BIODIVERSITAS
Volume 19, Number 4, July 2018
Pages: 1539-1551

ISSN: 1412-033X
E-ISSN: 2085-4722
DOI: 10.13057/biodiv/d190447

Modeling the predicted suitable habitat distribution of Javan hawk-eagle *Nisaetus bartelsi* in the Java Island, Indonesia

ILYAS NURSAMSI[1], RUHYAT PARTASASMITA[2,♥], NURVITA CUNDANINGSIH[1], HASNA SILMI RAMADHANI[1]

[1]Bird Conservation Society (BICONS). Bandung 40184, West Java, Indonesia.
[2]Department of Biology, Faculty of Mathematics and Natural Sciences, Universitas Padjadjaran. Jl. Raya Bandung-Sumedang Km 21, Jatinangor, Sumedang 45363, West Java, Indonesia. Tel.: +62-22-7796412, ♥email: rp2010rikkyo@gmail.com; ruhyat.partasasmita@unpad.ac.id

Manuscript received: 28 October 2017. Revision accepted: 24 July 2018.

Abstract. *Nursamsi I, Partasasmita R, Cundaningsih N, Ramadhani HS. 2018. Modeling the predicted suitable habitat distribution of Javan hawk-eagle* Nisaetus bartelsi *in the Java Island, Indonesia. Biodiversitas 19: 1539-1551.* Javan hawk-eagle (*Nisaetus bartelsi*) is an endemic raptor of Java Island. The conservation status of Javan hawk-eagle (JHE) according to IUCN is endangered (EN) and included in CITES Appendix II list, and this species is also protected by the Indonesian government law based on act no. 5, year 1990. The position of Javan hawk-eagle as a top predator is now very threatened by habitat fragmentation, wildlife trade, and the declining quality of its habitat. The primary purpose of this study was to give preliminary information about the distribution of predicted suitable habitat for JHE as a means of finding potential releasing sites, as an evaluation for habitat protection, and even as an option for the development of new JHE protected areas. However, mapping the spatial distribution of potential habitat for JHE using terrestrial survey is problematic because it requires enormous time, fund, and human resources. The most possible approach is by using Ecological Niche Modeling (ENM)/species distribution modeling (SDM). In this study, modeling exercise was conducted by using a maximum entropy method as an adaptation from Maxent software ver. 3.4.1, with the utilization of JHE-nest coordinate data and 16 environmental variables datasets as the main input. The predicted suitable habitat distribution map has shown a good match with historical and present records of JHE and has fairly succeeded in capturing a wide range of habitat patches from tiny spots to quite large suitable habitat. Modeling results also showed that altitude, annual mean temperature, and two types of land cover (closed shrub, and forest area) are considered to be most important variables affecting the distribution of potential habitat for JHE. Moreover, about 17.77% (23,209 km^2) area of Java Island has been projected to be suitable for Havan Hawk-Eagle's habitat, which mostly spread in mountainous areas while also appear in several lowland areas. This study suggests the importance of topographic, climatic, and land cover as pivotal predictors in determining the suitability of habitat for JHE. This study also shows that the modeling results have a good match with the historical records of JHE across the island, which suggests the overall accuracy of the model.

Keywords: Distribution habitat modelling, ecological niche modelling, Javan hawk-eagle, maximum entropy, *Nisaetus bartelsi*

INTRODUCTION

Biogeographic regions with a significant reservoir of biodiversity, known by the term “biodiversity hotspots," cover only 2.3% of the earth’s land surface but host 42% of the world’s vertebrates (Jha and Bawa 2006). Currently, none of these hotspots have more than one-third of its pristine habitat left, and all these whole regions face deforestation threat caused by human population growth and development; this pressure being exceptionally high in the tropical regions (Brooks et al. 2002). The tropical rainforests in Sundaland are part of the biodiversity hotspot. Sundaland is one part of the country of Indonesia with a high diversity of bird species, with the highest rates of deforestation in East Asia (Giam et al. 2011). The high biodiversity in Java is concentrated only in certain areas, and this is because it is strongly influenced by the extreme population growth and deforestation (Miettinen et al. 2011; Partasasmita 2009; Safana et al. 2018).

The response of species in areas threatened by deforestation is important to know (John and Skorupa 1987). While some species may be able to positively adapt to landscape changes made by human (Sodhi et al. 2010; Partasasmita et al. 2009), for most, the landscape changes that lead to decreased quality of habitat adversely affect the survival of the species (Fahrig 2007). In the effort to develop a conservation plan for the species threatened by deforestation and changes in habitat quality, the collection of data on their habitat preferences, as well as the availability of suitable habitats in an area, is vital (John and Skopura 1987). Conservation methods to assess the suitability of habitat for the species has grown to be able to build a model which relates species distribution to environmental characteristics (Guisan et al. 2006). The model could be a useful tool in the selection of protected areas for maximizing biodiversity conservation (Rodriguez et al. 2007).

Javan hawk-eagle (*Nisaetus bartelsi*) is an endemic raptor of Java Island which is currently severely threatened by both wildlife trade and habitat loss. Javan hawk-eagle (JHE) became one of the most endangered raptors in Indonesia (Rakhman 2012; Partasasmita et al. 2016);

consequently, Javan hawk-eagles are classified as 'Endangered' (EN) on the IUCN Red List and listed in Appendix II of CITES. Despite Javan hawk-eagles facing a severe threat to its existence, our knowledge of their habitat preferences and the distribution of its habitats in Java Island is limited. Various attempts to mapping the habitat distribution of Javan hawk-eagles habitats were limited only to recording occupied habitat; therefore data about habitat suitability for Javan hawk-eagle are often neglected. However, collecting these data through direct field surveys will require enormous human resources, funding, and time, then a different approach is needed.

In the last few decades, attention toward understanding the characteristics of preferred habitat of certain species and the distribution of potentially suitable habitat leads to a marked increase of interest in the use of Ecological Niche Modeling (ENM) (Merow et al. 2013; Fourcade et al. 2014). ENM, also known as Species Distribution Modeling (SDM), which was developed in the mid-1980 (Booth et al. 2014), comprehensively involving the utilization of statistic, ecology, Geographic Information System (GIS), and even Remote Sensing (RS) to develop estimation of suitable niche for species across predefined landscapes (Franklin and Miller 2009), while also can be extrapolated through different space and time (Guissan and Thuiller 2005; Elith and Leathwick 2009; Franklind and Miller 2009). This modeling will be useful for JHE conservation efforts as a means of finding potential releasing sites, as an evaluation for habitat protection, and even as an option for the development of new JHE protected areas.

Such modeling can be conducted using a variety of alternatives, including heuristic models (e.g., BIOCLIM—Beaumont and Hughes 2007), combinatorial optimization (e.g. GARP-Fitzpatrick et al. 2007), statistical models (e.g. GAMs-Jensen et al. 2008), and machine learning (e.g. ANN— Ostendorf et al. 2001; Berry et al. 2002; Harrison et al. 2006; MAXENT—Phillips et al. 2006) (Sinclair et al. 2010). Each of these approaches, indeed, has their advantages and disadvantages. Nevertheless, one of the most growing approaches of ENM is through the use of Maximum Entropy (Maxent) algorithms (Belgacem and Louhaichi 2013). Maxent modeling has a high potential for identifying distributions and habitat selection of wildlife given its reliance on only presence locations and has shown higher predictive accuracy than many other methods (Phillips et al. 2006; Baldwin 2009; Franklin and Miller 2009; Elith and Frankling 2013; Peterson et al. 2011; Remya et al. 2015). Being a general-purpose machine learning method, Maxent offers a precise and straight forward mathematical formulation to characterize probability distribution across a user-defined landscape (Phillips et al. 2006; Merow et al. 2013). Maxent is a software package which was developed for ENM/SDM given presence-only species records (without the need of absence data) and a "background" sample of environments in the region of interest (Phillips et al. 2006; Phillips and Dudık 2008). Therefore, we refer to this type of data requirements as "Presence-Background" (PB) data.

In general, Maxent works by applying the maximum entropy principle (Jaynes 1957) to fit the model so that the estimated distribution diverges from a uniform distribution as minimally as required to explain the observations (Guillera-Arroita 2014). Elith et al. (2011) have explained this software intuitively from a statistical point of view by looking at the environmental domain, even though the algorithm within this software works in geographic space (Philips et al. 2006). Herewith, we try to follow this interpretation to explain this software briefly. PB data are used to obtain a set of environmental characteristics at the presence site of species and at background location of study (which are a regular or random sample of the landscape or could be intended to match the recognized biases in the sampling process). Otherwise stated, Maxent examines the ratio of f_1/f, where f_1 is the probability distribution defining the characteristic of sites wherein the species occurs, and f is the probability distribution depicting the environmental attributes of the sites wherein the species is absent ($y = 0$) and present ($y = 1$). This ratio corresponds to the probability of presence given the environmental covariates z, thus $\Pr(y = 1|z) = \psi(z)$, but the scaling factor (the prevalence of the species over the landscape, $\Pr(y = 1) = \bar{\Psi}$) cannot be identified from PB data only (Elith et al. 2011; Hatic and Fithian 2013; Phillips and Elith 2013; Guillera-Arroita 2014). The simple output or the '*raw output*' of Maxent is the estimate of f_1/f scaled to sum to 1 over the fitted background and representing the probability distribution over sites x, given the species exist at site x; $\Pr(x|y = 1)$ (Phillips et al. 2006). Therefore, as currently implemented, that raw output represents $\psi(z)/(n.\bar{\Psi})$, where n is the total number of points in the background sample. Nonetheless, the raw output only represents relative suitability, as it is proportional to inhabitancy probabilities by a factor that is not identifiable without external data (Guillera-Arroita 2014).

With the purpose of estimating the ratio f_1/f, Maxent fits an exponential model so that $\log(f_1/f) = \eta(z)$, where $\eta(z)$ is a linear term of a set of features. Features, which in Maxent can belong to six classes (i.e., linear, product, quadratic, hinge, threshold, and categorical), represent a broaden set of transformations of the covariates (Phillips and Dudik 2008). Moreover, features offer a great flexibility to fit complex environmental relationship, and Maxent utilizes regulation to control the trade-off between model complexity and model fit as a means to avoid overfitting (Guillera-Arroita 2014). Nevertheless, instead of working with Maxent's "raw output," it is more common for users to work with "logistic output." Using a logistic transformation which based on a user-specified parameter 'tau,' this output scales the raw values into a scale of relative suitability ranging between 0 and 1 (Elith et al. 2011). This parameter is the prevalence for sites with 'average' environmental conditions under f_1 and by default is set to an arbitrary value ($\tau = 0.5$) (Elith et al. 2011). Therefore, the output represents the probability of the species occurs on each location/sites or can be interpreted as a probability of suitable habitat for the species based on the environmental variables included in the model.

This study was then conducted as an attempt to model the distribution of potential habitat for JHE across the Java Island, while also tried to understand the environmental characteristics of preferred habitat based on the available environmental variables. Climatic, topographic, Land use/ Land cover, and NDVI are variables used as predictors in determining the distribution of potential habitat suitability.

MATERIALS AND METHODS

Study sites

This study was carried out in Java Island which has been known as one of the 25 identified biodiversity hotspots by Myers et al. (2000), overlapped with the four closest biologically richest hotspots such as Indo-Burma, Peninsular Malaysia, Wallacea, and The Philippines. The field survey was conducted from February until December 2016 at nineteen locations across the Island, that we considered being representative of the niche breadth of the JHE based on reports from Sözer and Nijman (1924), Setiadi et al. (2000), and Prawiradilaga (2006). Field data collection was conducted to collect coordinate points of every JHE's nesting sites that were observed.

Java Island has approximately 133,930 km^2 of land area, with its altitude ranges from 0 m asl to about 3,676 m asl (meter above sea level). All of the locality points were collected both in the lowland and highland areas of Java. This island, like other areas in the equatorial zone, has only two seasons: wet season (during October-April) and Dry Season (during May-September). Java Island has a wide range of precipitation divided into different categories of the area. The western region of Java (Banten and West Java Provinces) and Central region of Java (Central Java and Special Region of Yogyakarta) have the same average rainfall at about 2,000 mm per year, but in some mountainous areas in western Java the number could reach up to 3,000-5,000 mm per year. Eastern area of Java, compared to the western region, has a less rate of precipitation at about 1900 mm per year (Qian et al. 2010). Likewise, the average temperature in Java can be ranged differently according to its altitude feature. Coastal areas have average temperature between 22^{0}C and 32^{0}C, while in higher areas with an altitude of between 400 and 1350 m asl, the average temperature ranges between 18^{0}C and 29^{0}C. Higher altitude generally means a lower range of temperature, in this case, the lowest temperature in Java Island can reach minus 4^{0}C which was recorded in Ranu Pani area (slopes of Mount Semeru) (Hariyati et al. 2013).

Procedures

Field data collection

Occurrence points of JHE were compiled from two primary sources, i.e., field survey and historical database. Field survey, aiming to collect the locality data of JHE's nest coordinates, was conducted by visiting sites mentioned above accompanied by local ornithologist or student who acknowledged the exact location of JHE's nest. The observation was conducted at a safe distance of about 50-70 meters from the nest-tree of the bird, and coordinates were taken using GPS handheld receiver (Garmin© eTrex 30). To determine the exact coordinate of the nest, we recorded the direction from observation point to the nest tree using a compass (Suunto© A-10 NH) and the distance between the nest tree and the observation point we took. These data were then used to adjust the position recorded at the observation point to the nest point using QuantumGIS ver 2.6 software. A total of 31 occurrence points were collected during this field survey.

The second source of occurrence points were collected from the Global Biodiversity Information Facility (GBIF 2017) database, which provides freely accessible occurrence points in its website (http://www.gbif.org) and birdlife database (http://www.birdlife.org/datazone/speciesfactsheet). From these databases, we collected occurrence points that were recorded no older than 2010 and recorded by human observation (not specimen records). All of the occurrence points were then carefully verified, and errors that may occur were corrected using Google Earth software (Google Earth Pro 2017). Indeed, strong geographic sampling biases may often present in such database which were derived

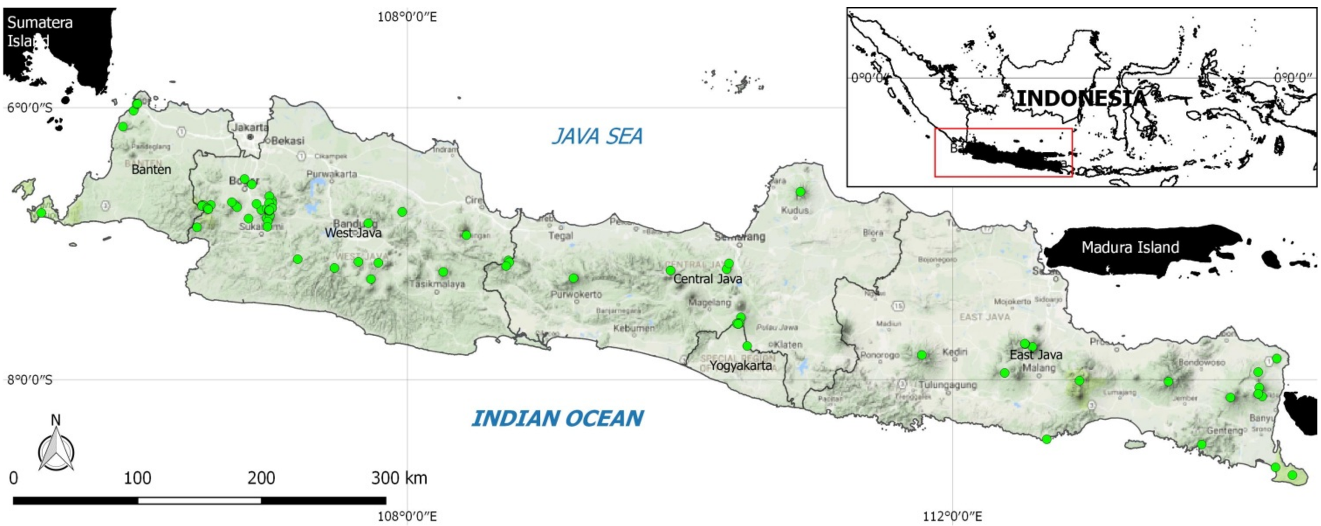


Figure 1. Study site and survey location of *N. bartelsi* across Java Island: Green points are surveyed locations. (Base map: Google Physical Maps, 2014)

from opportunistic observation and collection of records (Stolar and Nielsen 2014). Therefore, sampling bias correction is highly important and strongly advised to be conducted to minimize its strong influence on modeling prediction ability and later interpretation (Fourcade et al. 2013; Kramer-schadt et al. 2013; Fourcade et al. 2014). In their study, Fourcade et al. (2014) explained four types of biases that might be contained in such datasets, and then proposed five option methods of sampling bias correction which were carefully designed to overcome or minimize the effect of those biases. Subsequently, after identifying the type of sampling data biases contained in our occurrence data, we conducted two out of five sampling bias correction methods, i.e., (i) spatial filtering, performed by creating a grid of 3 km x 3 km cell size and randomly select only one point of occurrence per grid cell. Nonetheless, it should be noted that the size of this grid is not the representation of approximate species' dispersal capabilities, but rather as a result of modifying the 10-km radius rule of spatial filtering proposed by Kramer-Schadt et al. (2013) and Boria et al. (2014). The grid creation and point selections were conducted using QuantumGIS software ver. 2.18.14 (QGIS Development Team 2017). ii) Bias file creation, bias file is a probability surface represented by cell value which reflects the intensity of sampling effort across the area of study and gives a gradual weight to random background data used for modeling (Fourcade et al. 2014). Bias file can be artificially estimated using the aggregation of occurrences from closely related species (Phillips et al. 2009). However, in the real situation, this information is limited. Therefore, by following Elith et al. (2010), we produced a Gaussian kernel density map of the occurrence locations then rescaled it from 1 to 20 to be derived as bias file, instead of using our knowledge to create artificial bias file (Fourcade et al. 2014). This bias file was then included into Maxent modeling process through setting options (Dudik et al. 2005; Elith et al. 2010; Phillips et al. 2017). The remaining 17 points were then compiled with the occurrence points from the field survey to be used as input data.

Table 1. Climate and environmental variables used to build the models

Code	Name	Unit
Alt	Altitude	m asl
bio_1	Annual Mean Temperature	^{0}C×10
bio_2	Mean Diurnal Range	^{0}C×10
bio_3	Isothermality□	×100
bio_4	Temperature Seasonality	×100
bio_12	Annual Precipitation	mm
bio_13	Precipitation of Wettest Month	mm
bio_15	Precipitation Seasonality	mm
bio_18	Precipitation of Warmest Quarter	mm
bio_19	Precipitation of Coldest Quarter	mm
LandCover_Java	Land Cover in Java Island 2016	
broadleafjava	Broadleaf forest coverage	
Evergreenjava	Evergreen forest coverage	
Deciduousjava	Deciduous forest coverage	
treecoverjava	Tree coverage	
ndvi_all	Averaged annual NDVI value	

Environmental variables data collection and Maxent modelling

We selected the environmental variables in this study on the basis of earlier screenings of related variables expected to influence the existence of species (e.g., Prawiradilaga 2006; Syartinilia and Tsuyuki 2008; Fernandez and Gurrutxaga 2010; Sohl 2014; Ferrer-Sanchez and Rodriguez-estrella 2016). Environment variables datasets collected to be used in this study amounted to 26 variables which included nineteen Bioclimate layers, altitude, land cover data, NDVI, and forest coverage data in Java Island. Bioclimate data were extracted from WorldClim Bioclimate datasets ver. 2.0 that provides 19 climatic variables that were interpolated and modeled from observations and averaged over the period 1970 until 2000 at one km^2 resolution (http://www.worldclim.org). Elevation data was also acquired from the WorldClim database. The Normalized Difference Vegetation Index (NDVI) is an index of plant "greenness" or photosynthetic activity from satellite imagery instruments (http://earthobservatory.nasa.gov) and also used to analyze the density of vegetation and to separate the healthy vegetation and unhealthy or sparse vegetation (Devadas 2008; Genc et al. 2008; Szilárd et al. 2016). An average of annual NDVI data value was extracted from the SPOT-vegetation platform at 1 km^2 resolution (http://free.vgt.vito.be). Java Island land cover in 2016 was obtained from http://glcf.umd.edu/data/lc/. Forest coverage data were acquired from http://glcf.umd.edu/data/vcf/which consist of 4 types of forest coverage data, i.e., Evergreen forest coverage, Deciduous forest coverage, broadleaf forest coverage, and tree coverage data generally in Java. All of these layers were processed through several steps including resampling data, image cutting, and type file converting by using Qgis Software ver. 2.18.14 (QGIS 2017).

It has been proved that the high inter-dependency among the bioclimatic variables gives a raise to the issue of redundancy and multicollinearity (Bedia et al. 2012). Even though neglecting this multi-collinearity issue will not affect the predictive quality of the model significantly (Elith et al. 2011), it does, however, negatively affecting model interpretability, limiting any inference of the contribution of any correlated variables, and also hampering the ability of the model for extrapolation (Brauner and Shacham 1998; Van Gils et al. 2012, 2014). Consequently, we omitted the bioclimatic variables yielding correlation values above 0.95 (Spearman's rho coefficient) in the pairwise cross-correlation matrix of each dataset (intra-dataset correlations) (Bedia et al. 2013). SDM toolbox ver. 2.0 (Brown 2014) in ArcGIS ver.10.3 was used to perform the calculation and automatically removed each one of the two correlated variables. Finally, the remaining nine bioclimatic variables along with altitude, NDVI, Land cover, and Forest coverage layers were then compiled to be used as predictor variables in this study (table 1). Supplementary table on land cover class and its code representation could be found here (http://glcf.umd.edu/data/lc/).

Maxent modelling

Modeling exercise in this study was conducted using Maxent software ver. 3.4.1 (Phillips et al. 2017). Maxent has been proved to provide better results than other modeling algorithms with the basis of presence-only data (PO) and environmental variables (Philips and Dudik 2008; Summers et al. 2012). The popularization of Maxent is also due to its higher predictive accuracy than any other methods (Elith et al. 2006; Summers et al. 2012), with more than 1000 published studies using this software since 2005 (Merow et al. 2013; Fourcade et al. 2014). Furthermore, Maxent also offers a wide variety of setting options which will be different in each case and occasionally requires species-specific settings (Merow et al. 2013). Therefore, in this study, we tried to ensure that the setting options were adjusted to our specific study aims, hypothesis, and our intended a priori assumptions (Peterson et al. 2011; Araujo and Peterson 2012; Merow et al. 2013). The adjusted parameters were : (i) maximum iterations was set to 5,000 for each run to allow the model to have adequate time for converging, (ii) Convergence threshold was set to 1×10^{-6}, (iii) The model calculation was set to ten times (the averaged value was the one used as the result) using "cross-validate" as the replicated run type. Using "cross-validate" means to split the data ten times (10% per partition) then train the model ten times on 90% of the data, while testing it each time on the 10% partition alternately. To avoid over-fitting and to assume that the species responds directly to the predictors (vs. to correlated factors), we decided to "smooth" the model by choosing only hinge features (Elith et al. 2010). Furthermore, we doubled the "regularization multiplier" to reduce over-fitting to a lower level (Radosavljevic and Anderson 2013).

Data analysis

One of the main outputs of Maxent is a predictive map representing the distribution of potentially suitable habitat for the species. The degrees of predicted suitable habitat are linearly scaled from 0 (lowest) to 1 (highest) probability (Philips and Dudik 2008). Additionally, Maxent also calculated the variables' relative contribution to the model and how these variables affect the prediction. Alternate estimation of variable importance was also collected by running the jackknife test. The results of the jackknife test show which variable have the most useful information by itself and which variable appears to have the most information that is not present in other variables (Phillips et al. 2009). The predictive maps, which by default are in ASCII format, were further analyzed using QuantumGIS software ver. 2.18.14 (QGIS Development Team 2017). To allow us to quantify the geographical distribution of predicted suitable habitat, we applied binary calculation and categorizing the values into two categories (i.e., suitable and unsuitable) using the selected threshold rule in the setting option of Maxent. Selecting the threshold rule, indeed, is one of the many sources of bias that should be minimized by Maxent user (Phillips and Dudik 2008; Nenzen and Araujo 2011; Bean et al. 2012; Syfert et al. 2013). Selecting threshold rule should incorporate consideration of relative importance difference between commission error and omission error (Phillips and Dudik 2008; Nenzen and Araujo 2011; Bean et al. 2012; Syfert et al. 2013). Considering that reducing omission error is more important determinant than reducing commission error, Norris (2014) proposed “minimum training presence” or “fixed cumulative value 1” as the most appropriate rule. Liu et al. (2016) in their study also supporting those proposed threshold rule as appropriate for modeling a rare species. Therefore, we selected “minimum training presence” threshold rule to be used in this study. The predicted suitable habitat was then reclassified into three classes: low suitability (25 - 50% probability of occurrence), medium suitability, (51 - 75% probability of occurrence), and high suitability (>75% probability of occurrence), by using the "natural breaks (Jenks) classification method in Reclassify Analysis of ArcMap ver. 10.3.

Maxent will calculate an Area Under the receiver operating characteristic (ROC) Curve (AUC) to evaluate the model performance. AUC value ranges between 0 (lowest) and 1 (highest), whereby value from 0 to 0.5 represents that the model is no better than just random prediction, value below 0.7 is low, value between 0.7 and 0.9 is good, and value above 0.9 indicates high discrimination or indicates that the model is far better than random prediction (Araujo et al. 2005). Despite having been proved that AUC does not necessarily provide useful information to assess and/or to evaluate the model performance (Lobo et al. 2008; Bahn and McGill 2013; Aguirre-Gutiérrez et al. 2013), we reported it to illustrate that the predictions in this study perform better than any model with a set of random predictors. Additionally, we conducted True Skill Statistic (TSS) (also known as the Youden index) calculation as an additional measurement to evaluate the performance of the model by calculating the summary of sensitivity and specificity minus one (Youden 1950; Allouche et al. 2006). Several studies have also demonstrated the use of Kappa statistic as a post-hoc evaluation for the Maxent model (e.g., Duan et al. 2014; Ali and Hossein 2016; Bagheri et al. 2017). However, Kappa value is highly correlated to the prevalence of the locality points and the size of the study area which would generate some bias or misunderstanding (Lobo et al. 2008; Fourcade et al. 2017). Moreover, due to the fact that both AUC and Kappa are weighting commission and omission errors equally (Allouche et al. 2006; Lobo et al. 2008; Jimenez-Valverde 2012, 2014; Fourcade et al. 2017), Kappa, just like AUC, is more reliable if it is applied in PA (Presence-Absence) model. Consequently, in case of this study where presence only data were used, we assume that the use of TSS is more suitable than the Kappa statistic.

RESULTS AND DISCUSSION

Identifying important environmental variables and model evaluation

We generated the predicted distribution of potentially suitable habitat for JHE based on observed nest locations compounded with sixteen climatic and environmental variables. According to the calculation of the relative contributions of environmental variables to the Maxent model, there were three variables considered to have the most contribution to the model. These variables are representative of all major aspects of environmental variables included in the model, i.e., altitude (alt), Annual mean temperature (bio_1), and land cover, accounting for 58.6%, 21.6%, and 6.4%, contribution to the final result of the prediction, respectively (Table 2). The cumulative contributions of these variables contributed in a total of 86.6% to the model, whereas the remaining variables, each contributed less than 5% to the model, suggesting that the suitability of habitat for JHE are strongly influenced by the altitudinal factor, average temperature, and types of land cover in the area.

Additionally, we retrieved the alternate estimation of variable importance through the utilization of the jackknife test. The results showed that for the model, the environmental factor with the highest gain when used in isolation is annual mean temperature and altitude, which means that these variables appear to have the most useful information by itself (Phillips et al. 2008). Furthermore, temperature seasonality (bio_4) variable seemed to have the most unique information that is not present in the other variables as, according to the test, omitting this variable will reduce the regularized training gain the most (Phillips et al. 2008).

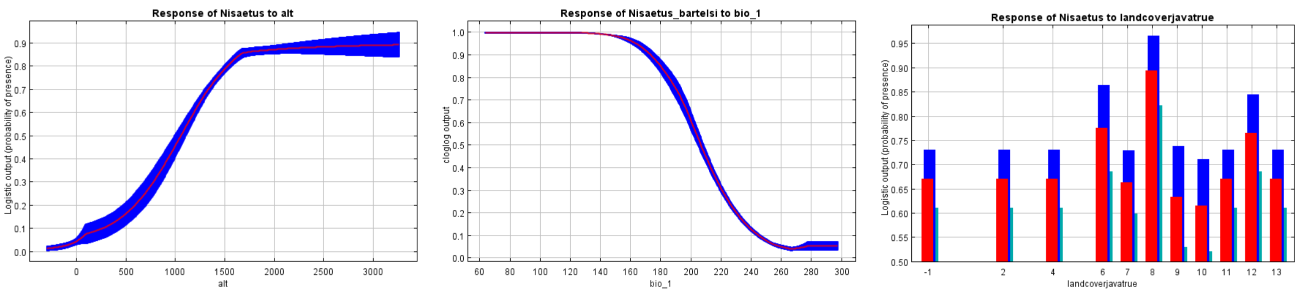
A *post-hoc* evaluation of ecological niche modeling is commonly performed to assess the statistical significance and the predictive performance of the model, before being used or interpreted in any procedure (Peterson et al. 2011). The Area Under the receiver operating characteristic (ROC) Curve (AUC) value may have been highlighted; it can be misleading and may poorly reflect the model accuracy (Lobo et al. 2008; Peterson et al. 2008; Jimenez-Valverde et al. 2013; Fourcade et al. 2014). Nevertheless, we retrieved the AUC value of 0.893 to indicate that the model built in this study performs better than any model with a set of random predictors, and to show the discrimination ability of the model (Lobo et al. 2008; Peterson et al. 2008; Jimenez-Valverde 2012, 2014; Fourcade et al. 2017). Furthermore, an additional evaluation of the model was conducted by calculating the True Skill Statistic (TSS) value. By calculating the summary of sensitivity and specificity minus one, we retrieved a TSS value of 0.87 for the model. This value, which is above 0.70, gives the impression that the model built for this study have a good degree of agreement, good predictive capacity, and also can be interpreted as preliminary evidence for the real ecological phenomenon, based on the environmental variables being used, rather than just statistical artifacts (Allouche et al. 2006; Li and Guo 2013).

The relationship between the models and the dominant environmental variables

In this study, we presented the response curves to illustrate how each of the prevailing environmental variables affects the model prediction. We used the response curve which represents model created using only the corresponding variable to reflect the dependence of predicted suitability both on the selected variable and on dependencies induced by the correlation between the selected variable and other variables (Phillips et al. 2008). The relationship between probability of presence and altitude (alt) (Figure 2.A) depicted that the probability of presence increased gradually along with the increase of altitude, reach above the 50% of probability of presence at the altitude of 1,200 m asl and reached its peak

Table 2. Percentages of variables contributing to the final model

Environmental variables	Contribution (%)
Altitude	58.6
Annual Mean Temperature	21.6
Land Cover	6.4
Temperature Seasonality	5
Broadleaf forest coverage	2.8
Ishotermality	2.3
Mean Diurnal Range	1
Precipitation of Coldest Quarter	0.7
Averaged annual NDVI value	0.4
Evergreen forest coverage	0.4
Tree coverage	0.3
Precipitation of Warmest Quarter	0.2
Annual Precipitation	0.1
Precipitation Seasonality	0.1
Precipitation of Wettest Month	0
Deciduous forest coverage	0



A B C

Figure 2. Response curves from Maxent for the most important variables for the species distribution model of JHE. A. Response curve for altitude variable in m asl (meters above sea level; B. Response curve for Annual Mean Temperature in ^{0}C*10; C. Response curve for land cover variable with every category represented by numbers

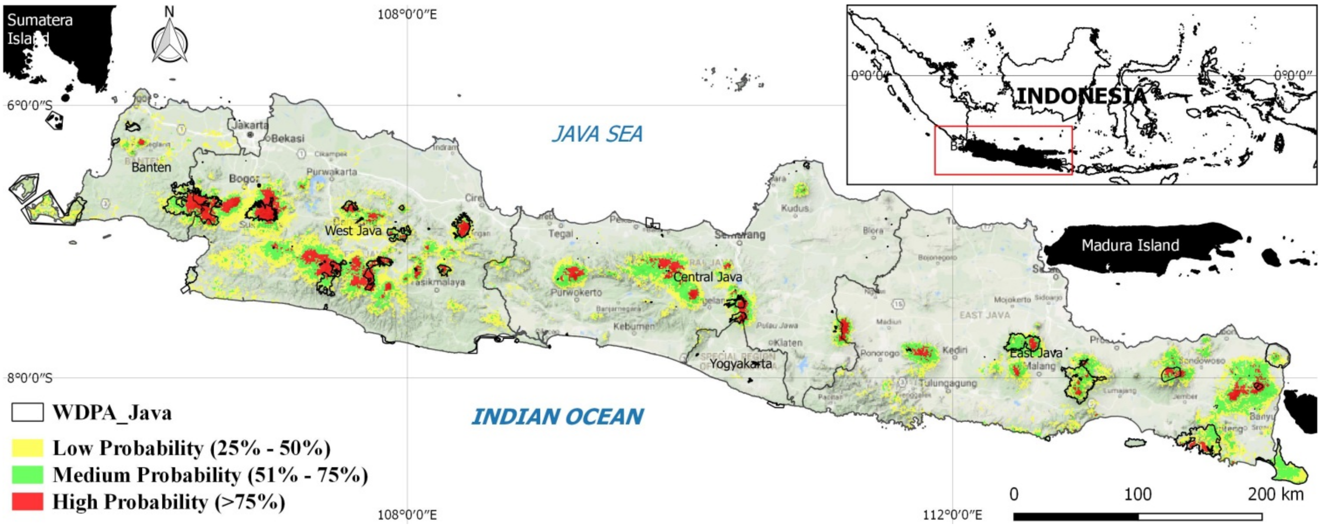


Figure 2. Predicted distribution of potential habitat for Javan hawk-eagle in across Java Island, indonesia (Base map: Google Physical Maps 2014)

(probability of presence = >90%) at the altitude of about 1800 m asl. Thus, it can be expected that the optimum altitude for JHE's habitat is at above 1,800 m asl. The annual mean temperature (bio_1) was another critical variable that affected the suitability of habitat for JHE (Figure 2.B). The curve shows that there was a negative correlation between the probability of presence and the average temperature, presenting that the probability of presence decreased with the increase of average temperature, wherein the lowest probability of presence occurred at the temperature above 24^0C. Regarding the land cover in Java Island, the response curve depict that forest area (no 8 in Figure 2.C) and closed shrubland (no. 6 in Figure 2.C) as having the most probability of species presence, with the probability value of 0.90 and 0.87, respectively.

Predicted distribution of potential suitable habitat for JHE

Projected distribution of predicted suitable habitat for JHE under current climate and environmental condition is shown in Figure 2. Subsequent to categorizing the output into two categories (suitable vs unsuitable) using the aforementioned threshold rule (see method), the predicted suitable habitat were then reclassified into three classes: low suitability (25-50% probability of occurrence), medium suitability (51-75% probability of occurrence), and high suitability (>75% probability of occurrence) to allow us to compare the changes in every class of probability under future climate projection. According to the result, about 17.77% (23,209 km^2) area of Java Island has been projected to be suitable for the JHE's habitat. The number consisted of 9.31% (12,163 km^2), 5.81% (7,585 km^2), and 2.65% (3,461 km^2) of low, medium, and high probability areas, respectively (Figure 2).

The predicted suitable habitat distributed mainly on the mountainous areas of Java Island. Nonetheless, the surrounding lowland areas also predicted to be suitable as JHE's habitat, despite mostly predicted to have low probabilities of presence. Altitudinally, the low probability areas were mainly distributed in lowland areas at the altitude of between 200 and 1100 m asl, whereas medium probability areas were mainly distributed at altitude of between 1100 and 1500 m asl. Furthermore, the models predicted that the high probability areas were mainly distributed in the highland region at the altitude of above 1500 m asl (Figure 3).

Discussion

This study represents an attempt to model the distribution of potential habitat for JHE across the island while also trying to gather information on its preferences of climatic and environmental conditions. In our modeling exercise, altitude and annual mean temperature were predicted as two of the most important factors determining the suitability of JHE's habitat (Table 2). The model in this study depicts a positive correlation between the probability of presence and increase in altitude, wherein the high probability of presence (above 50%) was mainly predicted at the altitude of above 1200 m asl. Regarding this altitudinal factor, it is in accordance with Van Balen et al. (2001) study which found that JHE is generally encountered in undulating, hilly, or mountainous terrain. Altitudinally, JHE species will be found at the altitude of between sea level and about 2500 m asl. However, this species are more frequently encountered in secondary forest and evergreen forest at above 1200 m asl (Partasasmita et al. 2017). This elevational preference is similar to some of the other raptor species such as Eleonora's falcon (*Falco eleonorae*), bearded vulture (*Gypaetus barbatus*), and lesser kestrel (*Falco naumanni*) (Donazar et al. 1993; Bustamante 1997; Urios and Martinez-abrain 2005).

Table 3. Predicted habitat patches in the mountainous areas of Java, Indonesia

Province	Patch (Area)	Size (km^2)[a]	Status	Past Records (1980 - 2005)
Banten	Ujung Kulon	217.41	NP	✓
	Mt. Aseupan	34.99	PF	✓
	Mt. Pulasari	9.89	PF	×
	Mt. Karang	47.69	PF	✓
West-Java	Mts. Gede-Pangrango	187	NP	✓
	Mt. Halimun-Salak	576.91	NP	✓
	Mt. Patuha	83.97	PF	✓
	Mt. Malabar	40.1	PF	✓
	Mts. Wayang-Windu	4.45	PF	✓
	Mt. Kendeng	52.1	PF/NR	✓
	Mt. Papandayan	61.8	PF/NR	✓
	Mt. Cikuray	94.7	-	✓
	Mt. Galunggung-Talagaboda	104	NR	✓
	TN. Ciremai	98.8	NP	✓
	Mt. Tangkuban Parahu	113	PF/NR	✓
	Mt. Kamojang-Guntur	104	NR	✓
Central-Java	Mt. Slamet	236	PF	✓
	Mts. Dieng (Kemulan, Sumbing, Sundoro)	262	PF	✓
	Mt. Merapi-Merbabu	119.9	PF	✓
	Mt. Telomoyo	61.5	-	×
	Mt. Ungaran	56.9	PF	✓
	Mt. Muria	94.8	PF	✓
East Java	Mt. Lawu	169	PF	✓
	Mt. Liman-Wilis	189	PF	✓
	Mt. Arjuna-Butak	527	PF/GFP /NR	✓
	Mt. TN Bromo-Tengger-Semeru	771	PF/NP	✓
	Mt. Argapura	671	WR	×
	Mt. Raung-Ijen	1091	PF/NR	✓
	Mt TN Baluran	102	NP	✓
	TN Meru Betiri	609	NP	✓
	TN Alas Purwo	370.3	NP	✓

Note: [a]Sum size of medium and high probability of presence areas. Status: NP, National Park; GFP, Grand Forest Park, NR, Nature Reserve; WS, Wildlife Sanctuary; PF, Protection Forest. Past Record References : Sozer and Nijman 1995; Hapsoro et al. 1998; Afianto 1999; Van Balen et al. 1999; 2001; Setiadi et al. 2000; BridLife International 2001; Utami 2001; Suparman 2002; Hendarsah 2003; Yuda et al. 2003; Mikoyan 2004.)

Furthermore, one of the main predictors of habitat suitability is energy availability, which can be crudely defined as mean average temperature (Lennon et al. 2000). It has been commonly known that altitude and temperature are highly correlated and it can be difficult to disentangle the variation of local temperature from that of altitude. The causal relationship between habitat suitability and temperature are still vague and unclear. However, we can identify two broad categories of how temperature affects the degree of habitat suitability, i.e., indirect and direct mechanisms. In the indirect mechanism, temperature affects the suitability of habitat through complex pathways involving its effects on resources availability, the density of population, competition, and other biotic interactions. Furthermore, the temperature may control the quantity and seasonal availability of prey species and, therefore, influence the population dynamics of JHE. On the other hand, a direct mechanism of how temperature may affect the species has been proposed by Turner et al. (1988; 1996), wherein the temperature is affecting the species directly on the energy budget of its homeotherms. Areas which have colder temperature impose greater thermoregulatory loads of species and force the species to devote relatively more energy to regulate their body temperature. As a consequence, less energy is available for other activities, such as for growing and reproducing. Whereas areas which have higher temperature will affect the physiological traits of the bird such as affecting breeding time, laying eggs pattern, and hatching time (Blondel 1985; Perrins and McCleery 1989; Woodburn 1997; Buse et al.1999; Parmesan and Yohe 2003; Parmesan 2007; Visser et al. 2009; Both et al. 2014). The characteristic of actually suitable habitat for JHE which is mainly on the higher altitude, wherein tend to have a lower temperature than the lowland areas, is in line with the pattern on the response curve model that suggests the most optimum range of temperature for JHE's suitable habitat is at between 8^0 and 20^0C.

The model exercise suggested that forest area and closed shrubland area as having the highest probability of presence accounting the probability value of 0.90 and 0.87, respectively. Accordingly, JHE's nests, during field observations, were generally encountered in mountain and hills areas which is still covered by the remaining natural forest of Java Island. Generally, natural forests in this island have been cleared due to various anthropogenic activities, and the remnants are now constrained to mountain areas (above 1200 m asl) with only limited areas of natural lowland forest (below 1200 m asl) remaining (Whitten et al. 1996; Prasetyo et al. 2009; Partasasmita et al. 2017). In the study conducted by Prawiradilaga (2006), it is stated that the home-range of JHE covers not only forest area but also production forest, cultivated area, and plantation areas. Nevertheless, an intensive study conducted by Kuswandono et al. (2003) and Nijman and Prawiradilaga (2003) showed that the forest areas (secondary and evergreen forests) are more frequently used by JHE as nest location than other habitat types. Furthermore, the model in this study also suggested that shrubland plays a vital role in the degree of habitat suitability as one of the preferred habitat types. Shrubland areas in Java are often found as an ecotone of between the forest areas and cultivated areas or plantation areas. Moreover, most of the prey species of JHE are small mammals such as squirrels (Sciuridae), small rodents (Muridae), tree shrews (Tupidae), and Lesser Mouse Deer (*Tragulus javanicus*) (Prawiradilaga 2006) which often found in shrubland areas. Accordingly, most of the JHE nest trees are located on the steep slope between the forest and shrubland areas.

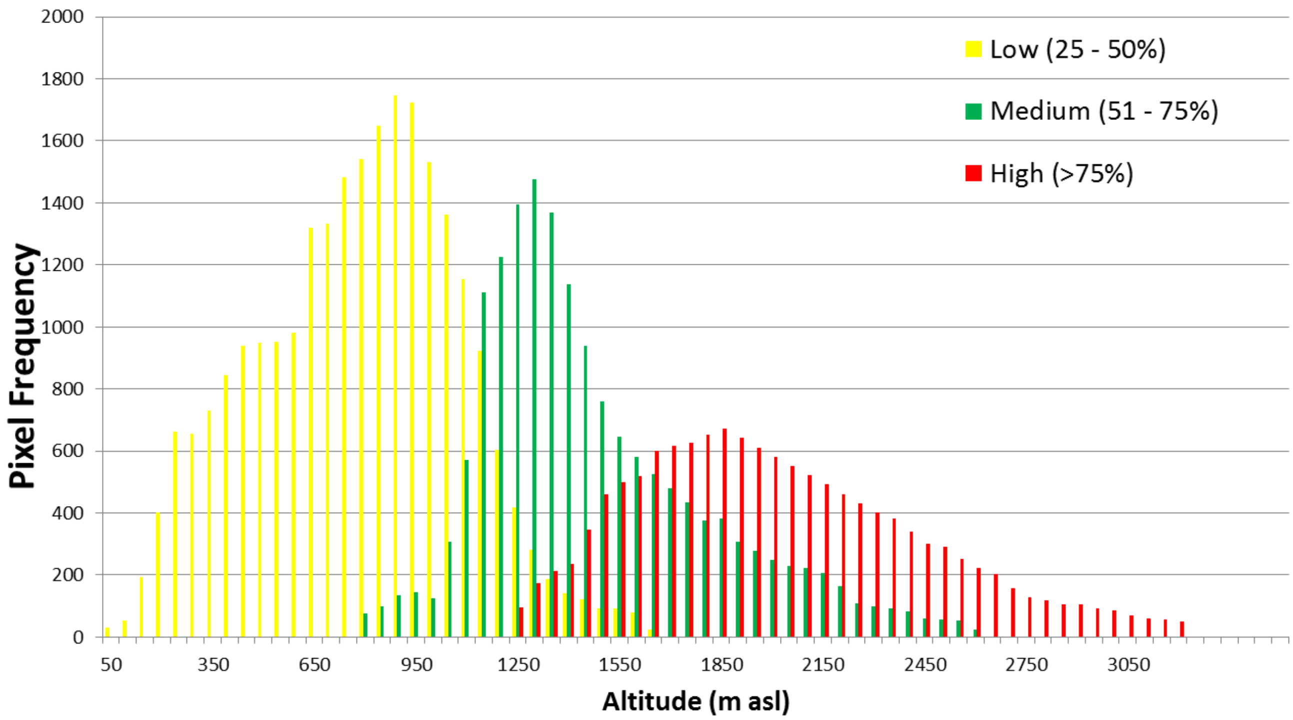


Figure 3. Predicted altitudinal distribution of JHE's suitable habitat across the Java Island, Indonesia

Various attempts on habitat modeling of JHE have been conducted using different approaches. By using logistic and autologistic regression models, Syartinilia and Tsuyuki (2008) modeled the distribution of JHE's habitat in Mt. Gede-Pangrango National Park (TNGP) and its surrounding area. Utilizing presence nests data, pseudo-absence data, which were generated through a random selection process, and several environmental variables, this study successfully identified the preferred habitat of JHE based on its environmental variables and modeling the habitat patches distribution surrounding the TNGP area. By validating the results with the historical data, this study also showed a significant overall accuracy of the results and the results also could be useful for conservation management activities of this species. Subsequently, Syartinillia et al. (2014) conducted a GIS-based habitat model of JHE by using an inductive approach in the entire Java Island. They demonstrated that by using autologistic regression, it is possible to extrapolate the preceding local study into the whole area of Java Island. Moreover, this study also developed an estimation of JHE population by dividing the area of predicted suitable habitat by assumed minimum and maximum home-range size. However, the predicted suitable area in this study was mostly distributed in the mountainous areas and failed to identify the suitability habitat of JHE in lowland areas, even though the species had been found in these locations. Afterward, in 2017, Nurfatimah et al. conducted a study to model the potential habitat of JHE in Central Java Province by utilizing multi-scale approach at different image resolutions, i.e., 30 m^2, 90 m^2, and 250 m^2. This study demonstrated the utilization of logistic regression to model JHE's habitat patches in multi-scale images. The results of this study were able to highlight the feasibility of using different image resolutions to model the distribution of predicted habitat for JHE, while also provided more options for the conservationist to choose the most suitable image scale for managing, planning, and monitoring species based on the scale of application.

Overlaying the World Database Protected Area of Java into the predicted map gives preliminary information that most of the predicted suitable areas fall into protected areas, wherein almost all of them are predicted to have medium to high suitability. Moreover, predictive maps also depict some of the predicted suitable habitats that fall outside the protected areas. The non-protected areas are mostly cultivated area and forest plantation area which are mainly owned and operated by the state-owned company. The predictive map also has shown a good match with historical records of JHE, with only three locations which were predicted to be suitable but neither historical nor current records can confirm it. Despite various measurements have been taken to minimize errors in the model caused by bias on the sampling data (see method), it is inevitable that such omission and commission errors may still present in the result of the model due to several reasons, i.e., (i) neither the dispersal rate nor the demography of meta-population of species was included in the model, since these variables are currently unavailable. A raptor species, such as *N. bartelsi,* has a wide dispersal range, and for this reason, modeling the niche for this type of species is considerably better if absence data were included because it is known that the ENM/SDM model utilizes the actual absence data, rather than pseudo-absences data. This is intended to produce a lower level of overprediction (Vaclavik and Meentemeyer 2009). (ii) The predictors used in this study have not yet comprehensively represented all of the environmental factors affecting the existence of the species, e.g., biotic interaction factor). iii) micro-climate variations affect the existence of species in the predicted areas but were not included in the model due to limited availability of data. Therefore, it is important to note that, like most of the ENM (SDM), the "predicted" distribution of suitable habitat does not represent the "true" prediction of the distribution of species, but rather the prediction of the distribution of "suitable" habitat based only on the predictors used in this study. Nonetheless, we may treat the results of this model as an appropriate representation of how the current climate condition and other variables shape the distribution of suitable habitat for JHE. Moreover, such modeling exercise provides critical information that can be utilized for research, planning, and management needs at landscape scales.

Building more ideal model requires the availability of multiple compounding factors which are expected to have either direct or indirect effect on the target species and its associated biota. Currently, however, such ideal packages of data are limited. This limitation, in the availability of more detailed ecological and physiological data, prevents the construction of more ideal models (Morin and Thriller 2009; Sinclair et al. 2010; Ellis 2011). Nonetheless, the recent development of new climate models and the refining of current climate models provide the opportunity to build more precise and ideal model. Further modeling attempt should also incorporate potential human-induced land use/land cover changes, biotic interactions between species in the regional ecosystems, more detailed ecological data, dispersal rates of species, meta-population demography, and better presence data which accurately represent the variability of ecological niche of species. In spite of all of the aforementioned limitations, this study provides the baseline of understanding the influence of macroclimate on shaping the distribution of potentially suitable habitat for JHE while finding out other possible areas which are currently unoccupied but likely can be occupied in the future. By using a different technique of species distribution modeling, such as profile technique (e.g., DOMAIN, ENFA) and Regression-based technique (e.g., GLM, GAM, and MARS), they may presents slightly different quantitative results and discrepancies in the potential distribution habitat may occur. Nonetheless, we believe that by using currently available resources of data, the overall trend and projection results would be similar.

ACKNOWLEDGEMENTS

We thank the DIKTI for partially funding this research. We also thank all parties who provided some nest site of Javan hawk-eagle coordinates data used by us. This research is part of our big research project to modeling the predicted suitable habitat for Javan hawk-eagle across the Java Island which later funded by Muhammad bin Zayed Conservation Fund. This paper publication is supported by ALG (Academic Leadership Grant) of Prof. Johan Iskandar. Therefore, authors would like to thank Rector of Padjadjaran University, Prof. Tri Hanggono has supported the publication.

REFERENCES

Afianto MY. 1999. Some ecological aspects of the Javan hawk-eagle *Spizaetus bartelsi* at G. Salak. Honors thesis, Bogor Agriculture University, Bogor [Indonesia].

Aguirre-Gutiérrez J, Carvalheiro LG, Polce C, van-Loon EE, Raes N, Reemer M, Biesmeijer JC. 2013. Fit-for-purpose: species distribution model performance depends on evaluation criteria - Dutch Hoverflies as a case study. PLoS One 8 (5): DOI: 10.1371/journal.pone.0063708.

Ali MZC, Hossein PS. 2016. Evaluation of Maxent method for habitat distribution modeling of three plant species in Garizat rangelands of Yazd province, Iran. Range Manag Agrof 37 (2): 142-147.

Allouche O, Tsoa A, Kadmon R. 2006. Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). J App Ecol 43 (1): 1223-1232.

Araujo M, Peterson AT. 2012. Uses and misuses of bioclimatic envelope modeling. Ecol 93 (7): 1527-1539.

Araujo MB, Pearson RG, Thuiller W. 2005. Validation of species-climate impact models under climate change. Glob Change Biol 11: 1504-1513.

Bagheri H, Ghorbani A, Zare Chahouki MA, Jafari AA, Sefidi K. 2017. Halophyte species distribution modeling with Maxent model in the surrounding rangelands of Meighan Playa, Iran. Appl Ecol Envi Res 15 (3): 1473-1484.

Bahn V, McGill BJ. 2013. Testing the predictive performance of distribution models. Oikos 122 (3): 321-331.

Baldwin, Roger A. 2009. Use of maximum entropy modeling in wildlife research. Entropy 11 (4): 854-866.

Bean WT, Stafford R, Brashares JS. 2012. The effects of small sample size and sample bias on threshold selection and accuracy assessment of species distribution models. Ecography 35: 250-258.

Beaumont LJ, Hughes L. 2002. Potential changes in the distributions of latitudinally restricted Australian butterfly species in response to climate change. Glob Change Biol 8: 954-971.

Bedia J, Herrera S, Guti´errez, JM. 2013. Dangers of using global bioclimatic datasets for ecological niche modeling. Limitations for future climate projections. Glob Planetary Change1-46. DOI: 10.1016/j.gloplacha.2013.04.005

Belgacem AO, Louhaichi M. 2013. The vulnerability of native rangeland plant species to global climate change in the West Asia and North African regions. Clim Ch 119: 451-463.

Berry PM, TP Dawson, PA Harrison, RG Pearson. 2002. Modeling potential impacts of climate change on the bioclimatic envelope of species in Britain and Ireland. Glob Ecol Biogeo 11:453-462.

BirdLife International. 2001. Threatened birds of Asia: the BirdLife International red data book. Cambridge.

Blondel J. 1985. Breeding strategies of the blue tit and coal tit (Parus) in mainland and island Mediterranean habitat: a comparison. J of Animal Ecol 54 (1): 531-556.

Booth TH, Nix HA, Busby JR, Hutchinson MF. 2014. BIOCLIM: the first species distribution modeling package, its early applications, and relevance to most current MAXENT studies. Divers and Distrib 20: 1-9.

Boria RA, Olson LE, Goodman SM, Anderson RP. 2014. Spatial filtering to reduce sampling bias can improve the performance of ecological niche models. Ecol Modell 275: 73-77.

Both C, Aleksandr V, Enemar A, Blaauw B, Cowie RJ, Dekhuijzen AJ, Eeva T, Enemar A, Gustafsson L, Ivankina EV, Ja¨rvinen A, Metcalfe NB, Nyholm NEI, Potti J, Ravussin PA, Sanz JJ, Silverin B, Slater FM, Sokolov LV, Torok J, Winkel W, Wright J, Zang H, Visser ME. 2004. Large-scale geographical variation confirms that climate change causes birds to lay earlier. Proc R Soc Lond B 271 (2): 1657-1662.

Brauner N, Shacham M. 1998. Role of range and precision of the independent variable in regression of data. Aiche J 44: 603-611.
Brown JL. 2014, SDMtoolbox: a Python-based GIS toolkit for landscape genetic, biogeographic, and species distribution model analyses. Methods Ecol Evol 5 (7): 1-7.
Buse A, Dury SJ, Woodburn RJW, Perrins CM, Good JEG. 1999. Effects of elevated temperature on multi-species interactions: the case of pedunculate oak, Winter Moth and Tits. Func Ecol 13 (1): 74-82.
Bustamante J. 1997. Predictive models for lesser kestrel Falco distribution, abundance, and extinction in southern Spain. Biol Conserv 80 (1): 153-160.
Charmantier A, McCleery RH, Cole LR, Perrins C, Kruuk LEB, Sheldon BC. 2008. Adaptive phenotypic plasticity in response to climate change in a wild bird population. Science 320 (2): 800-803.
Devadas R, Lamb DW, Simpfendorfer S, Backhouse D. 2008. Evaluating ten spectral vegetation indices for identifying rust infection in individual wheat leaves. Precis Agric 10: 459-470.
Dona´zar JA, Hiraldo F, Bustamante J. 1993. Factors influencing nest site selection, breeding density and breeding success in the bearded vulture (*Gypaetus barbatus*). J Appl Ecol 30 (1): 504-514.
Donald PF, Gedeon K, Collar NJ, Spottiswoode CN, Wondafrash M, Buchanan GM. 2012. The restricted range of the Ethiopian Bush-crow Zavattariornis stresemanni is a consequence of high reliance on modified habitats within narrow climatic limits. J Ornithol, DOI 10.1007/s10336-012-0832-4.
Duan RY, Xiao-Quan K, Min-Yi H, Sara V, Xiang J. 2016. The potential effects of climate change on amphibian distribution, range fragmentation and turnover in China. Peer J 4: 165-174.
Dudik M, Schapire RE, Phillips SJ. 2005. Correcting sample selection bias in maximum entropy density estimation. App Advan Neural Inform Process Sys 18: 181-197.
Elith J, Franklin J. 2013. Species distribution modeling. In: Levin SA (ed). Encyclopedia of Biodiversity Second Edition ed. Oxford: Academic Press, Oxford.
Elith J, Kearney M, Phillips S. 2010. The art of modeling range-shifting species. Methods Ecology Evol 1: 330-342.
Elith J, Leathwick JR. 2009. Species distribution models: ecological explanation and prediction across space and time. Annu Rev Ecol Evol Syst 40: 677-97.
Elith J, Phillips SJ, Hastie T, Dudik M, Chee YE, Yates CJ. 2011. A statistical explanation of Maxent for ecologists. Divers Distrib 17: 43-57.
Ellis CJ. 2011. Predicting the biodiversity response to climate change: challenges and advances. Syst Biodivers 9: 307-317.
Fernandez JM, Gurrutxaga M. 2010. Habitat suitability models for assessing bird conservation goals in ‘special protection areas’. Ardeola 57 (Especial): 79-91.
Ferrer-Sánchez Y, Rodríguez-Estrella R. 2016. How rare species conservation management can be strengthened with the use of ecological niche modeling: The case for endangered endemic Gundlach's Hawk and Cuban Black-Hawk, Glob Ecol Conserv 5 (1): 88-99.
Fitzpatrick MC, Weltzin JF, Sanders NJ, Dunn RR. 2007. The biogeography of prediction error: why does the introduced range of the fire ant over-predict its native range. Glob Ecol Biogeo 16 (1): 24-33.
Fourcade Y, Besnard AG, Secondi J. 2017. Paintings predict the distribution of species or the challenge of selecting environmental predictors and evaluation statistics. Global Ecol Biogeogr 12 (1): 1-12.
Fourcade Y, Engler JO, Besnard AG, Rödder D, Secondi J. 2013. Confronting expert-based and modeled distributions for species with uncertain conservation status: a case study from the Corncrake (*Crex crex*). Biol Conserv 167: 161 - 171.
Fourcade Y, Engler JO, Rodder D, Secondi J. 2014. Mapping species distributions with MAXENT using a geographically biased sample of presence data: A performance assessment of methods for correcting sampling bias. PLoS ONE 9 (5): e97122. DOI: 10.1371/journal.pone.0097122
Franklin J, Miller JA. 2009. Mapping species distributions: spatial inference and prediction. Cambridge University Press. New York.
GBIF.org (29th February 2016) GBIF Occurrence Download https://doi.org/10.15468/dl.ywhpmz
Genc H, Genc L, Turhan H, Smith SE, Nation JL. 2008. Vegetation indices as indicators of damage by the sunn pest (Hemiptera: Scutellaridae) to field-grown wheat. Afr J Biotech 7: 357-371.
Google Earth Pro. 2017. Download Google Earth Pro for PC, Mac, or Linux. https://www.google.com/earth/download/gep/agree.html.
Guillera-Arroita G, Jose J, Lahoz-Monfort, Elith. 2014. Maxent is not a presence-absence method: a comment on Thibaud et al. Meth Ecol Evol 5 (1): 1192-1197.
Guisan A, Thuiller W. 2005. Predicting species distribution: offering more than simple habitat models. Ecol Lett 8: 993-1009.
Hapsoro, Lesmana D, Kartiwa H, Mulyadi, Valentinus A, Purba C. 1998. Future from the high frontier: final report of Javan hawk-eagle surveys in West Java. Telapak Indonesia Foundation, Bogor.
Hariyati JH, Arisoesilaningsih E, Hakim L. 2013. Seedling growth of some native trees in Ranu Pani- Ranu Regulo restoration area, Bromo Tengger Semeru National Park. J Biodiv Environ Sci 3 (6): 47-55.
Harrison PA, PM Berry, N Butt, M New. 2006. Modeling climate change impacts on species' distributions at the European scale: implications for conservation policy. Env Sci Policy 9:116-128.
Hastie T, Fithian W. 2013. Inference from presence-only data; the ongoing controversy. Ecography 36 (1): 864-867.
Hendarsah G. 2003. Flight skill development, home range and movements of Javan hawk-eagle (Spizaetus bartelsi) during a post-fledging period (at 56-243 days) in Ciasem, Gunung Tangkuban Perahu Nature Reserve. In: Prawiradilaga DM (ed) Proceedings of the Second Symposium on Raptor of Asia. The Indonesian Committee for the Second Symposium of Asian Raptor Research & Conservation Network Bogor.
Jaynes ET. 1957. Information theory and statistical mechanics. Physical Review 106 (1): 620-630.
Jensen RA, J Madsen, M O’Connell, MS Wisz, H Toemmervik, F Mehlum. 2008. Prediction of the distribution of arctic-nesting pink footed geese under a warmer climate scenario. Glob Change Biol 14:1-10.
Jimenez-Valverde A, Acevedo P, Barbosa AM, Lobo JM, Real R. 2013 Discrimination capacity in species distribution models depends on the representativeness of the environmental domain. Glob Ecol Biogeo 22: 508-516.
Jimenez-Valverde A. 2012. Insights into the area under the receiver operating characteristic curve (AUC) as a discrimination measure in species distribution modeling. Glob Ecol Biogeo 21: 498-507.
Jimenez-Valverde A. 2014. Threshold-dependence as a desirable attribute for discrimination assessment: implications for the evaluation of species distribution models. Biodiversity and Conservation 23: 369-385.
Kramer-Schadt S, Niedballa J, Pilgrim JD, Schro¨der B, Lindenborn J, et al. 2013. The importance of correcting for sampling bias in Maxent species distribution models. Divers Distrib 19: 1366-1379.
Kuswandono D, Ekawati S, Mulyati, Murate T, Inoue T, Sakaguchi N. 2003. Javan hawk-eagle *Spizaetus bartelsi* conservation in Gunung Halimun National Park. Research on endangered species in GHNP. Research and Conservation of Biodiversity in Indonesia. 9: 62-70.
Lennon JJ, Greenwood JJD, Turner JRG. 2000. Bird diversity and environmental gradients in Britain: a test of the species-energy hypothesis. J Animal Ecol 69 (1): 581-598.
Li W, Guo Q. 2013. How to assess the prediction accuracy of species presence-absence models without absence data?. Ecograph 36 (7): 788-799.
Liu C, Newell G, White M. 2016. On the selection of thresholds for predicting species occurrence with presence-only data. Ecol Evol 6 (1): 337-348.
Lobo JM, Jiménez-Valverde A, Real R. 2008. AUC: a misleading measure of the performance of predictive distribution models. Glob Ecol Biogeogr 17 (2): 145-151.
Merow C, Matthew J, Smith, John A, Silander Jr. 2013. A practical guide to Maxent for modeling species’ distributions: what it does, and why inputs and settings matter. Ecography 36: 1058-1069.
Mikoyan L. 2004. Vegetation study in the home range of Javan hawk-eagle at Telaga Warna Nature Reserve, Tugu Village, Bogor, West Java. Honors thesis, Faculty of Biology, National University, Jakarta. [Indonesia]
Morin X, Thuiller W. 2009. Comparing niche- and process-based models to reduce prediction uncertainty in species range shifts under climate change. Ecol Lett 90: 1301-1313.
Myers, Norman, Russell MA, Cristina GM, et al. 2000. Biodiversity hotspots for conservation priorities. Nat 403 (6772): 853-858.
Nenzén HK, Araújo M. 2011. Choice of threshold alters projections of species range shifts under climate change. Ecological Modelling 222: 3346-3354.

Nijman V, Prawiradilaga DM. 2003. Tropical forest raptors as Indicators in biodiversity monitoring programs and conservation area selection: minimal area requirements for the raptor community of the Sundaic region. In: Nijman V, Prawiradilaga DM (eds) Quarterly report prepared for the Indonesian Institute of Sciences (LIPI). Univ Amsterdam & Puslitbang Biologi-LIPI, Bogor.

Nurfatimah C, Syartinilia, Mulyani YA. 2017. The potential habitat of Javan hawk-eagle based on multi-scale approach and its implication for conservation. IOP Conf. Series: Earth and Environmental Science 54 (1): 1-12.

Nussey DH, Postma E, Gienapp P, Visser ME. 2005. Selection on heritable phenotypic plasticity in a wild bird population. Science 310 (1): 304-306.

Ostendorf B, DW Hilbert, MS Hopkins. 2001. The effect of climate change on tropical rainforest vegetation pattern. Ecol Modell 145: 211-224.

Parmesan C, Yohe G. 2003. A globally coherent fingerprint of climate change impacts across natural systems. Nature 421: 37-42.

Parmesan C. 2007 Influences of species, latitudes and methodologies on estimates of phenological response to global warming. Glob. Change Biol. 13 (1): 1860-1872.

Partasasmita R, Atsuary ZIA, Husodo T. 2017. The use of forest canopy by various bird species in tropical forest montana zone, the Nature Reserve of Mount Tilu, West Java, Indonesia. Biodiversitas 18 (2): 453-457

Partasasmita R, Mardiastuti A, Solihin DD, Widjajakusuma R, Prijono SN. 2009. Community fruit eater bird habitat succession. Biosfera 26 (2): 90-99. [Indonesia]

Partasasmita R. 2009. Community Ecology of Frugivorous Bird: Eating Ecology and Shrub Succession in Panaruban, Subang [Dissertation]. Bogor Agricultural University, Bogor. [Indonesian]

Perrins CM, McCleer RH. 1989. Laying dates and clutch size in the great tit. Wilson Bulletin 101 (1): 236-252.

Perrins CM. 1991. Tits and their caterpillar food supply. Ibis 133 (1): 49-54.

Peterson AT, Papes M, Soberon J. 2008. Rethinking receiver operating characteristic analysis applications in ecological niche modeling. Ecol Modell 213: 63-72.

Peterson AT, SoberoÂn J, Pearson RG, Anderson RP, MartõÂnez-Meyer E, Nakamura M, et al. 2011. Ecological niches and geographic distributions (MPB-49). Princeton University Press. Princeton.

Peterson AT, Soberon J, Pearson RG, Martínez-Meyer E, Nakamura M, Araújo MB. 2011. Evaluating model performance and significance. In: A. Peterson AT, Soberón J, Pearson RG, Anderson RP, Martínez-Meyer E, Nakamura M, Araújo MB. (eds). Ecological Niches and Geographic Distributions. Princeton University Press. New Jersey.

Phillips SJ, Anderson RP, Dudík M, Schapire RE, Blair ME. 2017. Opening the black box: an open-source release of Maxent. Ecography 40 (7): 887-893.

Phillips SJ, Anderson RP, Schapire RE. (2006) Maximum entropy modeling of species geographic distributions. Ecological Modelling 190 (1): 231-259.

Phillips SJ, Anderson RP, Schapire RE. 2006. Maximum entropy modeling of species geographic distributions. Ecol model 190: 231-259.

Phillips SJ, Dudık M, Elith J, Graham CH, Lehmann A, et al. 2009. Sample selection bias and presence-only distribution models: implications for background and pseudo-absence data. Ecol Appl 19: 181-197.

Phillips SJ, Dudik M. 2008. Modeling of species distributions with Maxent: new extensions and a comprehensive evaluation. Ecography 31: 161-175.

Phillips SJ, Elith J. 2013. On estimating probability of presence from use-availability or presence-background data. Ecology 94 (1): 1409-1419.

Prasetyo LB, Kartodihardjo H, Adiwibowo S, Okarda B, Setiawan Y. 2009. Spatial Model Approach on Deforestation of Java Island, Indonesia. JIFS 6 (1): 37-44.

Prawiradilaga DM. 2006. Ecology and conservation of endangered Javan hawk-eagle *Spizaetus bartelsi*. Ornithol Sci 5 (1): 177-186.

QGIS Development Team, 2017. QGIS Geographic Information System. Open Source Geospatial Foundation. http://qgis.osgeo.org.

Qian JH, Robertson JW, Moron V. 2010. Interactions among ENSO, the Monsoon, and Diurnal Cycle in Rainfall Variability over Java, Indonesia. J Atm Sci 67: 3509-3524.

Radosavljevic A, Robert P. Anderson. 2013. Making better MAXENT models of species distributions: complexity, overfitting and evaluation. J. Biogeogr 41: 629-643.

Remya K, Ramachandran A, Jayakumar S. 2015. Predicting the current and future suitable habitat distribution of *Myristica dactyloides* Gaertn. using Maxent model in the Eastern Ghats, India. Ecol Engineer 82: 184-188.

Safana NG, Partasasmita R, Rakhman Z. 2018. Daily acticity of changeable hawk-eagle (Nisaetus cirrhatus) in Kamojang Eagle Conservation Center. J Biol Sci 5 (1): 57-63

Setiadi AP, Rakhman Z, Nurwatha PF, Muchtar M, Raharjaningtrah W. 2000. Status, distribution, population, ecology and conservation Javan hawk-eagle Spizaetus bartelsi Stresemann, 1924 on the southern part of West Java. Final Report BP/FFI/BirdLife International/YPAL-HIMBIO UNPAD, Bandung.

Sinclair SJ, White MD, Newell GR. 2010. How useful are species distribution models for managing biodiversity under future climates?. Ecol Soc 15: 8-16.

Sohl TL. 2014. The Relative impacts of climate and land-use change on conterminous United States bird species from 2001 to 2075. PLoS ONE 9 (11): e112251. DOI: 10.1371/journal.pone.0112251.

Sözer R, Nijman V. 1995. Behavioural ecology, distribution and conservation of the Javan hawk-eagle *Spizaetus bartelsi* Stresemann, 1924. Verslagen en Technische Gegevens 62: 1-122.

Stolar J, Nielsen SE. 2015. Accounting for spatially biased sampling effort in presence-only species distribution modeling. Divers Distrib 21 (5): 595-608.

Summers DM, Bryan BA, Crossman ND, Meyer WS. 2012. Species vulnerability to climate change: impacts on spatial conservation priorities and species representation. Glob Change Biol 18: 2335-2348.

Suparman U. 2002. Surveys on protected birds: Javan hawk-eagle and other raptors in southern Cianjur District. Final report for FFI-Indonesia. KPB CIBA, Cianjur (Indonesian).

Syartinilia, Tsuyuki S, Lee JS. Gis-based habitat model of Javan hawk-eagle (Spizaetus bartelsi) using an inductive approach in Java Island, Indonesia. In: Harris JD, Brown PL (eds). Wildlife: Destruction, Conservation, and Biodiversity. Nova Science Publishers. New York.

Syartinilia, Tsuyuki S. 2008. GIS-based modeling of Javan hawk-eagle distribution using logistic and autologistic regression models. Ornithol Sci 5 (1): 756-769.

Syfert MM, Smith MJ, Coomes DA. 2013. The effects of sampling bias and model complexity on the predictive performance of Maxent species distribution models. Plos One 8: 551-558.

Szilárd S, Zoltán G, Boglárka B. 2016. Specific features of NDVI, NDWI and MNDWI as reflected in land cover categories. Landsc Environ 10: 194-202.

Urios G, Martınez-Abraın A. 2005. The study of nest-site preferences in Eleonora's falcon *Falco eleonorae* through digital terrain models on a western Mediterranean island. J Ornith 147 (1): 13-23.

Vaclavik T, Meentemeyer RK. 2009. Invasive species distribution modeling (iSDM): Are absence data and dispersal constraints needed to predict actual distributions?. Ecol Model 220 (1): 3248-3258.

van Balen S, Sozer R, Nijman V. 1999. Distribution and conservation of the endemic Javan hawk-eagle *Spizaetus bartelsi*. Bird Conserv Int 9 (1): 333-349.

van Balen S. 1991. The Java Hawk Eagle *Spizaetus bartelsi*. WWGBP project report No. 1, March 1990. Ecology and conservation of endangered Javan hawk-eagle In: Chancellor R & Meyburg B-U (eds) Birds of Prey Bulletin No. 4. pp 33-39. World Working Group on Birds of Prey and Owls, Berlin, London & Paris.

van Balen, S, Nijman V, Sozer R. 2001. Conservation of the endemic Javan hawk-eagle *Spizaetus bartelsi* Stresemann, 1924 (Aves: Falconiformes): density, age-structure and population numbers. Zoology 70 (1): 161-173.

Van Gils H, Conti F, Ciaschetti G, Westinga E. 2012. Fine resolution distribution modeling of endemics in Majella National Park, Central Italy. Plant Biosys 146 (1): 276-287.

Van Gils H, Westinga E, Carafa M, Antonucci A, Ciaschetti G. 2014. Where the bears roam in Majella National Park, Italy. J Nat Conserv 22 (1): 23-34.

van Noordwijk AJ, McCleery RH, Perrins CM. 1995. Selection for the timing of great tit breeding in relation to caterpillar growth and temperature. J Animal Ecol 64 (1): 451-458.

Visser ME, Holleman LJM, Caro SP. 2009. Temperature has a causal effect on the avian timing of reproduction. Proc. R. Soc. B 276 (1): 2323-2331.
Whitten T, Soeriaatmadja R, Afiff SA. 1996. The ecology of Java and Bali: the ecology of Indonesia series, vol. 2. Periplus Editions, Singapore.
Woodburn RJW. 1997. The breeding ecology of the blue tit and great tit and the possible effect of climate change. [Thesis], University of Oxford, UK.
Youden WJ. 1950. Index for rating diagnostic tests. Cancer 3 (1): 32-35.
Yuda IP, Nurcahyo A, Atmojo H. 2003. Javan hawk-eagle at Mount Merapi, Yogyakarta, Indonesia. In: Prawiradilaga DM (ed) Proceedings of the Second Symposium on Raptor of Asia. The Indonesian Committee for the Second Symposium of Asian Raptor Research & Conservation Network, Bogor.