact species growth and spatial distribution patterns, is made possible by species distribution modeling under projected climate scenarios (Çoban et al., 2020). Mangrove ecosystems are sensitive to climatic factors due to their dependence on temperature, precipitation, and hydrological dynamics, which may alter their spatial distribution under future climate conditions (Friess et al., 2022). The projected suitability maps were subsequently used to assess potential spatial shifts in mangrove habitat under different climate scenarios.

RESULTS AND DISCUSSION

Mangrove ecosystems on Lombok Island represent an important coastal landscape that supports ecological stability and coastal livelihoods. These ecosystems generally occur along sheltered coastal zones, estuaries, and tidal flats where geomorphological conditions such as low elevation, sediment accumulation, tidal inundation, and salinity gradients regulate vegetation structure and species distribution. Previous ecological studies in Lombok have reported that mangrove communities are dominated by genera such as Rhizophora, Avicennia, and Sonneratia, which commonly occupy intertidal environments with muddy substrates and moderate salinity conditions (Irwansah et al., 2017; Sukuryadi et al., 2021). Mangrove ecosystems on West Lombok also play an important ecological and socio-economic role as coastal protection systems, nursery grounds for marine organisms, and sources of livelihood for local communities through fisheries and coastal resource utilization (Barbier et al., 2011; Salahuddin et al., 2024). However, these ecosystems have experienced increasing pressure due to land conversion, coastal development, and environmental change, which may alter mangrove distribution patterns across the island (Friess et al., 2019)

Model Performance and Variable Importance

The mangrove distribution model, which consists of presence and absence points derived from the classified mangrove dataset, was developed in this study using 1,359 spatial samples. 70% of the samples were used for model training and 30% for performance evaluation after the dataset was randomly split into training and testing subsets using a standard 70:30 split ratio. Based on environmental predictor variables, five machine learning algorithms RF, DT, NB, ANN, and SVM, were used to forecast the presence of mangroves.

As shown in Table 2, a number of accuracy metrics were used to assess each model's performance, including overall accuracy, precision, recall, F1-score, and Cohen's kappa coefficient. With an overall accuracy of 0.98, precision of 0.98, recall of 0.98, F1-score of 0.98, and kappa coefficient of 0.95, the Random Forest model showed the best predictive performance among the assessed algorithms. In comparison, the DT model achieved an accuracy of 0.90 and kappa of 0.72, followed by NB with an accuracy of 0.86 and kappa of 0.56. The ANN and SVM models showed lower performance, with accuracy values of 0.80 and 0.77 and kappa coefficients of 0.21 and 0.01, respectively. These results indicate that the RF algorithm provided the most reliable prediction for mangrove distribution among the tested models.

Table 2. Model Performance Evaluation

Metric	RF	DT	NB	ANN	SVM
Accuracy	0.98	0.90	0.86	0.80	0.77
Precision	0.98	0.91	0.87	0.85	0.82
Recall	0.98	0.91	0.86	0.81	0.77
F1-score	0.98	0.91	0.87	0.75	0.67
Kappa	0.95	0.72	0.56	0.21	0.01

The cross-validation results further demonstrated the variability in model performance across different algorithms, as indicated by their respective mean CV scores (Figure 2). Among the evaluated models, SVM achieved the highest mean CV score (0.79), followed by ANN (0.76), NB (0.75), RF (0.72), and DT (0.67). Despite SVM showing relatively consistent performance across validation folds, its lower overall accuracy and kappa coefficient in the testing phase suggest limited predictive capability compared to RF. Conversely, although RF exhibited a slightly lower mean CV score than some models, it maintained superior performance in accuracy-based evaluation metrics, indicating a more reliable balance between model stability and predictive accuracy. The cross-validation results for each algorithm are presented in graphical form to illustrate model stability across validation folds. These findings support the selection of RF as the most robust algorithm for subsequent spatial modeling of mangrove distribution under current and future climate scenarios. Feature importance analysis was performed to examine the relative contribution of environmental predictor variables influencing mangrove distribution, as presented in Figure 3.

The results indicate that precipitation-related variables showed consistently higher importance values across the evaluated models. In particular, precipitation of the warmest quarter (pwm), precipitation of the driest month in the warm season (pdmsumm), and annual precipitation (ptot) were identified as dominant predictors, with importance values exceeding 0.15 in RF and above 0.23 in NB and ANN models.

These findings highlight the role of seasonal and annual precipitation patterns in shaping mangrove habitat suitability.

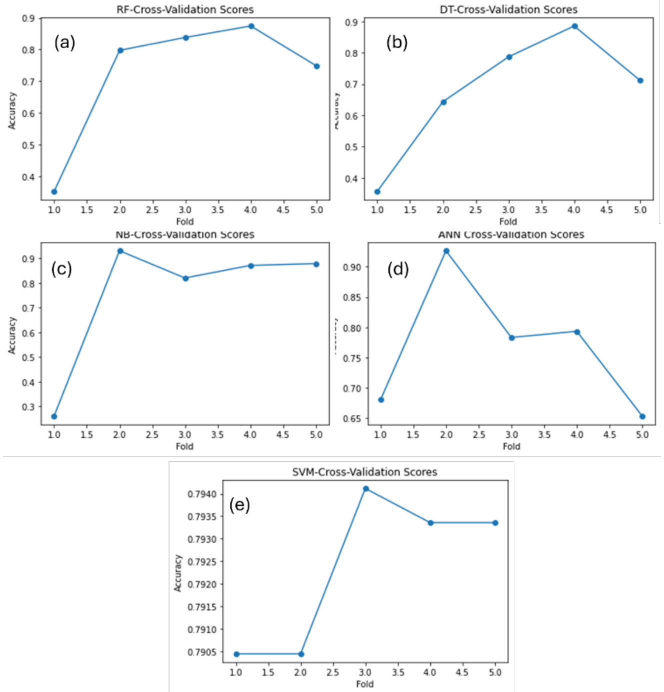

Figure 2. Cross-validation of (a) RF, (b) DT, (c) NB, (d) ANN, and (e) SVM.

Topographic variables such as elevation exhibited moderate importance across models, whereas aspect and slope generally showed lower contributions. Temperature-related variables including annual mean temperature (tavg), temperature of the coldest month (tcm), and temperature of the warmest month (twm) demonstrated moderate influence, particularly in NB, ANN, and SVM models. Overall, climatic variables associated with precipitation variability contributed more substantially to the prediction of mangrove presence compared to terrain and temperature conditions.

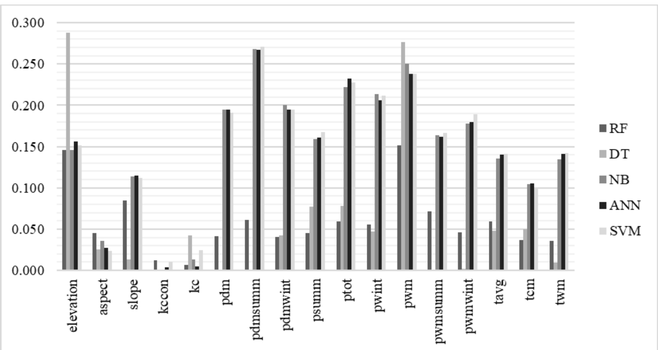

Figure 3. Feature importance of RF, DT, NB, ANN, and SVM models for mangrove prediction

Mangrove Habitat Projection

The spatial modeling results using the Random Forest (RF) algorithm indicate that the current suitable habitat for mangrove ecosystems on Lombok Island is primarily distributed along the southern and eastern coastal regions, which are characterized by low elevation and favorable climatic conditions (Figure 4). Mangroves are found naturally in intertidal zones in tropical and subtropical regions, where their spatial distribution is greatly influenced by environmental factors like salinity, temperature, and precipitationm(Giri et al., 2011). Based on the modeling results, the total area of suitable mangrove habitat under current climatic conditions is estimated at 12,443.64 ha.

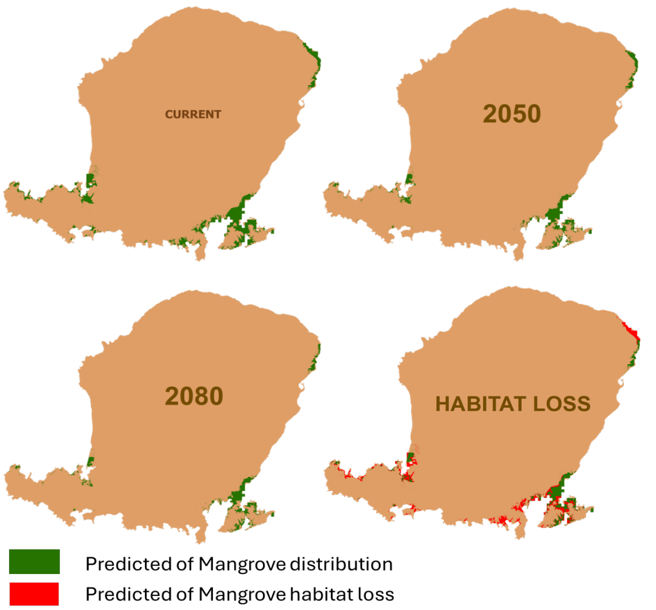

Figure 4. Current and projected mangrove habitat suitability under the RCP 8.5 climate scenario for 2050 and 2080 using the RF model

Future projections under the RCP 8.5 climate scenario indicate a substantial reduction in suitable mangrove habitats across Lombok Island by 2050 and 2080. The modeled suitable habitat area is projected to decline to approximately 7,255.19 ha by 2050 and further decrease to 6,336.84 ha by 2080. This projected reduction in suitable habitat is associated with anticipated changes in climatic conditions, particularly precipitation variability and temperature regimes that influence hydrological dynamics and salinity levels within intertidal ecosystems (Friess et al., 2022). Habitat suitability modeling integrated with future climate projections has been widely applied to assess potential spatial shifts in mangrove distribution under changing environmental conditions (Jaffé et al., 2025). The spatial comparison between current and projected distributions indicates that several presently suitable coastal zones may become less favorable under future climate conditions, resulting in localized habitat loss as illustrated in Figure 4.

The projected contraction of suitable mangrove habitats under the RCP 8.5 scenario may also be attributed to the sensitivity of mangrove ecosystems to changes in hydroclimatic conditions that regulate salinity balance, sediment dynamics, and tidal inundation patterns. Mangroves are typically confined to intertidal environments where their spatial distribution is controlled by climatic thresholds and coastal geomorphological processes (Giri et al., 2011). It is anticipated that changes in temperature and precipitation patterns will affect soil moisture levels and coastal hydrology, possibly changing the ecological niche that is conducive to the establishment and persistence of mangroves (Friess et al., 2022). In tropical coastal regions where climate variability directly impacts ecosystem resilience, habitat suitability modeling using machine learning techniques has been extensively used to simulate potential changes in mangrove distribution under future climate scenarios (Li et al., 2023;

Samal et al., 2022). Similar modeling approaches integrating spatial environmental variables have demonstrated the effectiveness of Random Forest algorithms in identifying potential shifts in mangrove habitats for conservation planning and ecosystem-based management (Febrianto et al., 2025; Jaffé et al., 2025).

These results emphasize how crucial it is to combine ecological knowledge with spatial modeling techniques in order to comprehend the possible effects of climate change on mangrove ecosystems. Mangrove habitats offer vital ecological services, such as protecting the coast, serving as marine species' breeding grounds, and sustaining fisheries that greatly boost coastal economies (Giri et al., 2011; Barbier et al., 2011). Therefore, identifying areas that are likely to experience habitat contraction under future climate conditions is important for guiding conservation planning and coastal ecosystem management. Spatial predictions generated from machine learning models can support decision-making by identifying priority areas for mangrove conservation, restoration, and adaptive coastal management strategies in response to climate-driven environmental changes (Barbier et al., 2011; Friess et al., 2022; Giri et al., 2011; Jaffé et al., 2025).

CONCLUSION

This study used environmental predictors derived from topographic and Köppen-Geiger climate variables to predict the suitability of mangrove habitats on Lombok Island using machine learning techniques. The Random Forest (RF) model showed the best predictive performance among the assessed algorithms for simulating the presence-absence distribution of mangroves. The findings show that the southern and eastern coastal regions of Lombok Island are currently home to the majority of suitable mangrove habitats. The spatial projections indicate a significant decline in suitable mangrove habitats in the future under the RCP 8.5 climate scenario. Under present circumstances, the total suitable area is expected to drop from 12,443.64 ha to roughly 7,255.19 ha by 2050 and then to 6,336.84 ha by 2080. These results demonstrate how future climatic variability, especially shifts in temperature and precipitation patterns, may affect the suitability of mangrove habitats. A spatially explicit framework for evaluating possible changes in mangrove distribution is provided by the integration of environmental variables with machine learning techniques, which can aid in the management of coastal ecosystems and conservation planning in the face of climate change.

ACKNOWLEDGMENTS

The authors would like to express their sincereappreciation to Saujana Climate Community for institutionalsupport and research facilitation, as well as to the Departmentof Informatics Engineering, Faculty of Science andTechnology, Universitas Qamarul Huda Badaruddin, foracademic support and technical resources. The authors alsoacknowledge the Department of Forest Engineering, Facultyof Forestry, Isparta University of Applied Sciences, Türkiye,for scientific collaboration and valuable methodologicalinsights. In addition, we thank the field assistants and localcommunities on Lombok Island for their contributions to datacollection and knowledge sharing related to mangroveecosystems. Finally, we extend our gratitude to all parties whocontributed, directly or indirectly, to the completion of thisresearch.

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