Journal of Natural Resources and Environmental Management
http://dx.doi.org/10.29244/jpsl.14.2.253

RESEARCH ARTICLE

The Habitat Suitability Modelling of Rhinoceros Hornbills (*Buceros rhinoceros*) in Java Island, Indonesia

Taufik Setiawan[a], Lilik Budi Prasetyo[b], Yeni A. Mulyani[b], Jarulis[c]

[a] Tropical Biodiversity Conservation Study Program, Graduate School, IPB University, IPB Darmaga Campus, Bogor, 16680, Indonesia
[b] Department of Forest Resources Conservation and Ecotourism, IPB University, IPB Darmaga Campus, Bogor, 16680, Indonesia
[c] Department of Biology, Faculty of Mathematics and Natural Sciences, University of Bengkulu, Kandang Limun, Bengkulu, 38122, Indonesia

Article History
Received
06 September 2023
Revised 04 October 2023
Accepted
05 December 2023

Keywords
environmental variables, Java Island habitat suitability, presence data, Rhinoceros hornbills

ABSTRACT

Rhinoceros hornbills (*Buceros rhinoceros*) are a bird species belonging to the Bucerotidae family, which is vulnerable based on the IUCN red list of species. This is due to habitat fragmentation, which reduced the Rhinoceros hornbill habitat on Java. Efforts and strategies are needed to maintain Rhinoceros hornbill habitats. Information on the suitability of the Rhinoceros hornbill habitat on Java Island is required to develop a Rhinoceros hornbill conservation strategy. This study aimed to determine a habitat suitability model that produces the highest accuracy, analyze hornbill habitat suitability, and identify environmental variables that affect the existence of rhinoceros hornbills. Habitat suitability models were processed using three algorithms: random forest, support vector regression, and MaxEnt. The data used to model habitat suitability were presence and environmental variables. The model was evaluated using various accuracy measures, namely overall accuracy, sensitivity (sn), specificity (sp), Area Under Curve (AUC), and kappa coefficient. The results of model processing showed that the random forest algorithm produced the highest average accuracy of 0.74. The most important environmental variables for the habitat suitability model were the distance from the road (16.62%), distance from the forest (12.73%), and land cover (12.47%). The habitat suitability model was divided into three classes: low suitability, covering 75,048 km^2 (55.94%); medium suitability, covering 52,911 km^2 (39.44%); and high suitability, covering 6,213 km^2 (4.63%). The results of the habitat suitability model showed that the habitat suitability class was the smallest in the area.

Introduction

Rhinoceros hornbills (*Buceros rhinoceros*) are bird species belonging to the Bucerotidae Family. Rhinoceros hornbills are characterized by their unique shape and orange-head protection [1]. According to Mackinnon et al. [2], hornbills are spread across several islands of Indonesia, including Sumatra, Java, and Kalimantan. According to the International Union for Conservation of Nature (IUCN), rhinoceros hornbills are categorized as vulnerable (VU). Conservation efforts are needed to protect and preserve the Rhinoceros hornbill so that the population does not decrease. Java Island is one of the Rhinoceros hornbill distribution islands in Indonesia. Java Island is one of the islands in Indonesia that has experienced massive forest loss and habitat fragmentation [3]. Habitat fragmentation on Java Island has led to the isolation of many wildlife populations and the threat of extinction [4]. According to the Ministry of Environment and Forestry, forest area data in Java Island was 3,212.7 ha. Forest loss on Java Island and habitat fragmentation are feared to impact habitat loss that threatens the existence and sustainability of rhinoceros hornbills on Java Island.

Based on these conditions, effective and efficient conservation strategies are needed. Complete information on hornbill habitat suitability models is required to provide an overview of hornbill habitats and can be considered when developing conservation strategies. Habitat suitability models can help determine locations

Corresponding Author: Taufik Setiawan taufiksetiawan437@gmail.com Tropical Biodiversity Conservation Study Program, Graduate School, IPB University, IPB Darmaga Campus, Bogor, Indonesia.

that need to be maintained or improved. Modeling hornbill habitat suitability on Java Island is essential to provide information on the level of hornbill habitat suitability on Java Island. The existence of habitat suitability model information can be considered by policymakers when developing hornbill conservation plans on Java Island.

Based on previous studies, many algorithms have been used to model the suitability of a species habitat. This research used three different algorithms, namely Random Forest (RF), Maximum Entropy (MaxEnt), and Support Vector Regression (SVR). These three algorithms have been widely used to model the distribution of habitat suitability for both flora and fauna. Research on hornbill distribution modeling has been conducted only by Jarulis [5], Hidayat and Febriani [6], who used the MaxEnt model. SVR and RF models have never been used to model hornbill habitat suitability. Therefore, this research is critical for comparing and determining the best model among MaxEnt, SVR, and RF. The determination of the best model among the three algorithms was based on the accuracy value generated by each algorithm. According to Cahyana [7], the difference in the level of accuracy produced by each method can also be considered separately when choosing the model used. This research will provide information on the best algorithm for modeling Rhinoceros hornbill distribution. In addition, this research is also expected to be considered by policymakers in hornbill conservation efforts, especially on Java.

Material and Method

Research Location and Time

The scope of the research location analyzed in this study was Java Island. The process of collecting secondary data on Rhinoceros Hornbill's presence on Java Island and data on environmental variables was conducted in January 2023. The hornbill presence data in this study were in the range of 2000–2023.

Figure 1. Map of research location.

Data Collection

Habitat suitability models used hornbill presence distribution data and data on environmental variables that affect hornbill distribution. The presence distribution data for hornbills used in this study were derived from secondary sources, including the scientific literature and websites. The presence of data collected in this study is in the range of 2000–2023 because the availability of data before 2000 is still relatively small. The scientific literature data were divided into two groups: books and journals. The book data comprised 32 points of presence, consisting of textbooks, theses, dissertations, and research reports. Journal data totaled 95 attendance points from journal articles, proceedings, and seminar/conference/symposium/workshop papers. Secondary data from books and journals collected were in publications between 2000–2023 because the availability of hornbill presence data from books and journal sources is still relatively small. In addition, data on the distribution of presence were obtained from the websites. The website used in this study is the Global Biodiversity Information Facility (GBIF). The data from the website obtained in this study comprised a total of 1,158 attendance points. This website provides complete data on the existence of fauna species and other organisms [5]. The initial presence data collected before the filtering process included 1,285 points of presence for one region in Indonesia.

Environmental factor data consisted of altitude, slope, temperature, rainfall, Normalized Difference Vegetation Index (NDVI), land cover, distance from the road, distance from the river, distance from the forest, distance from the farmland, distance from the plantation, distance from the settlement, and distance from food trees. Elevation and slope data were generated from DEM data processing downloaded from *portal.opentopography.org*. Temperature data was downloaded from *www.worldclim.org*. Rainfall data was downloaded from *www.chc.ucsb.edu*. The NDVI and closure data of Landsat 8 images were processed and downloaded to *Google Earth Engine*. Distance from the road and river data using RBI data downloaded from *tanahair.indonesia.go.id*. Distance from the forest, distance from the farmland, distance from the plantation, and distance from the settlement was obtained from the processing of land cover data. Meanwhile, distance from the food trees data was obtained from the GBIF website. The environmental factor data obtained were then converted into raster data in *the GeoTIFF* format.

Data Analysis

This study uses hornbill presence data and environmental factors. Presence data and environmental factors are analyzed using 3 types of algorithms, namely MaxEnt, RF, and SVR. The selection of these algorithms is due to machine learning algorithms that are often used and produce good accuracy. The data analysis process used in this study is shown in the flowchart (Figure 2).

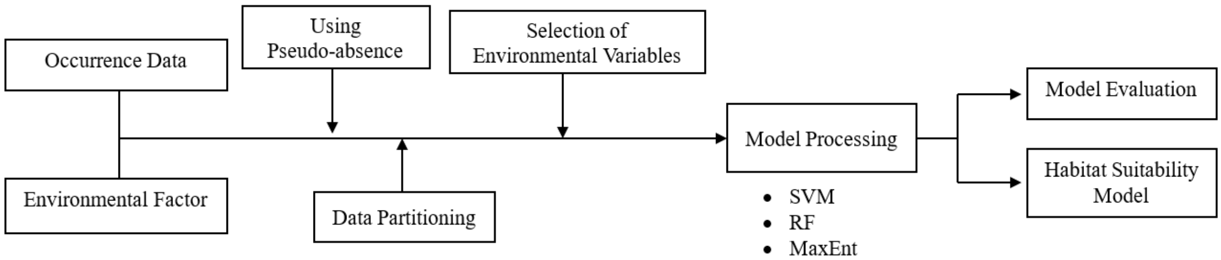


Figure 2. Research flowchart.

Data Pre-Processing

Data pre-processing is the initial stage before the data are used for modeling. Before being used as a model processing variable, a resampling process was performed on the variable to equalize its spatial resolution. Rhinoceros hornbill presence data were filtered previously. This process is essential for modeling the distribution of species habitats because it improves the quality of the data and accuracy of the model produced [8,9]. The filtering process was carried out with various considerations, namely, the presence points have the exact coordinates, eliminating duplicate presence data, and eliminating presence data outside Java Island. The number of Rhinoceros hornbill presence data collected for the Java Island area was 172 points, and then filtering was performed by eliminating duplicate presence data; thus, the presence data used in the model processing was 63 points.

Using Pseudo-absence Data

Presence and absence data are needed to model hornbill habitat suitability on Java. It is difficult to obtain animal absence data, which can be anticipated using pseudo-absence data. The amounts of pseudo-absence and presence data were the same. Furthermore, Barbet-Massin [10] recommended using the same pseudo-absence points as presence points. The estimation of pseudo-absence points in this study was based on the presence of forests in the study landscape, because Rhinoceros hornbills are highly dependent on the presence of forests. Therefore, pseudo-absence points were randomly selected from the areas outside the forest.

Data Partitioning

The presence and absence of data was then divided into training and test data. Training data are used to build models, and testing data are used to evaluate model performance [11]. Division was performed using the K-fold cross-validation method. Data division or partitioning was conducted using the dismo package in the R-Statistic application with a number K of 5 folds.

Selection of Environmental Variables

The initial stage that needs to be done in modeling is the selection of the environmental variables. The goal was to select the variables used in the model-processing process. One way to choose environmental variables is to conduct a multicollinearity test for all environmental variables. Multicollinearity is a condition of a linear relationship or high correlation between each independent variable. The multicollinearity test is used to test the linearity between one variable and another, such that the variables used in building the model do not affect each other [12,13]. A multicollinearity test was performed using the olsrr package in R-Statistics. This test was performed to obtain the Variance Inflation Factor (VIF). If the VIF value obtained is more than ten (>10), then one of the variables must be eliminated or reduced [14].

Model Processing

Model processing in this study used the MaxEnt, random forest, and support vector regression algorithms. All data from the three types of machine algorithms were processed using the R Studio software. MaxEnt is a machine-learning technique that can be used to predict the presence of data information only [15]. MaxEnt was applied using R-Studio using the dismo package [16]. Random forest (RF) is a machine learning technique with a bootstrap-based classification and regression tree method [17]. Random forest was implemented using R Statistics with the random forest package [18]. SVR is part of the Support Vector Machine (SVM) algorithm. SVR is the implementation of an SVM for regression. The regression output is a natural or continuous number [19]. Support Vector Regression was applied using the R-Statistic through package e1071 with the function SVM [20].

Model Evaluation

The results of model processing were then evaluated to determine the best model that produced the highest accuracy. The model was evaluated using various accuracy measures: sensitivity, specificity, Area Under Curve (AUC), and kappa coefficient. Overall accuracy describes the success of attendance and absenteeism being correctly classified in the resulting model [21]. Sensitivity is the chance of attendance being correctly classified and specificity is the chance of attendance being correctly classified [22]. AUC is the area under the Receiver Operating Curve *(ROC)* and is a standard method for identifying the prediction accuracy of distribution models [23]. The kappa statistic measures the model performance using the information in a mixture matrix [24] that ranges from –1 to +1, where +1 indicates good results and a value of zero or less than 0 indicates poor performance [25,26]. To classify potential presence, a probability threshold above 0.5 was used [22,27].

Hornbill Habitat Suitability Class Range

The hornbill habitat suitability is divided into three suitability classes. The three classes are low suitability class, medium suitability class, and high suitability class. This map provides a habitat suitability map for hornbills and determines which areas are most suitable for conservation and protection. The classes of the habitat suitability intervals are listed in Table 1.

Table 1. Habitat suitability category of rhinoceros hornbills [28].

No	Range	Suitability class
1	Minimum < S ≤ (mean – Std.)	Low suitability
2	(mean – Std) < S ≤ (mean + Std)	Medium suitability
3	S > (mean + Std)	High suitability

Note: Std = standard deviation; S = score; mean = average.

Results and Discussion

Selection of Environmental Variables

The selection of environmental variables must be performed in the early stages of modelling. This selection aims to select the variables that are used in the modelling process. One way to select environmental variables is to conduct a multicollinearity test for all environmental variables. A multicollinearity test determined the correlation between each environmental variable used in the model processing. Multicollinearity between these variables affects the accuracy of the model [29]. The results of the multicollinearity test between the environmental variables are presented in Table 2. Based on the results of the multicollinearity test, we found multicollinearity between the variables of altitude and temperature. This can be seen from the VIF values of the temperature and altitude variables. The VIF value for the temperature and altitude variables was more than 10 (>10). If multicollinearity exists between two variables, then one of the environmental variables must be selected for use in model processing [30]. The altitude variable was chosen because the higher a region, the lower (colder) its surface temperature. The lower the area, the higher (hotter) the surface temperature of the hotter [31]. In addition, several previous studies on multicollinearity tests have shown that altitude is widely chosen to model species distribution, such as in elephants [31], dare monkeys [32], and litter frogs [33].

Table 2. Multicollinearity test results.

Environmental Variables	VIF
Altitude	28.86
Slope	1.94
Temperature	31.51
Rainfall	1.78
NDVI	1.73
Land cover	1.28
Distance from road	1.24
Distance from river	1.06
Distance from forest	3.53
Distance from agricultural area	1.28
Distance from plantation	3.91
Distance from settlement	1.60
Distance from food tree	1.33

Note: the red color in the table indicates a correlation between variables.

Model Evaluation

The resulting model was evaluated by determining the overall accuracy, sensitivity, specificity, AUC values, and kappa coefficient. A comparison of the model performance is presented in Table 3. Table 3 presents the evaluation results of the Rhinoceros hornbill distribution model for each algorithm.

Table 3. Rhinoceros hornbill distribution model accuracy test.

Algorithm	OA		Sn		Sp		Kappa		AUC	
	x̄	s	x̄	s	x̄	s	x̄	s	x̄	s
Maximum Entropy	0.85	0.08	0.75	0.13	0.98	0.01	0.69	0.14	0.93	0.04
Random Forest	0.90	0.06	0.83	0.11	0.94	0.06	0.78	0.12	0.97	0.02
Support Vector Regression	0.83	0.10	0.67	0.14	0.94	0.06	0.63	0.15	0.93	0.05

Note: OA= *overall accuracy*; Sn= sensitivity; Sp= specificity, AUC= *area under curve*. The models that produce high accuracy are colored in red.

Based on the accuracy values generated, the random forest algorithm produced high accuracy from four accuracy measures, namely overall accuracy, sensitivity, kappa, and AUC, with consecutive values of 0.90 ± 0.06, 0.83 ± 0.11, 0.78 ± 0.12, and 0.97 ± 0.02, respectively. The MaxEnt algorithm exhibits specificity accuracy with a value of 0.98 ± 0.01. This accuracy comparison showed differences in the sensitivity and specificity between the three algorithms used in this study. The sensitivity value was used to determine the chance of attendance that was correctly classified in the model results. In contrast, the specificity value was used to determine the opportunity of absence being correctly classified in the model results. The random forest model produced the highest accuracy in terms of sensitivity, while the MaxEnt model produced the highest accuracy in terms of specificity.

There were differences in the accuracy values produced by each of these models, so that the best model selection could be seen from the average value generated from the overall accuracy, sensitivity, specificity, kappa, and AUC values. The average calculation results show that random forest produces the highest average value of 0.74. MaxEnt and support vector regression produced an average accuracy of 0.70 and 0.67, respectively. The random forest algorithm produces a higher model accuracy than the MaxEnt and support vector regression algorithms. According to Wijaya et al. [34], a random forest is an ensemble method consisting of several decision trees. The random forest algorithm is also a development of the decision-tree method. The development in a random forest uses several decision trees that are trained and broken down in each tree and then randomly subsets [35]. The random forest algorithm produces high accuracy because this algorithm is an algorithm that combines and averages the results of several decision trees, so the random forest algorithm is the algorithm used in the subsequent analysis.

Importance Variable

The Variable Importance Method (VIM) was used to determine the environmental variables that are important to the RF algorithm. The VIM method can be used to determine the significance of environmental variables in model processing. The method measures the extent to which an environmental variable can reduce model accuracy [36]. Furthermore, the calculation can use the mean decreased accuracy (%IncMSE) [37]. The greater the %IncMSE value, the greater the error value caused by randomizing an environmental variable's permutation, such that the importance value of the environmental variable increases [38]. The percentage increase in the Mean Square Error (%IncMSE) can identify environmental variables that are important for modeling using the random forest algorithm. %IncMSE expresses the increase in mean square error when a variable is randomly permuted ($MSE_{permuted}$) [38]. Mathematically, this formula is as follows:

$$\%\text{IMSE} = \frac{(MSE_{Permuted} - MSE)}{MSE} \text{ x } 100\% \quad (1)$$

The random forest algorithm produces environmental variables that are important for the habitat suitability model. The model results showed that distance from road resulted in the highest %IncMSE of 16.62%, followed by distance from forest (12.73%), land cover (12.47%), distance from settlement (12.26%), rainfall (11.04%), distance from plantation (10.11%), altitude (7.61%), NDVI (7.61%), slope (7.59%), distance from farmland (6.54%), distance from food trees (6%), and distance from the river (1.41%).

Table 4. Important environmental variables on habitat suitability.

Environmental variables	%IncMSE
Distance from road	16.62
Distance from forest	12.73
Land cover	12.47
Distance from settlement	12.26
Rainfall	11.04
Distance from plantation	10.11
Altitude	7.61
NDVI	7.61
Slope	7.59
Distance from farmland	6.54
Distance from food trees	6.0
Distance from river	1.41

Based on Table 4, the distance from the road is an essential variable for modeling because if the distance from the road is omitted or not used, it will significantly reduce the accuracy value of the %IncMSE by 16.62%. Conversely, the distance from the river variable produced the lowest %IncMSE value, indicating that if the distance from the river variable is not used in the model processing, the accuracy will be reduced by 1.41%.

However, distance from the river is still considered in the model processing because the distance from the river influences the presence of rhinoceros hornbills ecologically. According to Hidayat and Febriani [6], rivers are essential for animal survival in fulfilling water requirements. They are used as energy sources and for animal livelihoods, including Rhinoceros hornbills.

Effect of Environmental Variables on Prediction of Rhinoceros hornbill Presence

The effect of environmental variables on the presence of Rhinoceros hornbill can be observed from the response curve results obtained from the model processing results. The response curve predicts the presence of rhinoceros hornbills in each environmental variable. According to Phillips et al. [15], the closer the value is to 1, the higher is the chance of animal presence.

Topographical Factors

Based on the response curve of the altitude variable obtained from the model processing results, the possibility of hornbill presence was between 500 and 2,000 masl. This is in contrast to Hadiprakarsa and Kinnaird [39], who explained that the distribution of Rhinoceros hornbill species on the island of Sumatra is found at an altitude of 0–2,200 masl. This condition differs from the research of Jarulis [5], which states that, on average, all hornbill species in Indonesia prefer lower altitudes, namely, <1,500 masl. The effects of altitude on the presence of hornbills are more diverse among species. According to Bibby et al. [40], altitude is one of the most important factors for bird distribution. In addition, altitude also affects the vegetation used by birds as both nest trees and food trees. The fruit of ficus trees from the Moraceae family is a tree much favored by Rhinoceros hornbills. Ficus trees were found in the tropics at <1,500 masl. However, a few species of ficus trees can grow above 3,000 masl [41].

The slope is a topographic factor that affects hornbill distribution. The land slope response curve results showed that the probability of hornbill presence increased with increasing degrees of land slope (Figure 3). According to Hadiprakarsa [42], slope is one of the essential parameters for predicting hornbill presence. The possibility of hornbill presence was mainly found on land with a slope of more than 10°. This indicates that the more the slope level increases in an area, the more likely is the presence of Rhinoceros hornbills will be found. The Bucerotidae family lives in hilly regions with an undulating topography and steep slopes [43]. Kubangun et al. [44] stated that flat topographic areas generally experience more land change than steep topographic areas. Therefore, flat topographic regions are less suitable habitats for Rhinoceros hornbills.

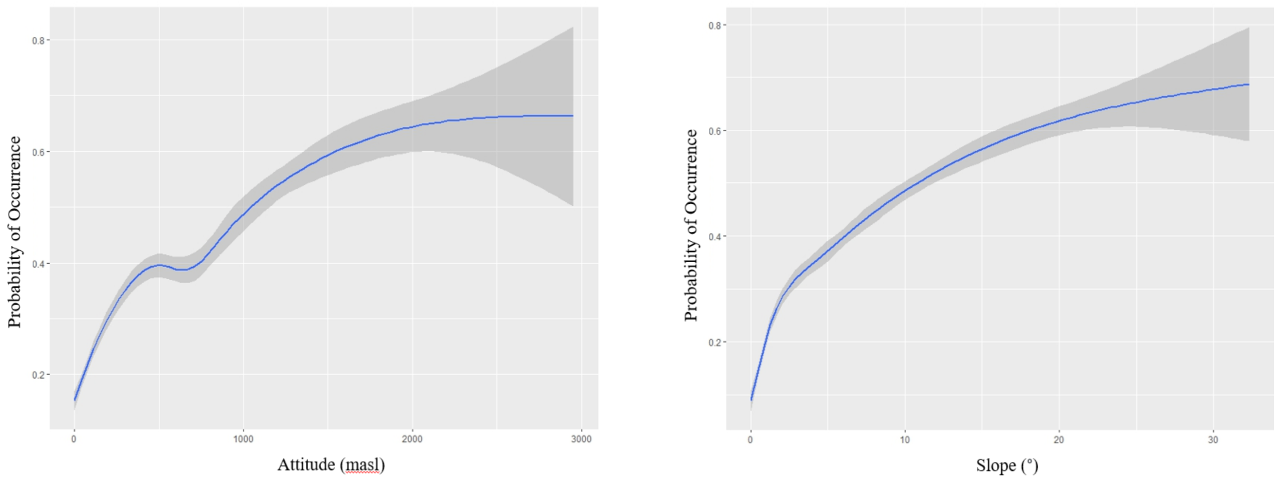


Figure 3. Land elevation and slope response curves.

Climatic Factors

The results of the response curve for rainfall showed that the probability of Rhinoceros hornbill presence increased in the range 2,000 to 4,500 mm (Figure 3). The possibility of hornbill presence decreased when rainfall was below 4,500 mm. Rhinoceros hornbill habitat is generally found in areas with moderate rainfall. In contrast, Kinnaird and O'Brien et al. [45] stated that hornbill species are usually located in areas with more than 3,000 mm/year of rainfall. Rainfall affects the availability of water for the hornbills. High rainfall can produce water used by hornbills to meet their needs, such as for drinking [46].

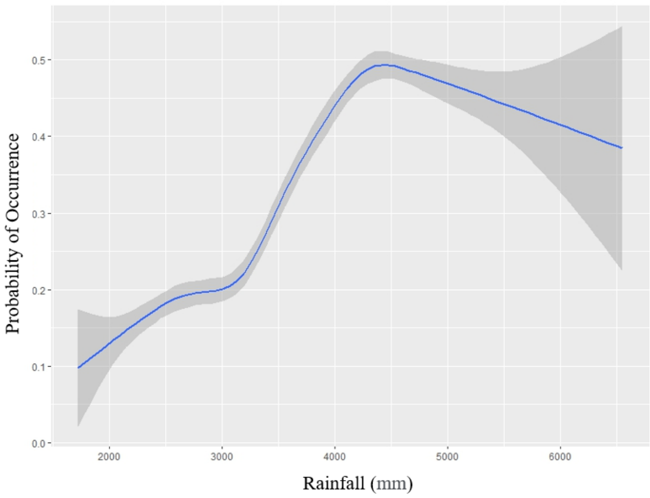


Figure 4. Rainfall response curve.

Biophysical Factors

In species distribution models, land-cover variables can influence the presence of species [27]. The land cover classes in the study included settlements (0), forests (1), water bodies (2), open land (3), shrubs (4), agricultural land (5), and plantations (6). The response curve results showed that Rhinoceros hornbill was mainly found in the forest. Hornbills use forest habitats dominated by trees to find food, perform activities, and breed. Trainor et al. [47] revealed that forests are the most essential habitat for the existence of birds because forests provide food, water, and shelter for birds in living life.

The NDVI is an index value that represents the greenness of an area. Generally, NDVI values range from –1 to 1. NDVI values close to 1 indicate excellent vegetation greenness, whereas NDVI values less than 0 indicate poor innocence. The range of NDVI values produced in this study is –0.23 to 0.85. The response curve results showed that the probability of Rhinoceros hornbill presence was in the NDVI range of 0.25 to 0.5. According to *Departemen Kehutanan* [48], NDVI values are grouped into three classes: –1–0.32 for low density, 0.32–0.42 for medium density, and 0.42–1 for dense canopy density. Based on the NDVI value class, it was concluded that the hornbill's chance of existence is in the medium- and thick-density classes. According to Rahman [49], dense vegetation in forested areas is essential for species survival, including Rhinoceros hornbills. Hornbill survival depends on forests dominated by large and tall trees. Hornbills use these trees for breeding, perching, and nesting purposes.

The response curve results for distance from the river showed that the probability of presence increased with distance from the river. Nevertheless, distance from the river remains essential for the life of rhinoceros hornbills because rivers provide water that can be an energy supply and a source of livelihood for trees used as food and nest trees for rhino hornbills. Previous research conducted by Hidayat and Febriani [6] stated that the distance from the river is essential in the presence of hornbills because the river is directly adjacent to the forest, thus showing the high need for water for the survival of Rhinoceros hornbills. Rivers are one of the sources of energy and a source of livelihood for animals, including Rhinoceros hornbills.

Food trees are an essential factor for the life of rhinoceros hornbills. Rhinoceros hornbills require food to fulfill their energy requirements. Fruits of *Ficus spp*. are the leading food source and are also favored by hornbills. According to Anggriawan et al. [50], the distribution of *Ficus spp*. is positively correlated with the hornbill distribution. The response curve results showed that the greater the distance from the food tree, the smaller the chance of hornbill presence (Figure 5). Therefore, food trees are essential for the survival of rhinoceros hornbills on Java.

Human Activity Factors

The environmental variable that can influence the distribution of rhinoceros hornbills is disturbance caused by human activities. Human activity factors are based on five types of environmental variables: distance from roads, distance from forests, distance from agricultural land, distance from plantations, and distance from settlements. The response curves of the five variables demonstrated different trends (Figure 6). The curves of distance from roads, distance from farmland, and distance from settlements showed an increase in the value of environmental variables that aligned with the increased likelihood of rhino hornbill presence. In contrast, the distance from forests and the distance from plantation curves showed a decrease in the value of environmental variables aligned with a reduction in the probability of rhinoceros hornbills.

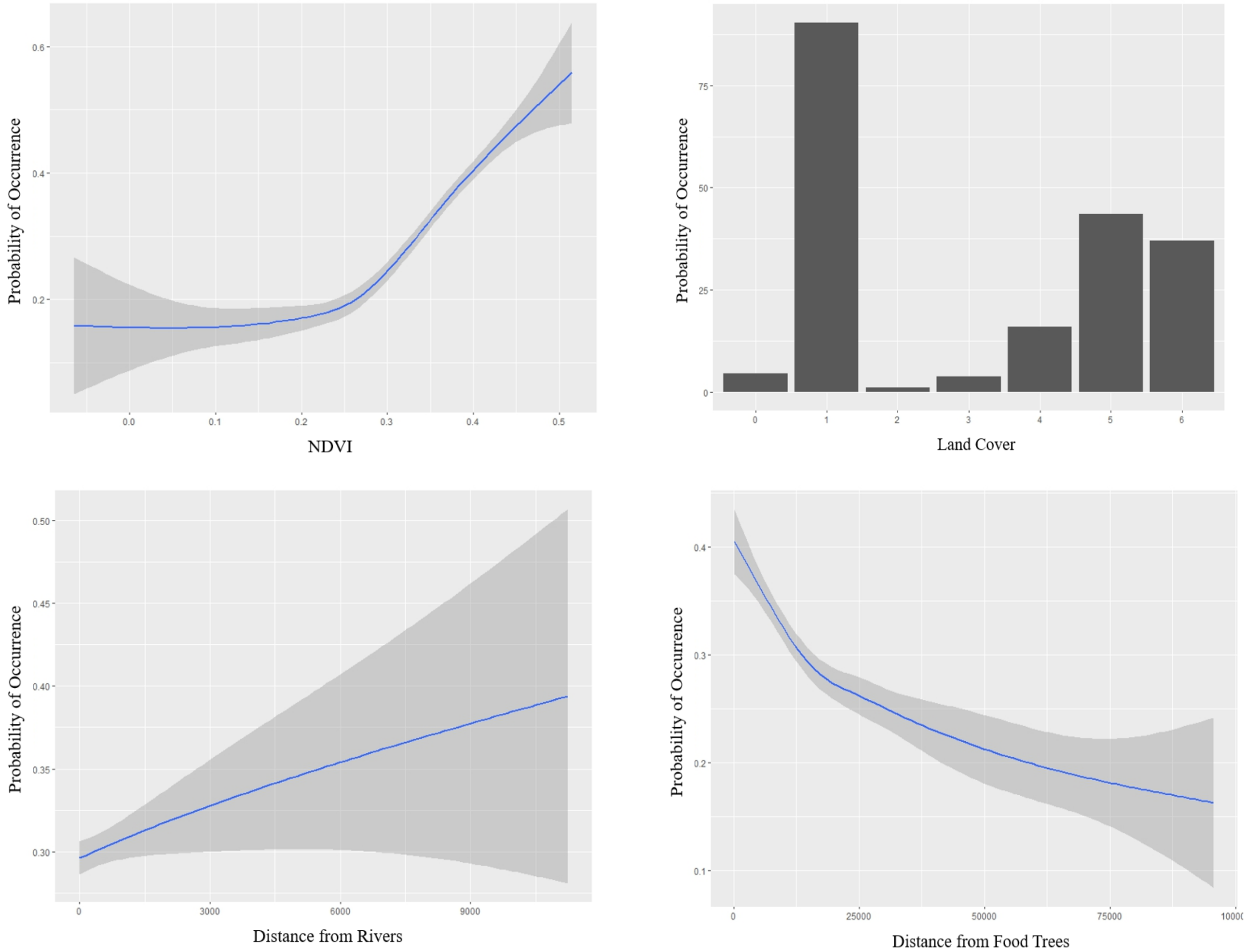
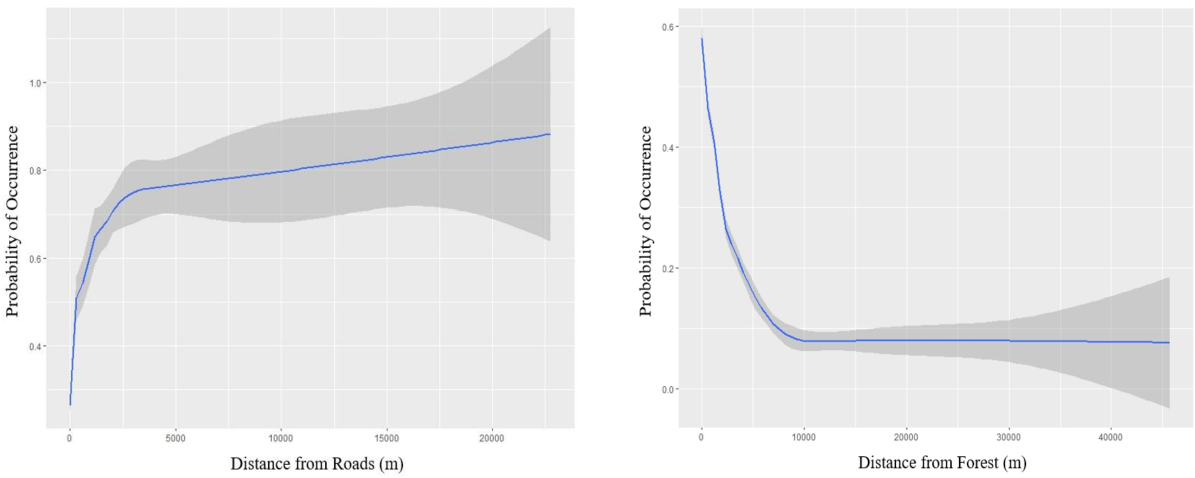


Figure 5. Response curves of NDVI, land cover, distance from the river, and distance from food trees.



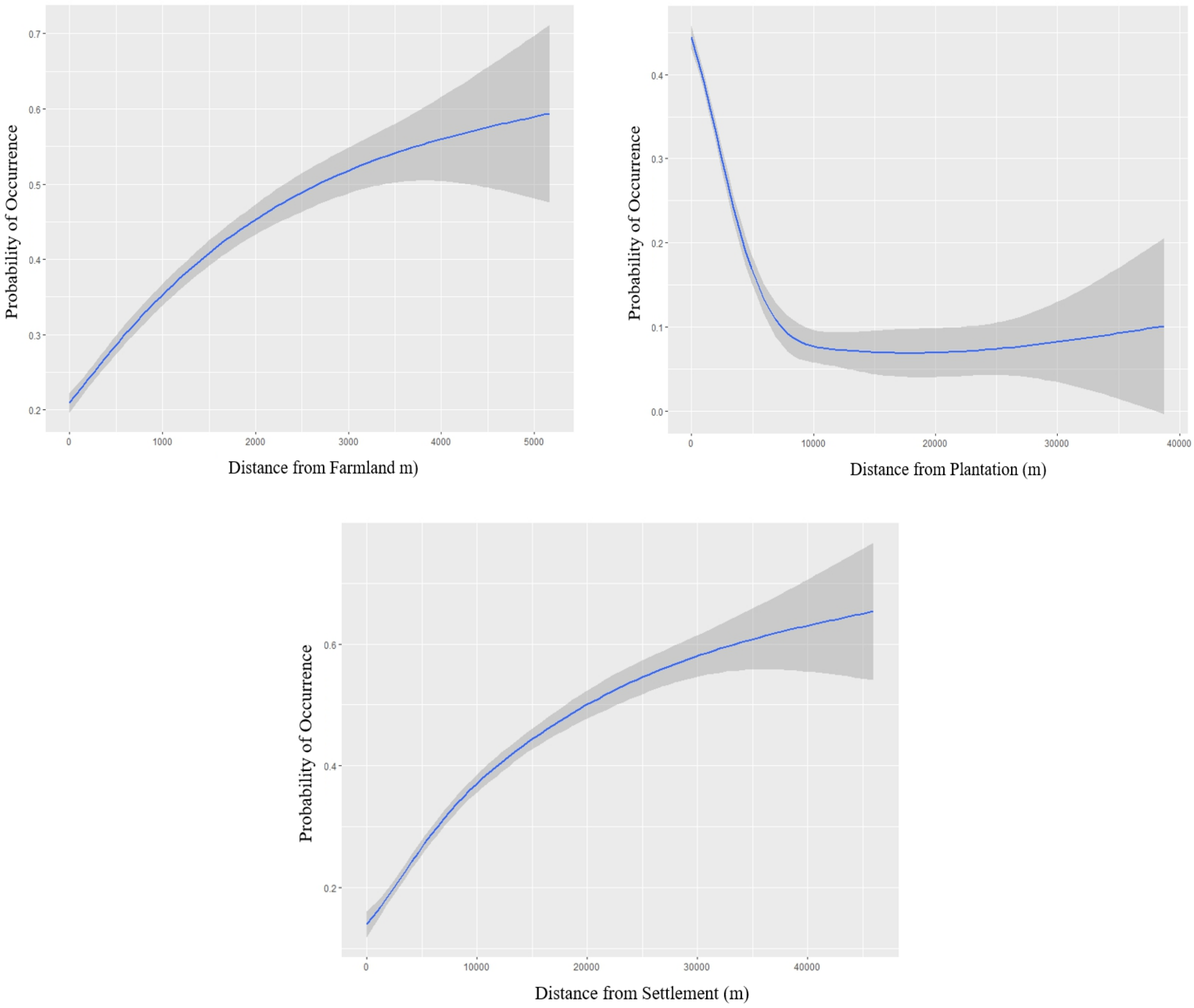


Figure 6. Response curves of distance from roads, distance from forest, distance from farmland, distance from plantation, and distance from settlement.

The distance from the road response curve in Figure 6 reveals that the greater the distance from the road, the greater the probability of hornbill presence. According to Hidayat et al. [51], the closer the road is to the presence of hornbills, the more threatened their existence. Easy access to hornbill habitats can facilitate hunting activities carried out by humans against hornbills. The results of the distance from the forest response curve showed that the greater the distance from the forest, the less likely the presence of hornbills. According to Kumara [52], hornbills generally live in forested areas far from human activities. In addition, according to research by Jarulis [5], hornbill encounters were found at a distance from the forest. This is because Rhinoceros hornbills do not resemble habitats disturbed by human presence or activity.

Based on the results of the response curve generated by the model, the greater the distance from the plantation, the lower the probability of Rhinoceros hornbill's presence. Therefore, Rhinoceros hornbills can avoid human disturbance. According to Syechalad and Muhammad [53], plantations are agricultural businesses that become an economic activity by cultivating crops that are controlled separately. In addition to being managed individually, plantations are governed by companies. Some hornbill species can also be found in plantation areas [54].

Distance from settlements is a human disturbance factor that affects the distribution of Rhinoceros hornbills. Rhinoceros hornbills are hornbill species that are sensitive to human presence, causing them to live away from human existence. The response curve generated from the model processing showed that the farther away from the settlement, the greater the chance of hornbill presence. According to Hidayat et al. [51], the closer to the settlement area, the higher the threat to hornbills due to later human access to hornbill habitats.

Rhinoceros hornbill Habitat Suitability

Random forest processing resulted in raster data with the lowest pixel value of 0.0034 and highest pixel value of 0.994. The standard deviation of the resulting data was 0.20, and the mean was 0.49. Based on the results of data processing that has been carried out, the division of hoses for the Rhinoceros hornbill habitat suitability class is presented in the following table 5. Based on the results of the suitability class area calculation and the suitability class map in Figure 7, the results show that the high suitability class has the smallest area. The area of the low habitat suitability class is 75,048 km^2 (55.94%) with two presence points, then the medium suitability class with an area of 52,911.77 km^2 (39.44%) with 15 presence points, and the high suitability class with an area of 6,213.76 km^2 (4.6%) with 46 presence points.

Table 5. Hornbill habitat suitability classes on Java Island.

No	Range	Suitability class	Occurrence point	Area (km^2)	Percentage (%)
1	0.0034 – 0.29	Low suitability	2	75.048,00	55.94
2	0.29 – 0.70	Medium suitability	15	52.911,77	39.44
3	0.70 – 0.994	High suitability	46	6.213,76	4.63

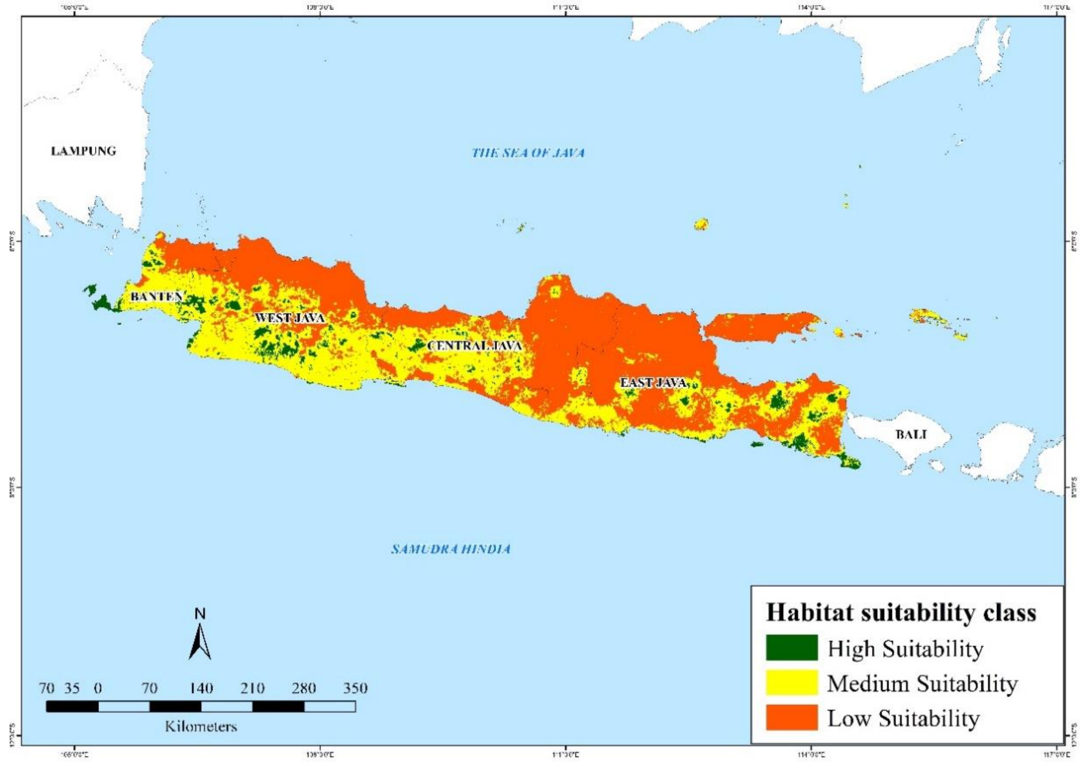


Figure 7. Map of Rhinoceros hornbill habitat suitability on Java Island.

The results of modeling hornbill habitat suitability on Java Island showed that suitable habitat for Rhinoceros hornbills on Java Island has the most minor proportion of area at 4.6%. The low area of suitable habitat for Rhinoceros hornbills indicates a severe threat to the preservation of Rhinoceros hornbills. Jarulis [5] revealed that the danger of hornbills in Indonesia is high. Therefore, it is necessary to increase hornbill conservation efforts to reduce and prevent the rate of hornbill extinction, especially Rhinoceros hornbills on Java Island. Therefore, this must be a concern for all parties, including the central government, local governments, and associated stakeholders, to preserve the Rhinoceros hornbill habitat on Java Island. Thus, policies such as making areas with high suitability levels into priority zones in habitat development and Rhinoceros hornbill protection are needed.

In addition, there needs to be a plan and action to restore forest and non-forest areas to become habitats for Rhinoceros hornbills on Java Island. Pramana et al. [32] stated that to conserve animals, there must be collaborative conservation efforts between various parties, including the government, area managers, and local communities. Therefore, cooperation from various related parties, such as the Ministry of Forestry and Environment, the relevant Regional Forestry Service, and related stakeholders who have concerns about hornbill conservation efforts must be carried out so that these plans and actions can be carried out effectively and efficiently.

Conclusion

The model processing results revealed that random forest produced a higher average accuracy of 0.74. Therefore, the random forest was the best algorithm that could be used in processing habitat suitability models. The environmental variables that were important to the Rhinoceros hornbill habitat suitability model on Java Island were distance from roads (16.62%), distance from forests (12.73%), and land cover (12.47%). High habitat suitability resulted in a small area of 6,213.76 km2 (4.6%). The small proportion of high habitat suitability indicates that this is a severe concern for policymakers and related stakeholders. Therefore, there is a need to plan to preserve the habitat and population of rhinoceros hornbills on Java. A critical step in conserving Rhinoceros hornbill habitats and populations is to protect habitats in areas with high suitability levels and to restore hornbill habitats in areas with low suitability levels.

The suggestion obtained from this study is the need for additional Rhinoceros hornbill distribution points to improve the resulting model. Additional distribution points were obtained through direct survey activities in the field. However, actions will require considerable costs and human resources, considering the vast area of Java. In addition, the algorithm used in this study can be applied to model hornbill habitat suitability on islands other than Java. Thus, it can determine the algorithm that produces the highest accuracy and also know the level of hornbill suitability other than on Java Island.

References

1. Kemp, A. *Bird Families of the World I: The Hornbills, Bucerotiformes*; Oxford University Press: Oxford, UK, 1995;
2. Mackinnon, J.; Phillips, K.; Balen, B.V. *Burung-Burung di Sumatera, Jawa, Bali, dan Kalimantan (Termasuk Sabah, Serawak, dan Brunei Darussalam)*; Burung Indonesia: Bogor, ID, 2010;
3. Sodik, M.; Pudyatmoko, S.; Yuwono, P.S.H.; Imron, M.A. Okupansi Kukang Jawa (*Nycticebus javanicus* E. Geoffroy 1812) di Hutan Tropis Dataran Rendah di Kemuning, Bejen, Temanggung, Jawa Tengah. *Jurnal Ilmu Lingkungan* **2019**, *13*, 15–27, doi:10.22146/jik.46141.
4. Pudyatmoko, S.; Djuwantoko; Sabarno, Y. Evidence of banteng (*Bos javanicus*) decline in Baluran National Park, Indonesia. *Journal of Biological Sciences* **2007**, *7*, 854–859, doi:10.3923/jbs.2007.854.859.
5. Jarulis. Karakteristik Marfologi dan Genetik Burung Rangkong (Aves: Bucerotidae) serta penyebarannya di Indonesia. Dissertation, Bogor Agricultural University, Bogor, ID, 2019.
6. Hidayat, R.Z.; Febriani, N. Pemodelan probabilitas sebaran habitat untuk menentukan kawasan prioritas konservasi burung rangkong gading (*Rhinoplax vigil*) di Geopark Silokek, Kabupaten Sijunjung. *Konservasi Hayati* **2021**, *1*, 35–43.
7. Cahyana, A.N. Pemodelan Spasial Kesesuaian Habitat Elang Jawa (*Nisaetus bartelsi* Stresemann, 1924) di Taman Nasional Gunung Halimun Salak. Thesis, Bogor Agricultural University, Bogor, ID, 2015.
8. Rais. Estimasi Data yang Hilang dengan menggunakan Proses Penyaringan dalam Pemodelan Data Time Series. *Jurnal Ilmiah Matematika Terapan* **2011**, *8*, 41–51, doi:10.22487/2540766X.2011.v8.i1.150.
9. Sinaga, A.; Muslim; Suseno, H. Pemodelan Distribusi Radionuklida di Muara Sungai Cisadane Perairan Teluk Jakarta Berdasarkan Data Radiologi dan Oseanografi. *Jurnal Oseanografi* **2015**, *4*, 713–717.
10. Barbet-Massin, M.; Jiguet, F.; Albert, C.H.; Thuiller, W. Selecting pseudo-absences for species distribution models: How, where and how many? *Methods in Ecology and Evolution* **2012**, *3*, 327–338, doi:10.1111/j.2041-210X.2011.00172.x.
11. Hastie, T.; Tibshirani, R.; Friedman, J. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*; 2nd ed.; Springer series in statistics New York: New York, USA, 2009; Volume 1.
12. Kutner, M.H.; Nachtsheim, C.J.; Neter, J.; Li, W. *Applied Linear Statistical Models*; 5th ed.; McGraw-Hill: New York, USA, 2005;

13. Franklin, J. *Mapping Species Distribution: Spatial Inference and Prediction*; Cambridge University Press: New York, USA, 2009;
14. Sunaryo, S.; Setiawan, S.; Siagian, T.H. 2015. Mengatasi Masalah Multikolinearitas dan Outlier dengan Pendekatan ROBPCA (Studi Kasus Analisis Regresi Angka Kematian Bayi di Jawa Timur). *Jurnal Matematika, Sains, dan Teknologi* **2015**, 12, 1–10.
15. Phillips, S.J.; Anderson, R.P.; Schapire, R.E. Maximum entropy modeling of species geographic distributions. *Ecological Modelling* **2006**, *190*, 231–259, doi:10.1016/j.ecolmodel.2005.03.026.
16. Hijmans, R.J.; Phillips, S.; Leathwick, J.; Elith, J. Dismo: Species Distribution Modeling. R Package Version 1.0-12. 2015. Available online: http://CRAN.R-project.org/package=dismo (accessed on 14 July 2021).
17. Cutler, D.R.; Edwards, J.T.C.; Beard, K.H.; Cutler, A.; Hess, K.T.; Gibson, J.; Lawler, J.J. Random forests for classification in ecology. *Ecology* **2007**, *88*, 2783–2792, doi:10.1890/07-0539.1.
18. Liaw, A.; Wiener, M. Classification and Regression by randomForest. *R News*. **2002**, *2*, 18–22.
19. Adhani, G.; Buono, A.; Faqih, A. Support Vector Regression Modelling for Rainfall Prediction in Dry Season Based on Southern Oscillation Index and NINO 3.4. In 2013 International Conference on Advanced Computer Science and Information Systems (ICACSIS), Sanur Bali, ID, 28–29 September 2013, pp. 315-320, doi: 10.1109/ICACSIS.2013.6761595.
20. Meyer, D. *Support Vector Machine, The Interface to Libsvm In Package E1071*; FH Technikum Wien: Austria, 2012;
21. Congalton, R.G.; Green, K. *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*; CRC Press, Inc: Florida, USA, 1999;
22. Condro, A.D. Dinamika Distribusi Spasial Primata: Perubahan Iklim dan Impilkasinya Terhadap Pengelolaan Konservasi. Thesis, Bogor Agricultural University, Bogor, ID, 2020.
23. Lobo, J.M.; Jimenez-Valverde, A.; Real, R. AUC: a misleading measure of the performance of predictive distribution models. *Global Ecology and Biogeography* **2008**, *17*, 145–151, doi:10.1111/j.1466-8238.2007.00358.x.
24. Duan, R.Y.; Kong, X.Q.; Huang, M.Y.; Fan, W.Y.; Wang, Z.G. The Predictive Performance and Stability of Six Species Distribution Models. *PLoS ONE* **2014**, *9*, e112764, doi:10.1371/journal.pone.0112764.
25. Allouche, O.; Tsoar, A.; Kadmon, R. Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). *Journal of Applied Ecology* **2006**, *43*, 1223–1232, doi:10.1111/j.1365-2664.2006.01214.x.
26. Cohen, J. A coefficient of agreement for nominal scales. *Educational and Psychological Measurement* **1960**, *20*, 37–46, doi:10.1177/001316446002000104.
27. Pearson, R.G.; Dawson, T.P. Predicting the impacts of climate change on the distribution of species: Are bioclimate envelope models useful? *Global Ecology and Biogeography* **2003**, *12*, 361–371, doi:10.1046/j.1466-822X.2003.00042.x.
28. Rahmat, U.M.; Santosa, Y.; Prasetyo, L.B.; Kartono, A.P. Pemodelan Kesesuaian Habitat Badak Jawa (*Rhinoceros sondaicus* Desmarest 1822) di Taman Nasional Ujung Kulon. *JMHT*. **2012**, *XVIII*, 129–137, doi: 10.7226/jtfm.18.2.129.
29. Pearson, R.G.; Raxworthy, C.J.; Nakamura, M.; Peterson, A.T. Predicting species distributions from small numbers of occurrence records: a test case using cryptic geckos in Madagascar. *Journal of Biogeography* **2007**, *34*, 102–117, doi: 10.1111/j.1365-2699.2006.01594.x.
30. Ghozali, I. *Aplikasi Analisis Multivarite dengan SPSS, Cetakan Keempat*; Badan Penerbit Universitas Diponegoro: Semarang, ID, 2009;
31. Nugraha, D.A. Distribusi, Wilayah Distribusi, Dan Pemodelan Habitat Gajah Sumatra (*Elephas maximus sumatranus* temminck 1847) di Lanskap Sumatra Bagian Tengah. Thesis, Universitas Gajah Mada, Yogyakarta, ID, 2019.
32. Pramana, G.T.S.; Prasetyo, L.B.; Iskandar, E. The habitat suitability modelling of dare monkey (*Macaca maura*) in Bantimurung Bulusaraung National Park, South Sulawesi. *Journal of Natural Resources and Environmental Management* **2023**, *13*, 57–67, doi:10.29244/jpsl.13.1.57–67.

33. Putri, A.; Kusrini, M.D.; Prasetyo, L.B. Pemodelan Kesesuaian Habitat Katak Serasah (*Leptobrachium Hasseltii* Tschudi 1838) dengan Sistem Informasi Geografis di Pulau Jawa. *Journal of Natural Resources and Environmental Management* **2019**, *10*, 12–24, doi: 10.29244/jpsl.10.1.12-24.
34. Wijaya, S.H.; Batubara, I.; Nishioka, T.; Ul-Amin, M.A.; Kanaya, S. Metabolomic Studies of Indonesian Jamu Medicienes: Prediction of Jamu Efficacy and Identification of Important Metabolites. *Molecular Informatics* **2017**, *36*, 1–15, doi:10.1002/minf.201700050.
35. Supriyadi, R.; Gata, W.; Maulidah, N.; Fauzi, A. Penerapan algoritma random forest untuk menentukan kualitas anggur merah. *Jurnal Ilmiah Ekonomi dan Bisnis* **2020**, *13*, 67–75.
36. Mercadier, M.; Lardy, J.P. Credit Spread Approximation and Improvement Using Random Forest Regression. *European Journal of Operational Research* **2019**, 277, 351–365.
37. Strobl, C.; Boulesteix, L.; Zeileis, A.; Hothorn, T. Bias in random forest variable importance measures: Illustrations, sources, and a solution. *BMC Bioinformatics* **2007**, *8*, 1–21, doi:10.1186/1471-2105-8-25.
38. Liang, H.; Guo, Z.; Wua, J.; Chena, Z. GDP spatialization in Ningbo City based on NPP/VIIRS night-time light and auxiliary data using random forest regression. *Advances in Space Research* **2020**, *65*, 481–493, doi:10.1016/j.asr.2019.09.035.
39. Hadiprakarsa, Y.; Kinnaird, M.F. Foraging characteristics of an assemblage of Four Sumatran hornbill species. *Bird Conservation International* **2005**, *14*, S53–S62.
40. Bibby, C.; Jones, M.; Marsden, S. *Survei Burung*; SMKG Mardi Yuana: Bogor, ID, 2000;
41. Berg, C.C.; Corner, E.J. *Flora Malesiana – Series 1*; Nationaal Herbarium Nederland: Netherland, 2005; Volume 17, pp. 1–702.
42. Hadiprakarsa, Y. Forest patch occupancy by sumatran hornbills in a fragmented landscape of southern sumatran, Indonesia. Thesis, The University of Georgia, Georgia, USA, 2008;
43. Johns, A.D. The use primary and selectively logged rainforest by Malaysian Hornbills (Bucerotidae) and Implications for their Conservation. *Biological Conservation* **1988**, *40*, 179–190.
44. Kubangun, S.H.; Haridjaja, O.; Gandasasmita, K. Model perubahan penutupan/ penggunaan lahan untuk identifikasi lahan kritis di Kabupaten Bogor, Kabupaten Cianjur, dan Kabupaten Sukabumi. *Majalah Ilmiah Globe* **2016**, *18*, 21–32.
45. Kinnaird, M.F.; O'Brien, T.G. Fast foods of the forest: the influence of figs on primates and hornbills across Wallace's Line. In *Tropical Fruit and Frugivores: The Search for Strong Interactions*; Dew, J.L., Boubli, J.P., Eds.; Zoological Society of San Diego: San Diego, USA, 2005; pp. 155–184.
46. Kamal, S.; Agustina, E.; Azhari. Populasi rangkong papan (*Buceros bicornis*) di ekosistem Tahura Pocut Meurah Intan Provinsi Aceh. *Jurnal Biologi* **2018**, *14*, 10–19.
47. Trainor, C.; Lesmana, D.; Gatur, A. *Importance of forest in The West Side of Timor land-First Study of Biodiversity and Socio-economic Information in Timor island of Nusa Tenggara Timur*; PKA/Birdlife International/WWF: Bogor, ID, 2000;
48. Departemen Kehutanan. *Pedoman Inventarisasi dan Identifikasi Lahan Kritis Mangrove*; Departemen Kehutanan Direktorat Jenderal Rehabilitasi Lahan dan Perhutanan Sosial: Jakarta, ID, 2005;
49. Rahman, H. Spatial Assessment of Landscape Structure Changes an Ecological Connectivity in Pariaman. *Journal of Remote Sensing GIS dan Technology* **2020**, *6*, 10–22.
50. Anggriawan, V.; Hariyadi, B.; Muswita. Keanekaragaman jenis rangkong dan tumbuhan pakannya di Harapan Rainforest Jambi. *Biospecies* **2015**, *8*, 73–79.
51. Hidayat, R.A.; Febriani, N.; Hanif, M.; Rahman, H. Modeling of conservation priority the Helmeted Hornbill (*Rhinoplax vigil*) in Silokek Geopark Area, West Sumatera. *Preprints* **2020**, 2020090676. doi:10.20944/preprints202009.0676.v1.
52. Kumara, I. Karakteristik Spasial Habitat Burung Rangkong di Taman Nasional Danau Sentarum. Thesis, Bogor Agricultural University, Bogor, ID, 2006.
53. Syechalad; Muhammad, N. *Perkebunan dalam Kajian Sosial Ekonomi*; Yayasan PENA: Banda Aceh, ID, 2009;
54. Datta, A. Hornbill abundance in unlogged forest, selectively logged forest, and a forest plantation in Arunachal Pradesh, India. *Oryx* **1998**, *32*, 285–294.