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Modelling habitat suitability of sugar palm (*Arenga pinnata*) in Andongrejo Resort, Meru Betiri National Park, East Java, Indonesia

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Abstract. *Hikmat A, Zuhud EAM, Sandra E, Al Manar P, Putri FDW, Ayuba HA. 2025. Modelling habitat suitability of sugar palm (*Arenga pinnata*) in Andongrejo Resort, Meru Betiri National Park, East Java, Indonesia. Biodiversitas 26: 4077-4089.* Sugar palm (*Arenga pinnata*) is a species of the Arecaceae family with considerable economic, social, and ecological importance. This study aimed to model the habitat suitability of sugar palm and generate a suitability map based on the relationship between known presence points and key environmental variables. Using Maximum Entropy (MaxEnt) modelling, habitat suitability was predicted and classified based on the relationship between known occurrences and environmental variables. Seven environmental variables were found to contribute to the habitat suitability model. Among them, temperature (49.5%), altitude (29%), and distance from the river (7.7%) were identified as the most influential. The model achieved a high level of accuracy, with an Area Under the Curve (AUC) value of 0.942, indicating excellent predictive performance. Habitat suitability in the Andongrejo Resort, Meru Betiri National Park, East Java, Indonesia, was categorized into five classes: not suitable (11.17 ha), less suitable (4,882.56 ha), quite suitable (144.28 ha), suitable (42.96 ha), and very suitable (33.64 ha). The findings show that highly suitable habitats occupy a much smaller area compared to less suitable ones, which could threaten the long-term survival of sugar palm populations in the region. Notably, areas with high habitat suitability were mainly found within the forest zone, covering approximately 29.24 ha. These findings provide spatial guidance for habitat management, including restoration and conservation planning, particularly in the forest zones where suitable habitats are concentrated.

Keywords: Ecological niche model, environmental variables, maximum entropy, raster, response curve

INTRODUCTION

Arenga pinnata, a member of the Arecaceae family, holds considerable economic, ecological, and social significance. Economically, this species provides palm sugar, fruit, fiber, sago from its stems, and leaf ribs. Ecologically, it contributes to soil and water conservation, microclimate regulation, and carbon sequestration. Furthermore, cultivating sugar palm supports livelihoods, promotes public health initiatives, and conserves traditional ancestral knowledge. These multifaceted benefits are supported by its extensive distribution across Indonesia, from Sabang to Merauke (Haryoso et al. 2020). The near-complete utilization of the sugar palm from roots, stems, and leaves to fiber, flowers, and fruits (Haryoso et al. 2020; Zuhud et al. 2020), establishes it as a culturally important multipurpose tree species (Imraan et al. 2023).

In many forest-edge communities, particularly in Java, sugar palms have historically constituted a fundamental component of local livelihoods. These palms are intricately linked with indigenous customs, festivals, and artisanal industries, such as the production of palm sugar, which frequently involves cooperative labor and traditional techniques passed down through generations. Nevertheless, sugar palm populations have faced several threats in recent decades. Unsustainable harvesting, land use changes, agricultural expansion, and habitat destruction, especially from deforestation and infrastructure projects, have reduced their natural range in certain areas. Additionally, declining interest among younger generations and a lack of cultivation incentives have further endangered the continuation of sugar palm-based traditions and land management practices.

Sugar palm is a perennial species characterized by a stem diameter of 40-60 cm and a height of 25-30 m. Its fibrous root system can extend up to 7 m, and its leaves typically measure 8-10 m in length. The tree generally produces 10-15 dense fruit bunches (Haryoso et al. 2020). All parts of the plant possess economic utility, serving as resources for food, handicrafts, construction, and traditional medicine (Alam et al. 2023). Additionally, sugar palm offers environmental advantages by mitigating soil erosion, an effect attributed to its extensive and deep root system (Faadhilah et al. 2023). The species exhibits semi-tolerance, requiring shade during early growth stages (Furqoni et al. 2018), and demonstrates optimal performance in fertile soils at elevations ranging from 500-800 meters above sea level. Productivity tends to be suboptimal when grown outside this elevational range (Apriyanto et al. 2021). Sugar palm thrives in well-drained soils, such as loose, volcanic soils on mountain slopes and sandy soils near riverbanks. It favors regions with consistent year-round rainfall, particularly those with annual precipitation between 1,200 and 3,500 mm and average temperatures of 20-25°C, conditions that maintain adequate soil moisture (Malamassam 2020).

Meru Betiri National Park represents one of the regions where the sugar palm is found. This park, spanning 56,626.04 ha across Jember and Banyuwangi Districts in East Java Province, was formally established under the Decree of the Minister of Forestry Number 3629/Menhut-VII/KUH/2014, dated 6 May 2014. The Meru Betiri National Park Center operates as a Technical Implementation Unit (UPT) under the Directorate General of Natural Resources and Ecosystem Conservation (KSDAE), with the responsibility of managing and conserving the park's natural resources. To facilitate ecological restoration, the park authority developed an Ecosystem Recovery Plan (RPE) for 2016-2020 and implemented Annual Ecosystem Recovery Work Plans (RKT-PE) from 2016 to 2022. These restoration initiatives included conservation partnerships focused on rehabilitation, specifically enrichment planting with community collaboration across 1,000 ha within the Wonoasri, Andongrejo, and Sanenrejo resort areas (SPTN Region II Ambulu).

Given the ecological and economic importance of sugar palm, an investigation into its habitat suitability and the environmental factors influencing its distribution is warranted, particularly within the Andongrejo Resort of Meru Betiri National Park. The presence of sugar palm trees in Meru Betiri National Park is crucial for the local community. They are used by the locals for various purposes, particularly the fruit, which is used for sugar palm fruit. Therefore, a more nuanced understanding of habitat preferences is urgently needed to guide restoration and conservation efforts. Maximum Entropy (MaxEnt) modelling provides a robust methodology for predicting species distribution and classifying habitat suitability based on known occurrences and environmental variables (Phillips et al. 2006; Gunawan et al. 2021). This model can be understood as a form of penalized logistic regression that avoids overfitting by regularizing the parameters (Elith et al. 2011). This makes MaxEnt not only robust in prediction but also capable of managing the high complexity of ecological data. MaxEnt has become increasingly valuable for predicting species range shifts under climate and land-use change scenarios, identifying conservation priorities, and optimizing reforestation and agroforestry strategies (Wang et al. 2024). The growing use of this modelling approach has improved understanding of species distributions and potential threats under both current and future environmental conditions (Wang et al. 2024). This study aimed to create a habitat suitability map for sugar palm by modelling the relationship between the presence of sugar palm and environmental variables that influence it at the Andongrejo Resort in Meru Betiri National Park. The results of this model are intended to guide sustainable management practices by park authorities, local communities, and government agencies.

MATERIALS AND METHODS

Study area

This research was conducted in July 2024 at the Andongrejo Resort, located in Meru Betiri National Park, East Java Province, Indonesia (Figure 1). Geographically, the park is situated between 113°27'23"-113°58'11"E and 8°20'31"-8°35'09"S. Administratively, the park spans two districts: Jember and Banyuwangi. It is managed through three sectors, Ambulu, Kalibaru, and Sarongan (Siddiq et al. 2023). Data processing and analysis were carried out at the Bioprospection and Plant Utilization Laboratory, Department of Forest Resources Conservation and Ecotourism, Faculty of Forestry and Environment, Institut Pertanian Bogor, Indonesia.

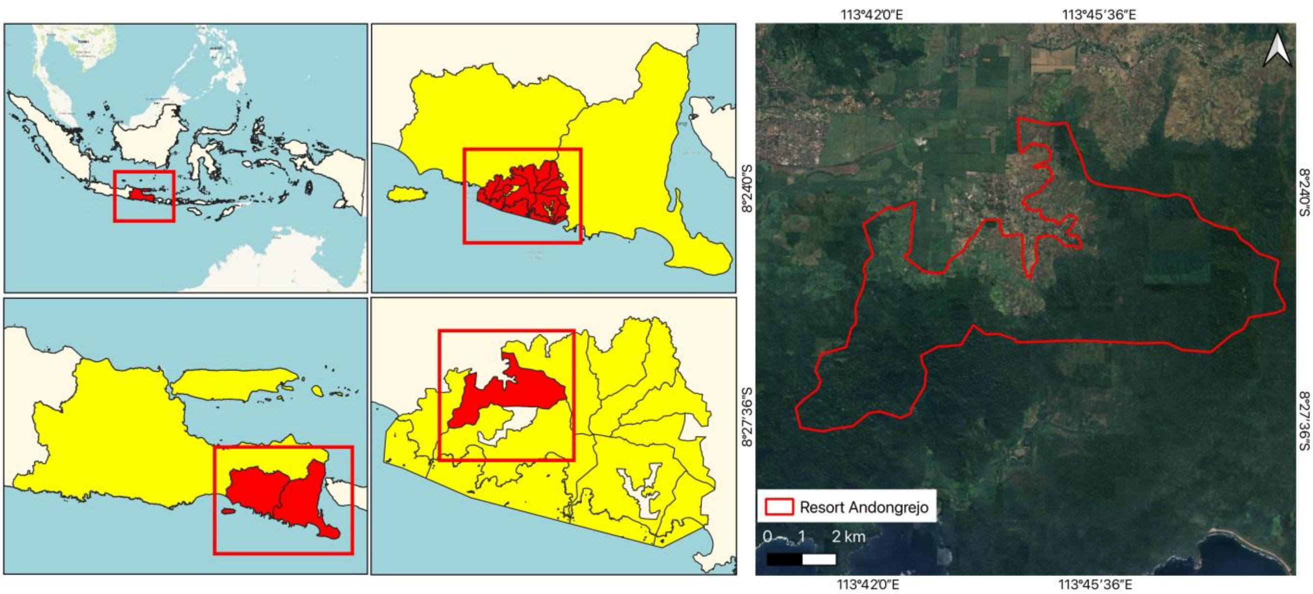

Figure 1. Research location at Resort Andongrejo, Meru Betiri National Park, East Java Province, Indonesia

Materials and tools

The study utilized thematic maps (e.g., area, land cover, elevation, slope, rainfall, temperature, NDVI, and NDMI maps), a laptop with Microsoft Office, a Garmin GPSMAP 64s for georeferencing, ArcGIS 10.8 software for spatial analysis, and MaxEnt software version 3.4.4 for species distribution modelling. GIS raster and vector used comprised Landsat 8 OLI imagery, Digital Elevation Model (DEM) data, and official boundary maps of Meru Betiri National Park.

Data collection methods

Data for this study were gathered from both primary and secondary sources. The primary data included presence-only occurrence points of *A. pinnata*, collected through purposive sampling during field surveys conducted at the Andongrejo Resort in Meru Betiri National Park. Sampling sites were chosen based on local knowledge, accessibility, and visible signs of sugar palm presence, such as mature trees and sap collection activities. Each presence point was georeferenced with a handheld GPS device with about ±5 m accuracy, and the coordinates were recorded in decimal degrees using the WGS 84 datum.

Secondary data were sourced from a review of the published literature and open-access environmental datasets. These included topographic and elevation data from the National Digital Elevation Model (DEMNAS) and the United States Geological Survey (USGS), land cover and hydrology data from the Geospatial Information Agency (BIG), and bioclimatic variables from WorldClim v2 (Table 1). These datasets provided the environmental predictors used in the MaxEnt modelling process.

Data analysis

Maximum Entropy (MaxEnt)

Maximum Entropy (MaxEnt) is a widely employed method in ecological modelling for predicting species distribution based solely on presence data (Capezzuto et al. 2018; Coro and Bove 2022; Coro et al. 2024). MaxEnt functions by correlating species occurrence records with pertinent environmental variables to generate spatial predictions of potential habitats (Mousazade et al. 2019). This model can be understood as a form of penalized logistic regression that avoids overfitting by regularizing the parameters (Elith et al. 2011). This makes MaxEnt not only robust in prediction but also capable of handling the high complexity of ecological data.

In this study, MaxEnt version 3.4.4 was used. The model was run using 15 bootstrap replicates and a maximum of 5,000 iterations, with 25% of the presence data randomly partitioned as the test data for validation. Within the MaxEnt interface, options such as "Create response curves", "Make pictures of prediction", and "Do jackknife to measure variable importance" were enabled. All environmental variables were formatted as ASCII raster files with the same coordinate systems, resolutions, and extents. Basic and advanced settings were maintained as default, except for the disabling of options that could cause duplication or data redundancy. These settings were selected to ensure consistent and reproducible results.

The model was constructed by inputting georeferenced presence data of *A. pinnata* along with selected environmental variables presumed to influence its distribution. The resulting output is a habitat suitability map, indicating the probability of sugar palm occurrence across the landscape. This map serves as a species distribution model, providing insights into habitat zones that are suitable or unsuitable for sugar palm growth (Figure 2).

The following steps detail the complete data processing procedure employed in the MaxEnt analysis for modelling the habitat suitability of sugar palm (*A. pinnata*). First, sugar palm occurrence data were collected during field observations. The location of each encounter point, representing a site where *A. pinnata* was found was recorded using a GPS device. These coordinate points were compiled and saved in Microsoft Excel, and subsequently exported in Comma-Separated Values (CSV) format for input into MaxEnt. Next, land cover data were obtained directly from the Meru Betiri National Park authority. This land cover information was provided in ASCII (.asc) format, ensuring compatibility with MaxEnt. For elevation and slope data, the national Digital Elevation Model (DEM) data were utilized. Preparing these variables involved an initial step of reprojecting the DEM data to align its projection system with that of the study area. Following reprojection, the slope gradient variable was generated using the Slope tool within the GIS software.

To derive the distance from the river variable, spatial data were acquired from the Landforms of Indonesia map. This variable was calculated through a two-step GIS operation: first, the river network within the study boundary was extracted using the extraction by mask function; second, the Euclidean Distance tool was applied to compute a continuous distance raster from the nearest river or water source. This raster was then saved in ASCII format. Temperature and rainfall datasets were obtained from the WorldClim database. These bioclimatic variables were processed and extracted using GIS tools to generate spatial maps of temperature and rainfall distributions across the study area.

Table 1. Types, sources, and types of data for determining the suitability of sugar palm habitats

Data/Input	Source	Data type
Attendance data	Field observation	-
Altitude	DEMNAS indonesia.go.id	Continuous
Slope	DEMNAS indonesia.go.id	Continuous
Land cover	Earthexplorer.usgs.gov	Categorical
Distance from the River	Badan Informasi Geospasial	Continuous
NDVI	Earthexplorer.usgs.gov	Continuous
NDMI	Earthexplorer.usgs.gov	Continuous
Rainfall	Worldclim	Continuous
Temperature	Worldclim	Continuous
Literature study	Internet, journals, books, scripts, thesis, dissertation	-

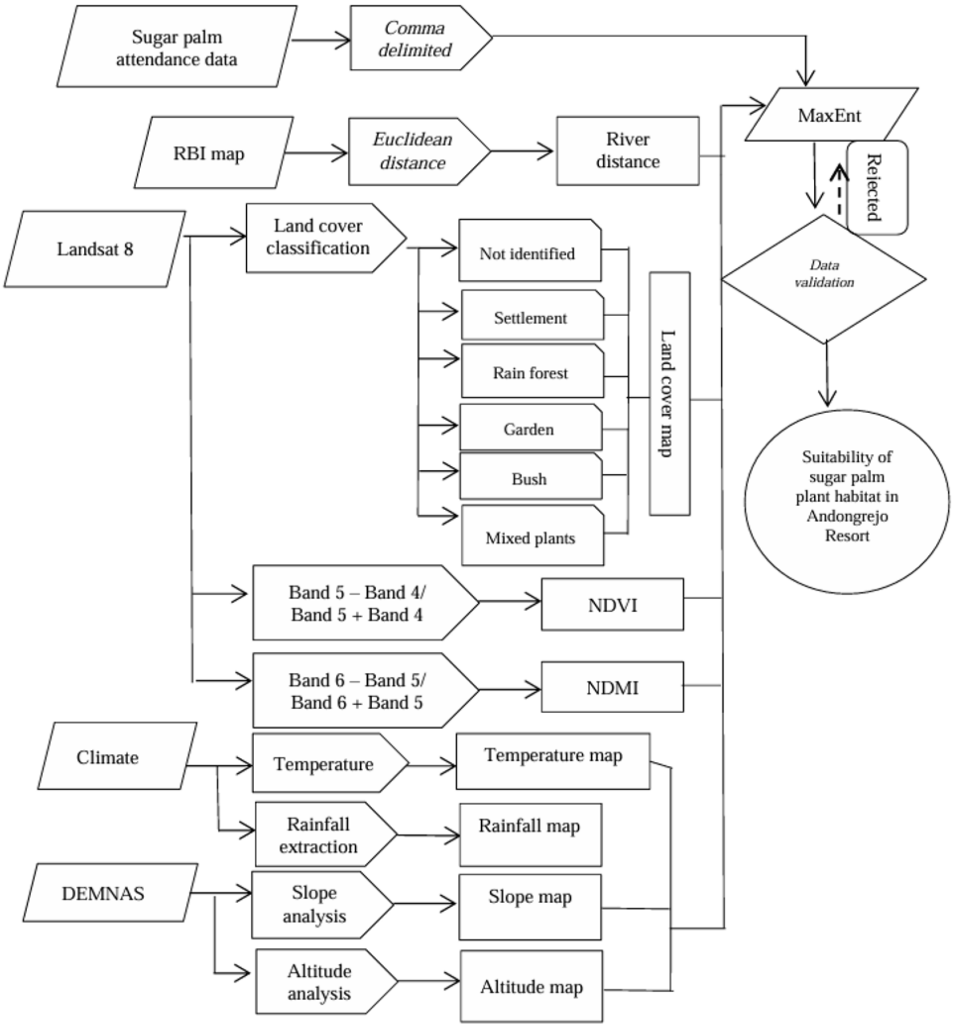

Figure 2. Procedure for processing data on the suitability of sugar palm habitat

All outputs were stored in ASCII (.asc) format. Similarly, Normalized Difference Vegetation Index (NDVI) and Normalized Difference Moisture Index (NDMI) variables were generated from Landsat 8 imagery. NDVI was calculated using Bands 4 and 5, while NDMI was derived from Bands 5 and 6. These indices were computed using the Raster Calculator tool and subsequently clipped to the study boundary using extraction by mask. The resulting NDVI and NDMI raster were also saved in ASCII format. All environmental variables used in MaxEnt, including rainfall, distance from river, altitude, NDVI, NDMI, slope, and temperature, were standardized to ensure matching coordinate systems, cell sizes, and spatial extents. The sugar palm presence data from the Andongrejo Resort area were added to the sample column in MaxEnt, while the environmental layers filled the corresponding environmental columns with raster.

Within the MaxEnt program interface, the options "create response curves," "make pictures of prediction," and "do jackknife to measure variable importance" were enabled by checking their respective boxes. The output directory was defined, and the modelling process proceeded under these settings. Within the basic settings menu, all options were enabled except "skip if output exists." A random test percentage of 25% was applied to reserve a portion of the data for model validation. Additionally, 15 replicates were specified using the Bootstrap method for the replicate run type. In the advanced settings menu, all options were selected except "add all samples to the background," "write plot data," and "append summary results to the maxentResults.csv file." These selections were made to facilitate a clear and focused computation of model performance metrics, particularly the Area Under the Curve (AUC). All other settings remained unchanged and adhered to the default parameters set by the MaxEnt.

Recent studies have highlighted the importance of methodological rigor and variable selection in MaxEnt analyses. For instance, Mahatara et al. (2021) applied MaxEnt to model *Dalbergia latifolia* in Nepal, stressing the need for consistent raster formats and appropriate replication methods to improve prediction accuracy. Similarly, Omar et al. (2025) demonstrated that enabling jackknife and response curve options enhances ecological interpretation when modelling the distribution of

Micromeria serbaliana. In tropical forest contexts, Lah et al. (2021) emphasized the value of including vegetation indices and soil parameters when modelling *Melaleuca cajuputi*. These examples reinforce the reliability of the procedure applied in this study and underscore that maintaining standardization across datasets and enabling MaxEnt diagnostic tools contribute substantially to the robustness of sugar palm habitat suitability modelling.

Multicollinearity analysis

To examine the correlation relationships among the environmental variables used in the MaxEnt modelling process, multicollinearity analysis was conducted (Pradhan 2016; Pradhan and Setyawan 2021; Singh et al. 2023). Multicollinearity, a statistical condition where two or more predictor variables show a strong linear relationship, can compromise the interpretation of model outputs. For this analysis, environmental variable data were initially extracted from raster format into a tabular format using ArcGIS. The resulting data table was then imported into Microsoft Excel for correlation analysis. Following the guidelines of Pearson et al. (2007), any variable pair exhibiting a Pearson correlation coefficient of ≤-0.75 or >0.75 was considered highly collinear, and one variable from such a pair was excluded to mitigate redundancy in the model.

Model validation

Model validation was performed to assess the predictive accuracy of the MaxEnt model using the Area Under the Curve (AUC) metric, derived from the Receiver Operating Characteristic (ROC) curve. AUC values range from 0.5 to 1, with higher values indicating superior model performance. Based on the evaluation criteria proposed by Nahm (2022), model accuracy was classified as fail (0.5<AUC<0.6), poor (0.6<AUC<0.7), fair (0.7<AUC<0.8), good (0.8<AUC<0.9), and excellent (AUC>0.9).

Determination of habitat suitability class

The MaxEnt model produced a continuous habitat suitability surface for *A. pinnata*, with values ranging from 0 to 1. To facilitate interpretation of this continuous variable, it was transformed into a categorical variable comprising five distinct habitat suitability classes viz. very unsuitable (0), less suitable (0.00-0.25), quite suitable (0.25-0.50), suitable (0.50-0.75), and very suitable (0.75-1.00), following the methodology of Phillips and Dudík (2008) and Çoban et al. (2020).

RESULTS AND DISCUSSION

Sugar palm presence points

Sugar palm (*A. pinnata*) is widely distributed across the Meru Betiri National Park, with a significant presence in the Andongrejo Resort area, particularly within the Tumpak Gesing block. According to Zuhud et al. (2020), sugar palm plants are notably abundant in this region of the park. Each sugar palm tree was marked and tagged using a Global Positioning System (GPS) for precise location tracking. The study identified 104 presence points of sugar palms, distributed across the rainforest land cover within the study area (Figure 3).

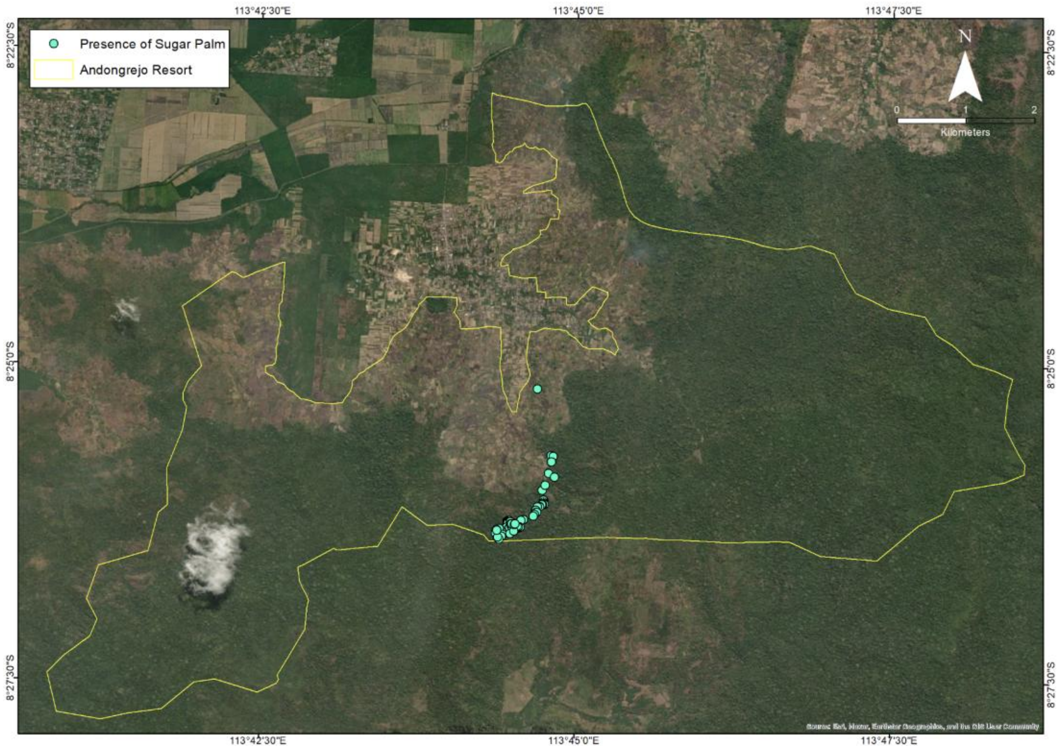

Figure 3. Point of presence of sugar palm at Andongrejo Resort, Meru Betiri National Park, East Java, Indonesia

Variable selection multicollinearity

Multicollinearity analysis is employed to identify strongly correlated variables, with one of the correlated variables subsequently excluded from the MaxEnt model analysis (Cao et al. 2021). In factor analysis, multicollinearity can lead to detrimental effects, including an unreliable factor structure, inconsistent loadings, inflated standard errors, reduced discriminant validity, and challenges in the interpretation of factors. Additionally, it can result in reduced stability, hindered replication of factors, misinterpretation of factor importance, increased instability in parameter estimation, diminished power to detect the true factor structure, compromised model fit indices, and biased factor loadings (Kyriazos and Poga 2023). Seven environmental variables, viz., distance from river, Normalized Difference Moisture Index (NDMI), Normalized Difference Vegetation Index (NDVI), Slope, temperature, altitude, and landcover, were determined to be free from significant collinearity.

Model validation

Model validation was assessed using the Area Under the Curve (AUC) value obtained from the MaxEnt analysis (Çoban et al. 2020). The AUC value represents the probability that the model will assign a randomly selected presence site a higher suitability score than a randomly selected absence site. It evaluates the model's performance across all possible thresholds, with an AUC greater than 0.5 indicating performance better than random chance (Wang et al. 2021). A higher AUC value, approaching 1, signifies greater discriminatory ability, indicating a more sensitive and descriptive model (Zhao et al. 2018). The model validation results demonstrate that the sugar palm distribution model at Andongrejo Resort achieved an excellent classification, with an AUC value of 0.942, suggesting a strong consistency between the predicted and observed sugar palm distributions (Figure 4).

Variable selection using multicollinearity

The predicted values from the MaxEnt modelling range from 0 to 1, where values closer to 1 indicate a higher probability of sugar palm presence, and values closer to 0 suggest a lower probability of occurrence. The sugar palm habitat suitability model was generated through 15 replications using the Bootstrap method, with 25% random test points and 5,000 iterations. Habitat suitability reflects the capacity of a given region to support a species (Muhammed et al. 2022; Edosa and Erena 2024). This modelling incorporated several environmental variables, including land cover, altitude, slope, distance from river, Normalized Difference Vegetation Index (NDVI), and temperature, to identify areas suitable for sugar palm (*A. pinnata*) within Andongrejo Resort. The areas with the highest suitability are depicted in dark green, while regions with the lowest suitability are represented in red (Figure 5).

The habitat suitability analysis for sugar palm at the Andongrejo Resort resulted in five suitability categories: not suitable, less suitable, quite suitable, suitable, and very suitable. The areas corresponding to each category are 11.17 ha, 4,882.56 ha, 144.28 ha, 42.96 ha, and 33.64 ha, respectively (Table 2). Areas classified as suitable and very suitable are predominantly located in the lowland regions.

The results of the sugar palm habitat suitability modelling at the study site indicate a significantly smaller area of very suitable habitat (33.64 ha) compared to the less suitable habitat (4,882.56 ha). This disparity presents a potential threat to the persistence of sugar palm populations in the resort, particularly concerning a potential decline in population size. Areas with high suitability for sugar palm habitat are primarily concentrated within the forest zone, covering a total area of 29.24 ha (Table 2).

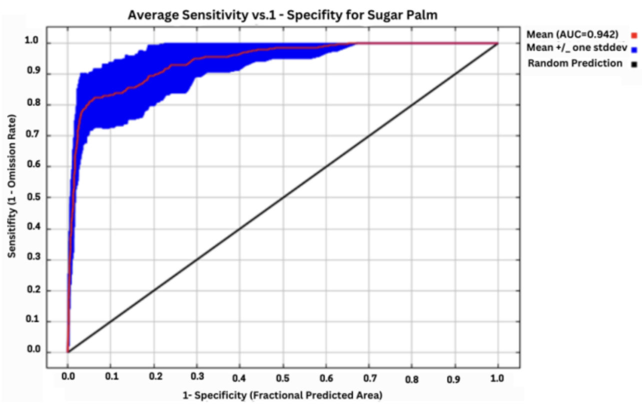

Figure 4. AUC (Area Under Curve) value in the sugar-palm habitat suitability model

Table 2. Habitat suitability area per zone at Andongrejo Resort, Meru Betiri National Park, East Java, Indonesia

Zone	Area of suitable habitat (ha)					Total
	Not suitable	Less suitable	Quite suitable	Suitable	Very suitable	
Core	11.17	2,367.51	70.20	16.71	3.50	2,469.09
Special	0.000	10.27	0.11	0.57	0.90	11.85
Utilization	0.000	10.50	0.00	0.00	0.00	10.50
Rehabilitation	0.000	1,136.91	3.15	0.27	0.00	1,140.33
Forests	0.000	1,320.00	70.82	25.41	29.24	1,445.47
Traditional	0.000	37.37	0.000	0.00	0.00	37.37
Total	11.17	4,882.56	144.28	42.96	33.64	5,114.61
Percentage	0.2	95.5	2.8	0.8	0.7	100

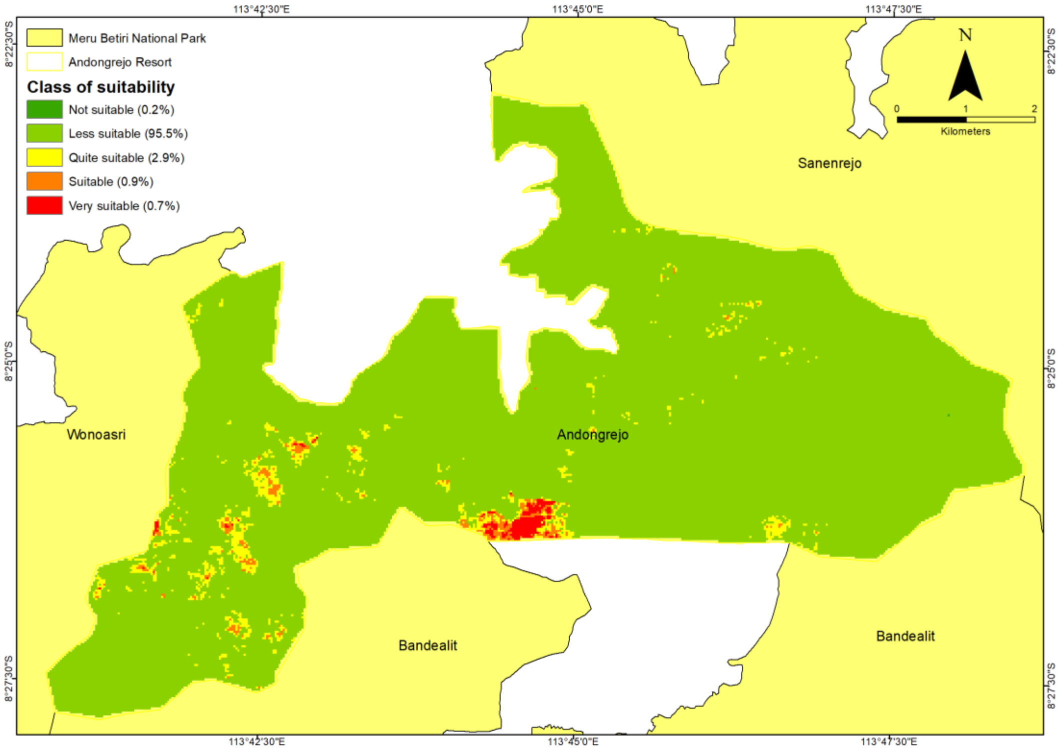

Figure 5. Habitat suitability map of sugar palm in Andongrejo Resort, Meru Betiri National Park, East Java, Indonesia

Environmental variable influence on sugar palm habitat suitability

The MaxEnt model identified key environmental variables influencing the habitat suitability of sugar palm at Andongrejo Resort, quantified using Percentage Contribution (PC) and Permutation Importance (PI) (Table 3). Percentage Contribution (PC) indicates each variable's relative influence on the model. Temperature exhibited the highest PC (49.5%), followed by altitude (29.0%), suggesting their strong influence. Distance from river, slope, land cover, NDVI, and NDMI had lower PC values (7.7%, 7.5%, 5.0%, 0.7%, and 0.6%, respectively). Permutation Importance (PI) reflects the model's sensitivity to each variable. Altitude showed the highest PI (79.6%), indicating the model's greater sensitivity to this variable. Temperature had a lower PI (9.9%), suggesting less sensitivity compared to its contribution. Other variables had low PI values (≤4.7%). (Table 3).

These findings are in line with previous habitat suitability studies of tropical trees, which often emphasize the role of elevation and temperature. For example, *D. latifolia* in Nepal showed elevation as the dominant predictor, followed by the temperature of the driest quarter (Mahatara et al. 2021). This parallels our result, where elevation drives model sensitivity, while temperature provides the largest percentage contribution. Similarly, in *M. serbaliana* from the Sinai Peninsula, precipitation in the driest quarter, temperature, and elevation were key determinants (Omar et al. 2025), suggesting that precipitation can also be critical in shaping habitat suitability, although it contributed minimally in our model. Moreover, research on *M. cajuputi* in Malaysia highlighted the importance of soil properties, seasonal precipitation, and temperature (Lah et al. 2021), implying that additional variables, such as soil and precipitation dynamics, may enhance future sugar palm modelling.

These comparisons strengthen the hypothesis that while altitude consistently governs model sensitivity, the relative importance of climatic and edaphic variables may vary across species and landscapes. In the case of sugar palm, the high contribution of temperature but lower sensitivity compared to elevation suggests that the species' ecological niche is strongly constrained by topography, but moderated by climatic gradients. Future work should therefore consider integrating precipitation layers, soil data, and refined vegetation indices to capture more nuanced environmental interactions.

Table 3. Influence of environmental variables on the MaxEnt model

Environment variables	PC (%)	PI (%)
Temperature	49.5	9.9
Altitude	29.0	79.6
Distance from river	7.7	4.7
Slope	7.5	4.3
Land cover	5.0	0.0
NDVI	0.7	0.6
NDMI	0.6	1.0

Notes: PC: Percentage Contribution, PI: Permutation Importance, NDMI: Normalized Difference Moisture Index, NDVI: Normalized Difference Vegetation Index

Figure 6 presents the outcomes of the comprehensive jackknife test, employed to assess the importance and contribution of each environmental variable to the MaxEnt model for predicting sugar palm distribution (Yuan et al. 2020; Gustantia et al. 2021). This diagnostic tool systematically evaluates how each variable influences the model's predictive performance, as measured by the regularized training gain (Gustantia et al. 2021). The jackknife analysis provides three key metrics for each environmental variable: the regularized training gain when the model is constructed using only that specific variable (blue bars); the gain of the full model incorporating all environmental variables (red bar); and the gain when the model is built using all variables except the one in question (cyan bars). The red bar serves as a baseline for overall model performance. The blue bars indicate the predictive power of each variable in isolation. In comparison, the cyan bars highlight the unique contribution of each variable by showing the reduction in gain upon its removal. Analysis of these results revealed the relative contributions of the environmental variables to the sugar palm distribution model at Andongrejo Resort. Temperature exhibited a high blue bar, indicating strong predictive power when used alone, and supporting its identification as the most influential variable in model construction (Yuan et al. 2020). In contrast, NDVI displayed a low blue bar, suggesting limited capacity as a sole predictor and thus representing the least influential variable among those tested (Yuan et al. 2020). Additionally, omitting altitude led to a significant decrease in gain, with the cyan bar dropping noticeably below the red bar. This supports the importance of altitude in the model, as removing it substantially lowers predictive performance, aligning with the idea that removing a highly contributive variable reduces model accuracy (Elith et al. 2011).

The model output also includes environmental variable response curves, which illustrate the relationship between each variable and the predicted probability of species presence (Ma and Sun 2018). These response curves typically depict the predicted probability of presence on a scale from 0 to 1, where values closer to 0 indicate a low probability, and values closer to 1 suggest a higher probability (Phillips et al. 2006). Response of habitat suitability of *A. pinnata* to the gradient of temperature, altitude, distance from river, slope, land cover, NDVI, and NDMI is presented below.

Temperature

The response curve for temperature showed a relatively narrow optimal range for predicted sugar palm presence (Figure 7). The predicted probability was high, near a clog-log output of 1.0, at temperatures around 23.8°C to just below 24.0°C. Beyond 24.0°C, there was a sharp decline in the predicted probability, reaching a low plateau around a clog-log output of 0.3 for temperatures between approximately 24.2°C and 24.8°C. Interestingly, the probability then showed a sudden increase at temperatures around 24.9°C to 25.0°C, reaching a moderate level of around 0.8. This suggested that sugar palm presence in the Andongrejo Resort was most strongly associated with a specific, relatively cool temperature range around 23.8-24.0°C. While Muda and Awal (2021) indicated a broader annual temperature requirement of 19 to 27°C for sugar palm, this localized model highlighted a more precise optimal temperature within the study area. The unexpected increase in predicted presence at the higher end of the observed temperature range (around 25°C) could suggest a more complex relationship or potentially the influence of other interacting environmental factors.

Altitude

The response curve for altitude showed a unimodal relationship with the predicted probability of sugar palm presence (Figure 8). As altitude increased from low elevations (below 100 m asl), the predicted presence probability rapidly increased, peaking sharply around 300 meters above sea level (m asl). Beyond this peak, the probability declined as altitude exceeded 400 m asl. This pattern suggests that sugar palm in the Andongrejo Resort exhibited a strong preference for a specific altitudinal range around 300 m asl, aligning with the concept that plant species grow best and produce fruit within certain altitudinal ranges (Millang 2021). While Hasibuan et al. (2023) noted a broader growth range (0-1400 m asl) with optimal growth between 500 and 700 m asl, the model for this specific location indicated a more restricted optimal zone at a lower altitude. This suggests localized environmental factors within the Andongrejo Resort may influence the specific altitudinal suitability for sugar palm.

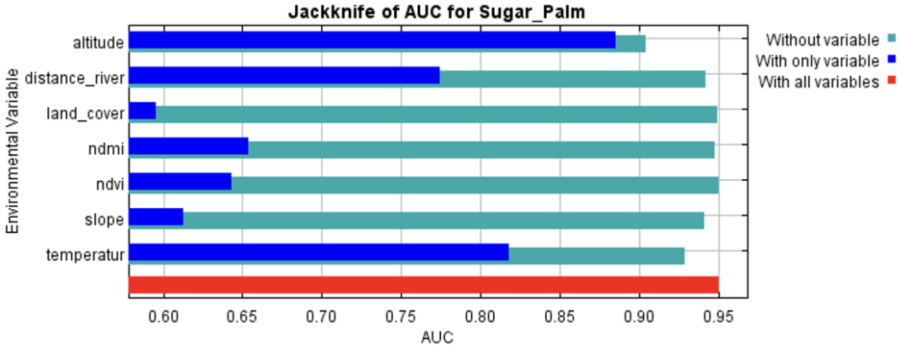

Figure 6. Graph of jackknife test results on environmental variables

Distance from river

The response curve for distance from the river showed a unimodal relationship with the predicted probability of sugar palm presence (Figure 9). At a distance of 0 meters, the predicted presence probability was low. As the distance increased from the river, there was a rapid increase in the predicted probability, peaking at a distance of approximately 300 meters with a clog-log output near 0.8. Beyond this peak, the predicted probability declined sharply as the distance from the river increased, approaching very low values at distances greater than 1,500 meters. This suggested that sugar palm presence was highest at a moderate proximity to rivers (around 300 meters) in the Andongrejo Resort. While the lowest presence was predicted directly adjacent to rivers, the sharp peak at a short distance indicated a strong positive association within a certain range. Beyond this optimal distance, the suitability rapidly decreased, aligning with findings suggesting sugar palms thrive in areas close to rivers but perhaps not directly within the immediate riparian zone (Imraan et al. 2023; Mujetahid et al. 2023).

Slope

The response curve for slope illustrated a negative relationship with the predicted probability of sugar palm presence (Figure 10). At very low slope values (approaching 0%), the predicted presence probability was high, plateauing near a clog-log output of 1.0. As the slope increased beyond approximately 5%, there was a gradual and then more rapid decline in the predicted presence probability. By the time the slope reached around 30%, the predicted probability had decreased significantly, approaching very low values at slopes exceeding 40%. This suggested that flatter areas were more suitable for sugar palm occurrence in the Andongrejo Resort. This finding aligned with Fadhilla et al. (2023), who noted that while sugar palms possess a strong root system allowing growth on varied slopes, steeper slopes could hinder water absorption due to increased surface runoff, thus reducing habitat suitability.

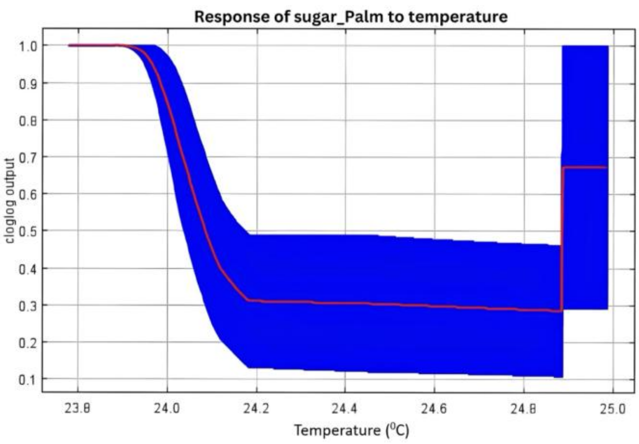

Figure 7. Response of sugar palm (*Arenga pinnata*) to temperature in Andongrejo Resort Forest Area of Meru Betiri National Park, East Java, Indonesia

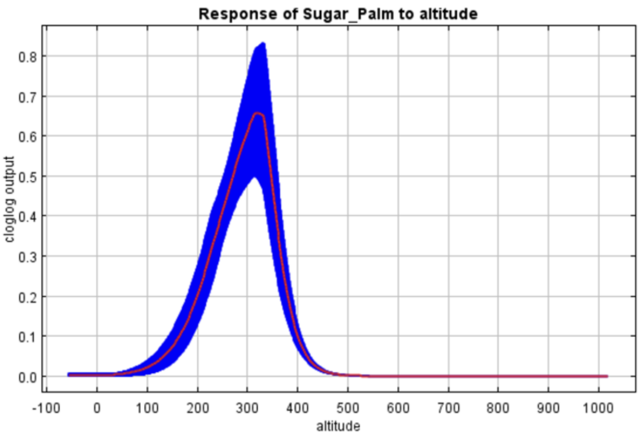

Figure 8. Response of sugar palm (*Arenga pinnata*) to altitude in Andongrejo Resort Forest Area of Meru Betiri National Park, East Java, Indonesia

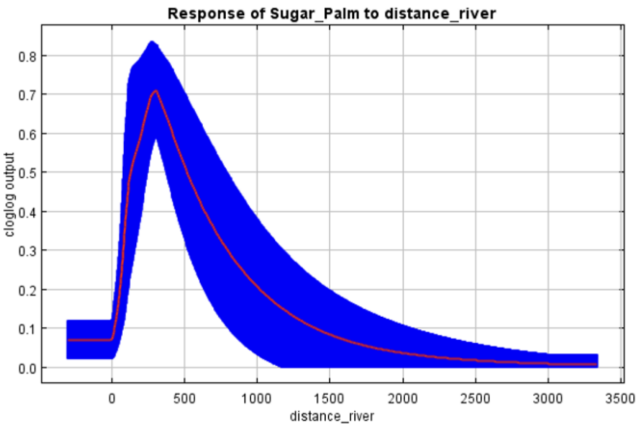

Figure 9. Response of sugar palm (*Arenga pinnata*) to distance from river in Andongrejo Resort Forest Area of Meru Betiri National Park, East Java, Indonesia

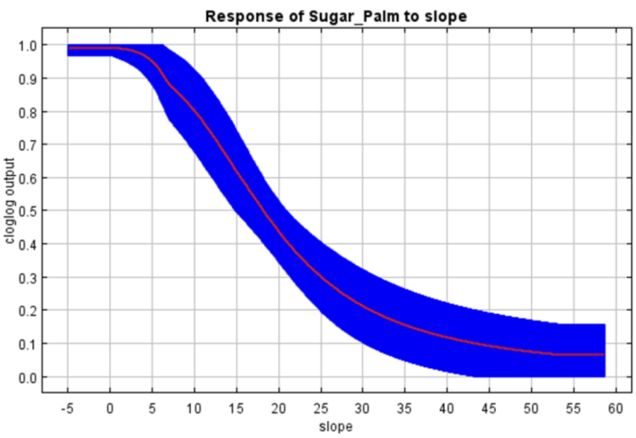

Figure 10. Response of sugar palm (*Arenga pinnata*) to slope in Andongrejo Resort Forest Area of Meru Betiri National Park, East Java, Indonesia

Land cover

The response curve for the land cover variable indicates that sugar palms are most frequently found in rainforest environments, suggesting their preference for and suitability to these habitats (Figure 11). Sugar palms are less commonly observed in primary forests but are typically found in secondary forests near human settlements (Imraan et al. 2023). This distribution pattern is likely influenced by the availability of water and nutrients in forested areas, as well as the palm's ability to tolerate competition from other vegetation, which supports its growth.

Normalized Difference Vegetation Index (NDVI)

The NDVI response curve indicated a non-linear relationship with predicted sugar palm presence (Figure 12). High presence probability was observed at low NDVI (0.05-0.20), suggesting a preference for open canopy, potentially providing the beneficial filtered light. Beyond NDVI 0.20, a gradual decline occurred until 0.45, followed by a sharp decrease at higher NDVI (0.45-0.60). While shade is crucial for sugar palm seedling development, with 56% shade increasing biomass and root volume (Widarawati et al. 2023), excessively dense vegetation (high NDVI) may create competition for resources, negatively impacting suitability. An optimal canopy density, rather than maximum greenness, appears most conducive for sugar palm occurrence in Andongrejo Resort, highlighting a complex interaction between vegetation density and habitat suitability.

Normalized Difference Moisture Index (NDMI)

The response curve for Normalized Difference Moisture Index (NDMI) showed a unimodal relationship with the predicted probability of sugar palm presence (Figure 13). At very low NDMI values (around -0.40), the predicted presence probability was low. As NDMI values increased, there was a sharp rise in the probability, peaking at an NDMI of approximately -0.25 with a clog-log output around 0.7. Beyond this peak, the predicted presence probability gradually declined as NDMI values increased towards positive values (around 0.10). This suggested that sugar palm presence was highest at a specific intermediate range of moisture conditions, as indicated by NDMI. Very dry conditions (low NDMI) and increasingly moist conditions (higher NDMI) appeared less suitable for sugar palm occurrence in the Andongrejo Resort based on this model. While Zuhud et al. (2020) noted sugar palm abundance at forest edges, which could be more humid, this response curve suggested an optimal moisture range rather than a continuous positive correlation with increasing moisture as captured by NDMI across the broader landscape of the study area.

Conservation implications

The study's findings have significant implications for conservation planning and landscape management in the Meru Betiri National Park. The habitat suitability model identified ecologically favorable sites for *A. pinnata* growth and persistence, notably in lowland forest zones with modest river proximity and optimal temperature-altitude combinations. These findings can directly inform enrichment planting initiatives in areas where natural regeneration is restricted or absent, thereby contributing to the recovery of degraded ecosystems (Al Manar et al. 2025; Hikmat et al. 2025).

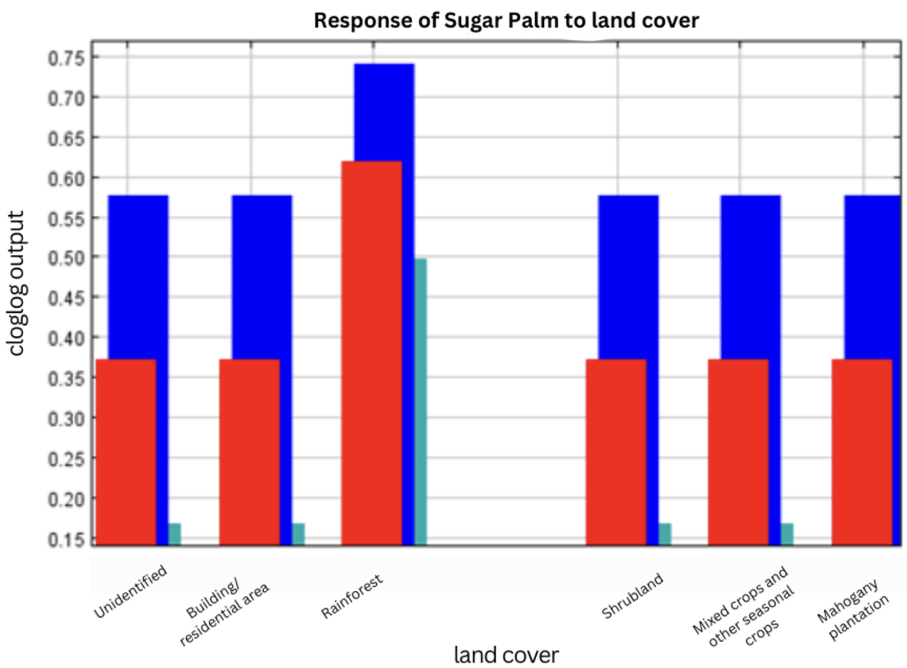

Figure 11. Response of sugar palm (*Arenga pinnata*) to land cover in Andongrejo Resort Forest Area of Meru Betiri National Park, East Java, Indonesia

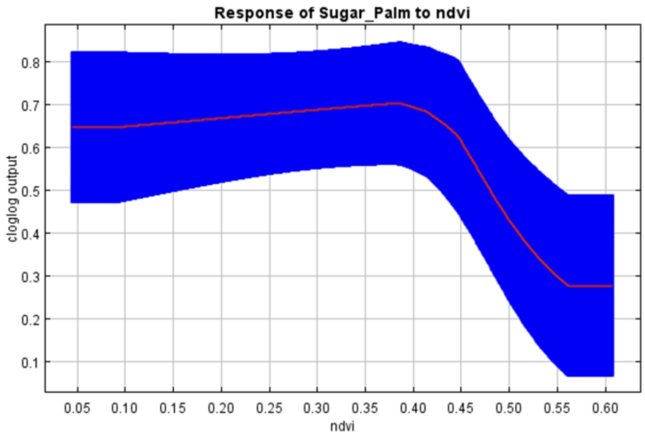

Figure 12. Response of sugar palm (*Arenga pinnata*) to NDVI in Andongrejo Resort Forest Area of Meru Betiri National Park, East Java, Indonesia

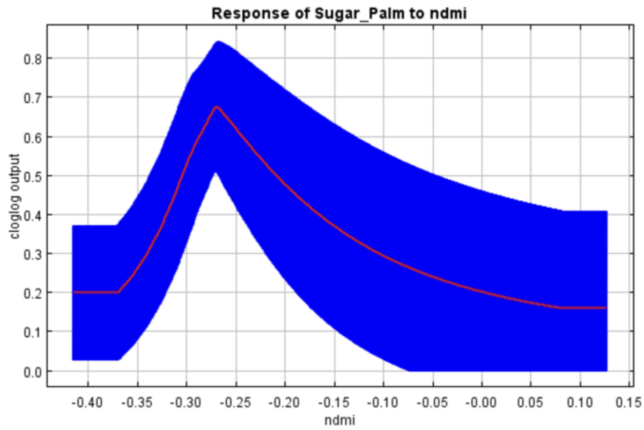

Figure 13. Response of sugar palm (*Arenga pinnata*) to NDMI in Andongrejo Resort Forest Area of Meru Betiri National Park, East Java, Indonesia

Furthermore, including habitat suitability models in zoning methods may improve the design of core conservation zones and buffer zones. This technique improves landscape connectedness and minimizes fragmentation, both of which are necessary for long-term species resilience in the face of changing environmental conditions (Guisan et al. 2017; Wang et al. 2024). Species distribution modelling can help national park managers target restoration resources to regions with the best ecological return, leading to improved cost efficiency and impact (DeMatteo et al. 2017; Pecchi et al. 2019).

Given the reported challenges to *A. pinnata* populations, such as habitat degradation and limited recruitment, predictive habitat mapping provides a scientific foundation for prioritizing intervention zones, particularly in areas under anthropogenic pressure. The use of MaxEnt in this context demonstrates the promise of spatial modelling as a decision-support tool for forest restoration and biodiversity conservation in protected areas (Tesfamariam et al. 2022; Rubanschi et al. 2024). From a conservation perspective, this modelling approach supports a shift from reactive to proactive ecosystem management. By identifying future-suitable habitats under current and projected environmental conditions, park managers can anticipate ecological shifts and design adaptive restoration strategies. Such foresight is crucial for maintaining the ecological niches of species, particularly in climate-vulnerable lowland forests.

Furthermore, identifying highly appropriate zones for *A. pinnata* will allow the development of complex agroforestry systems that combine sugar palms with other native species. Such systems can deliver long-term ecological and economic advantages while preserving biodiversity and ecosystem services (Fu et al. 2023). These agroforestry mosaics can function as semi-natural habitats, increase structural complexity and providing refugia for wildlife species while simultaneously reducing pressure on primary forest zones. Agroforestry techniques are especially beneficial in buffer and rehabilitation zones, where combining conservation goals with livelihood methods is critical. Thus, agroforestry practices are strategic tools for participatory conservation. By engaging local communities in restoration through culturally relevant land-use models, conservation becomes socially legitimate and ecologically grounded. The incorporation of spatial habitat modelling into agroforestry planning allows for more adaptable and site-specific land-use decisions, boosting resilience and sustainability across forested landscapes (Freitas et al. 2014).

In conclusion, the distribution model for sugar palm (*A. pinnata*) in Andongrejo Resort not only elucidates the key environmental variables influencing its habitat suitability but also provides practical applications for conservation strategies. Seven variables were identified as contributing factors; among these, temperature (49.5%), altitude (29.0%), and distance from river (7.7%) exhibited the highest percentage contributions. The habitat suitability analysis categorized the total area as not suitable (11.16 ha), less suitable (4,882.56 ha), quite suitable (144.28 ha), suitable (42.97 ha), and very suitable (33.64 ha). Notably, suitable and very suitable habitats were mainly found in lowland regions. This spatial clustering may be partially attributable to sampling bias due to a higher sampling intensity in lowland areas, which could have led to an underestimation of habitat suitability in less-sampled zones. Importantly, the distribution model provides a scientifically grounded tool for informing forest management strategies, including spatial zoning for conservation priorities, identification of target areas for enrichment planting, and delineation of buffer zones to enhance landscape connectivity and mitigate edge effects. These practical applications can contribute to the more effective and sustainable management of *A. pinnata* populations within broader forest ecosystems, engaging forest managers and conservation policymakers. Moreover, the results can be directly used to support national park management in designing restoration programs by identifying ecologically optimal zones for planting sugar palms. These insights are valuable for selecting sites for enrichment planting, conserving priority habitats, and optimizing land-use planning in rehabilitation and buffer zones. The model output also supports the integration of sugar palms into complex agroforestry systems, especially in community-managed landscapes, thus aligning conservation goals with local livelihoods. Such evidence-based planning strengthens adaptive management strategies under current and future climate scenarios, keeping researchers and policymakers engaged and interested in the potential of this research.

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REFERENCES

Al Manar P, Zuhud EAM, Hikmat A, Hidayat S, Robika, Meilanto, Wilyan R, Munggaran IK. 2025. Kelekak agroforestry in Central Bangka, Indonesia: Species diversity, challenges, and conservation strategies. Jurnal Sylva Lestari 13 (1): 264-282. DOI: 10.23960/jsl.v13i1.1070.

Alam AS, Pribadi H, Rafiudin, Rifandi. 2023. Determination of palm sugar production cost by forestry farm communities in Obo Village, District of Nuhon, Banggai Regency, Central Sulawesi. IOP Conf Ser Earth Environ Sci 1253: 012051. DOI: 10.1088/1755-1315/1253/1/012051.

Apriyanto E, Utama SP, Nugroho PBA, Siswahyono, Tarigan EMU. 2021. The potency of sugar palm (*Arenga piñata*) household industry to contribute into the farmer's income in Sindang Jaya Village, Rejang Lebong. Adv Biol Sci Res 13: 504-509. DOI: 10.2991/absr.k.210609.076.

Cao Z, Zhang L, Zhang X, Guo Z. 2021. Predicting the potential distribution of *Hylomecon japonica* in China under current and future climate change based on Maxent model. Sustainability 13 (20): 11253. DOI: 10.3390/su132011253.

Capezzuto F, Sion L, Ancona F, Carlucci R, Carluccio A, Cornacchia L, Maiorano P, Ricci P, Tursi A, D'Onghia G. 2018. Cold-water coral habitats and canyons as essential fish habitats in the southern Adriatic and northern Ionian Sea (central Mediterranean). Ecol Quest 29 (3): 9-23. DOI: 10.12775/EQ.2018.019.

Çoban HO, Örücü ÖK, Arslan ES. 2020. MaxEnt modelling for predicting the current and future potential geographical distribution of *Quercus libani* Olivier. Sustainability 12 (7): 2671. DOI: 10.3390/su12072671.

Coro G, Bove P. 2022. A high-resolution global-scale model for COVID-19 infection rate. ACM Trans Spat Algorithms Syst 8 (3): 1-24. DOI: 10.1145/3494531.

Coro G, Sana L, Bove P. 2024. An open science automatic workflow for multi-model species distribution estimation. Intl J Data Sci Anal 20: 1131-1150. DOI: 10.1007/s41060-024-00517-w.

DeMatteo KE, Rinas MA, Zurano JP, Selleski N, Schneider RG, Arguelles CF. 2017. Using niche-modelling and species-specific cost analyses to determine a multispecies corridor in a fragmented landscape. Plos One 12 (8): e0183648. DOI: 10.1371/journal.pone.0183648.

Edosa BT, Erena MG. 2024. Wildlife habitat suitability analysis and mapping the former dhidhessa wildlife sanctuary using GIS-based analytical hierarchal process and weighted linear combination methods. Heliyon 10: e33921. DOI: 10.1016/j.heliyon.202.e33921.

Elith J, Phillips SJ, Hastie T, Dudík M, Chee YE, Yates CJ. 2011. A statistical explanation of MaxEnt for ecologists. Divers Distrib 17 (1): 43-57. DOI: 10.1111/j.1472-4642.2010.00725.x.

Faadhilah A, Karuniasa M, Tumuyu SS. 2023. Land suitability assessments for the palm plantation (*Arenga pinnata* L.) as non-timber forest product using geographic information system. Jurnal Teknik Pertanian Lampung 12 (4): 957-967. DOI: 10.23960/jtep-l.v12i4.957-967.

Fadhilla S, Hakim L, Agustian A, Lubis YS, Siregar AW. 2023. The diversity of utilizations, tapping flow discharge, and conservation of sugar palm (*Arenga longipes* Mogea) cultivated in Langkat, North Sumatra, Indonesia. Biodiversitas 24 (1): 122-132. DOI: 10.13057/biodiv/d240116.

Freitas A, Dias E, Diogo V, Smits W. 2014. Interactive spatial decision support for agroforestry management. In: Lee D, Dias E, Scholten H (eds). Geodesign by Integrating Design and Geospatial Sciences. Springer, Cham. DOI: 10.1007/978-3-319-08299-8_10.

Fu B, Liu Y, Meadows ME. 2023. Ecological restoration for sustainable development in China. Natl Sci Rev 10 (7): nwad033. DOI: 10.1093/nsr/nwad033.

Furqoni H, Junaedi A, Wachjar A, Yamamoto Y. 2018. Growth responses of sugar-palm (*Arenga pinnata* (Wurmb.) Merr.) seedlings to different shading levels. Trop Agric Dev 62 (2): 55-59. DOI: 10.11248/jsta.62.55.

Guisan A, Thuiller W, Zimmermann NE. 2017. Habitat Suitability and Distribution Models: With Applications in R. Cambridge University Press, Cambridge. DOI: 10.1017/9781139028271.

Gunawan, Rizki MI, Anafarida O, Mahmudah N. 2021. Modelling potential distribution of *Baccaurea macrocarpa* in South Kalimantan, Indonesia. Biodiversitas 22 (8): 3230-3236. DOI: 10.13057/biodiv/d220816.

Gustantia N, Osawa T, Adnyana IWS, Novianto D, Chonnaniyah. 2021. Spatial-temporal habitat suitability for lemuru fish (*Sardinella lemuru*) using the Second-generation Global Imager (SGLI) and Maximum Entropy model in the Bali Strait, Indonesia. IOP Conf Ser Earth Environ Sci 944: 012066. DOI: 10.1088/1755-1315/944/1/012066.

Haryoso A, Zuhud EAM, Hikmat A, Sunkar A, Darusman D. 2020. Ethnobotany of sugar palm (*Arenga pinnata*) in the Sasak Community, Kekait Village, West Nusa Tenggara, Indonesia. Biodiversitas 21 (1): 117-28. DOI: 10.13057/biodiv/d210116.

Hasibuan HS, Wisnubroto MP, Rezki D, Yulistriani. 2023. Identification and morphological characterization of sugar palm plants (*Arenga pinnata* Merr.) growing on different altitudes. Jurnal Budidaya Pertanian 19 (2): 99-105. DOI: 10.30598/jbdp.2023.19.2.99.

Hikmat A, Zuhud EAM, Al Manar P, Wilyan R, Munggaran IK, Hidayat S, Robika. 2025. Diversity and utilization of plants in kelekak agroforestry in Air Mesu Village, Central Bangka District, Bangka Belitung Islands, Indonesia. Biodiversitas 26 (3): 1105-1113. DOI: 10.13057/biodiv/d260309.

Imraan M, Ilyas RA, Norfarhana AS, Bangar SP, Knight VF, Norrrahim MNF. 2023. Sugar palm (*Arenga pinnata*) fibers: New emerging natural fibre and its relevant properties, treatments and potential applications. J Mater Res Technol 24: 4551-4572. DOI: 10.1016/j.jmrt.2023.04.056.

Kyriazos T, Poga M. 2023. Dealing with multicollinearity in factor analysis: The problem, detections, and solutions. Open J Stat 13 (3): 404-424. DOI: 10.4236/ojs.2023.133020.

Lah NZA, Yusop Z, Hashim M, Salim JM, Numata S. 2021. Predicting the habitat suitability of *Melaleuca cajuputi* based on the MaxEnt species distribution model. Forest 12 (11): 1449. DOI: 10.3390/f12111449.

Ma B, Sun J. 2018. Predicting the distribution of *Stipa purpurea* across the Tibetan Plateau via the MaxEnt model. BMC Ecol 18: 10. DOI: 10.1186/s12898-018-0165-0.

Mahatara D, Acharya AK, Dhakal BP, Sharma DK, Ulak S, Paudel P. 2021. Maxent modelling for habitat suitability of vulnerable tree *Dalbergia latifolia* in Nepal. Silva Fenn 55 (4): 10441. DOI: 10.14214/sf.10441.

Malamassam D. 2020. The management model for sugar palm in educational forest of Universitas Hasanuddin. IOP Conf Ser Earth Environ Sci 486: 012108. DOI: 10.1088/1755-1315/486/1/012108.

Millang S. 2021. Productivity of pangi (*Pangium edule* Reinw.) and biodiversity of agroforestry systems at various altitudes in Toraja Regency, South Sulawesi. IOP Conf Ser Earth Environ Sci 886: 012062. DOI: 10.1088/1755-1315/886/1/012062.

Mousazade M, Ghanbarian G, Pourghasemi HR, Safaeian R, Cerda A. 2019. Maxent data mining technique and its comparison with a bivariate statistical model for predicting the potential distribution of *Astragalus fasciculifolius* Boiss. in Fars, Iran. Sustainability 11 (12): 3452. DOI: 10.3390/su11123452.

Muda NA, Awal A. 2021. Sugar palm (*Arenga pinnata* Wurmb Merr.): A review on plant tissue culture techniques for effective breeding. IOP Conf Ser Earth Environ Sci 715: 012016. DOI: 10.1088/1755-1315/715/1/012016.

Muhammed K, Anandhi A, Chen G. 2022. Comparing methods for estimating habitat suitability. Land 11 (10): 1754. DOI: 10.3390/land11101754.

Mujetahid A, Muin AVF, Wulan S. 2023. Potential of aren (*Arenga pinnata*) in KHDTK Hasanuddin University Educational Forest, Rompegading Village, Cenrana District, Maros Regency. IOP Conf Ser Earth Environ Sci 1277: 012013. DOI: 10.1088/1755-1315/1277/1/012013.

Nahm FS. 2022. Receiver operating characteristic curve: Overview and practical use for clinicians. Korean J Anesthesiol 75 (1): 25-36. DOI: 10.4097/kja.21209.

Omar K, Mohamed A, Shaltout M, Elgamal I, Bidak LM. 2025. Future habitat dynamics of critically endangered endemic plants in the St. Catherine protected area, South Sinai, Egypt: Climate change perspectives on mountain ecosystems. BMC Ecol Evol 25: 68. DOI: 10.1186/s12862-025-02408-5.

Pearson RG, Raxworthy CJ, Nakamura M, Peterson AT. 2007. Predicting species distributions from small numbers of occurrence records: A test case using cryptic geckos in Madagascar. J Biogeogr 34: 102-117. DOI: 10.1111/j. 1365-2699.2006.01594.x.

Pecchi M, Marchi M, Burton V, Giannetti F, Moriondo M, Bernetti I, Bindi M, Chirici G. 2019. Species distribution modelling to support forest management: A literature review. Ecol Model 411: 108817. DOI: 10.1016/j.ecolmodel.2019.108817.

Phillips SJ, Anderson RP, Schapire RE. 2006. Maximum entropy modelling of species geographic distributions. Ecol Model 190:231-259. DOI: 10.1016/j.ecolmodel.2005.03.026.

Phillips SJ, Dudík M. 2008. Modelling of species distribution with Maxent: New extensions and a comprehensive evaluation. Ecography 31: 161-175. DOI: 10.1111/j.0906-7590.2008.5203.x.

Pradhan P, Setyawan AD. 2021. Filtering multi-collinear predictor variables from multi-resolution rasters of WorldClim 2.1 for Ecological Niche Modelling in Indonesian context. Asian J For 5 (2): 111-122. DOI: 10.13057/asianjfor/r050207.

Pradhan P. 2016. Strengthening MaxEnt modelling through screening of redundant explanatory bioclimatic variables with variance inflation factor analysis. Researcher 8 (5): 29-34. DOI: 10.7537/marsrsj080516.05.

Rubanschi S, Hof C, Weisser WW, Meyer ST. 2024. Assessing the conservation and restoration potential of biotopes in a central European region. Biodivers Conserv 33: 2305-2328. DOI: 10.1007/s10531-024-02841-w.

Siddiq AM, Kholiq N, Subchan W, Maulahila HI. 2023. Habitat suitability model for banteng (*Bos javanicus*) in Meru Betiri National Park, Indonesia. Biodiversitas 24 (2): 1296-1302. DOI: 10.13057/biodiv/d240272.

Singh P, Singh S, Paprzycki M. 2023. Detection and elimination of multicollinearity in regression analysis. Intl J Knowl Based Intell Eng Syst 27 (1): 105-111. DOI: 10.3233/KES-221622.

Tesfamariam BG, Gessesse B. Melgani F. 2022. MaxEnt-based modelling of suitable habitat for rehabilitation of *Podocarpus* forest at landscape-scale. Environ Syst Res 11: 4. DOI: 10.1186/s40068-022-00248-6.

Wang F, Yuan X, Sun Y, Liu Y. 2024. Species distribution modelling based on MaxEnt to inform biodiversity conservation in the Central Urban Area of Chongqing Municipality. Ecol Indic 158: 111491. DOI: 10.1016/j.ecolind.2023.111491.

Wang Y, Chao B, Dong P, Zhang D, Yu W, Hu W, Ma Z, Chen G, Liu Z, Chen B. 2021. Simulating spatial change of mangrove habitat under the impact of coastal land use: Coupling MaxEnt and Dyna-CLUE models. Sci Total Environ 788: 147914-147914.

Wang Y, Liu M, Xia F, Wang Y, Song D, Liu Y, Li S. 2024. Big cats persisting in human-dominated landscape: Habitat suitability and connectivity of leopards in central North China. Landsc Ecol 39: 94. DOI: 10.1007/s10980-024-01896-y.

Widarawati R, Syarifah RNK, Prakoso B. 2023. Leaf character of sugar palm on various shades and concentrations of liquid organic fertilizer. Jurnal Kultivasi 22 (2): 125-130. DOI: 10.24198/kultivasi.v22i2.42439.

Yuan Y, Tang X, Liu S, Zhang J. 2020. The major factors influencing distribution of three species of *Dendrobium*: Analysis of potential ecologically suitable distributions. J Appl Res Med Aromat Plants 19: 100275. DOI: 10.1016/j.jarmap.2020.100275.

Zhao D, He HS, Wang WJ, Wang L, Du H, Liu K, Zong S. 2018. Predicting wetland distribution changes under climate change and human activities in a mid- and high-latitude region. Sustainability 10 (3): 863. DOI: 10.3390/su10030863.

Zuhud EAM, Al Manar P, Zuraida, Hidayati S. 2020. Potency and conservation of aren (*Arenga pinnata* (Wurmb) Merr.) in Meru Betiri National Park, East Java-Indonesia. Junal Manajemen Hutan Tropika 26: 212-221. DOI: 10.7226/jtfm.26.3.212.