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ARTICLE

Species Distribution Modelling Using Bioclimatic Variables on Critically Endangered Endemic Species (Macrocephalon Maleo) in Sulawesi

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Abstract

The island of Sulawesi isolates migratory fauna from Asia and Australia and creates animal combinations such as the Maleo (Macrocephalon Maleo). The Maleo population is experiencing a downward trend due to habitat fragmentation, deforestation, and threats by humans. This study aims to model the potential distribution of Maleo using several famous current and future models as a result of climate change throughout the island of Sulawesi, not only in its natural habitat but beyond its natural habitat. Bioclimatic variables and in situ attendance data were used in this study. The method used is Maximum Entropy by evaluating the GLM, SVM, and RF algorithms to find the best model. The RF model is quite good in modeling the Maleo distribution based on a comparison of statistical tests (AUC = 0.99, COR = 0.96, TSS = 0.99, Deviance = 0.14) and data from observations (92.31%). This species requires an ideal climatic environment to support its reproduction in nature. In the future, Lambusango Wildlife Sanctuary will become more vulnerable to climate change.

Keywords: Species distribution model, Macrocephalon Maleo, Bioclimatic, Climate change

1. Introduction

As one of the largest islands in the Wallacea region. The island of Sulawesi isolates migratory fauna from Asia and Australia. The isolation of the fauna found in this area creates a combination of animals from two continents. Sulawesi Island has various types of fauna as well as being home to several endemic species, such as the Maleo (Macrocephalon Maleo). Maleo habitat requires special natural conditions with soil surface temperatures around 29.4–36 °C obtained from solar heat or volcanic heat (Coates & Bishop 1997; Bashari et al., 2021). This species utilizes natural heat sources (geothermal) or stretches of sand on the beach to serve as spawning grounds (Mustari, 2021). Communal nesting patterns are hypothesized to be an evolutionary strategy to satisfy natural egg predators (Gorog et al., 2005). The female lays 8–12 eggs in the hole with the help of solar radiation and/or geothermal heat. This typically lasts over a 2–3 month period, and peaks in some locations during the regionally varying dry season. The eggs will then hatch without further parental support. Maleo prefers to live in pairs, and are more terrestrial, shy, and timid (Coates & Bishop 1997; Bashari et al., 2021;

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Mustari, 2021). The character and behavior of this species strongly describe its living environment which is closed and far from all forms of human activity.

Based on data from BirdLife International, in 2019 the global Maleo population is estimated to be only 8000–14,000 individuals with a population trend that continues to decline (Bashari et al., 2021) due to habitat degradation and egg hunting so the Maleo habitat is damaged and eliminated by natural changes (Froese & Mustari, 2019; Bashari et al., 2021). Egg-taking by humans is the single biggest driver of maleo decline (Summers et al., 2023). For centuries humans across Sulawesi have exploited the maleo's egg as a prized delicacy (Dekker 1990). If sold, Maleo eggs can fetch up to IDR 20,000–40,000 (USD $2–3) (Maulany et al., 2021; Tasirin et al., 2021). In some areas, maleo has also declined or disappeared even in areas with strong local *adat* traditions (Argeloo & Dekker 1996; Summers et al., 2023). The rainforest as Maleo's habitat is also being degraded. In the 21st century, 14.3% of forest cover across the species' range has been lost, while its flanks have become increasingly fragmented (Global Forest Watch 2021). This situation not only has the impact of reducing the quantity and quality of available habitat, but the further effect is causing the remaining sub-populations of maleo to also become increasingly isolated from one other, compromising their overall genetic diversity and long-term resilience (Stephens and Sutherland, 1999).

The IUCN organization categorizes Maleo's status as Critically Endangered (CR). This status indicates a high level of threat and has the potential to become extinct soon if conservation action is not taken immediately. Maleo is also included in Appendix I CITES so trading activities are also prohibited. Maleo is also protected under the law and legislation (Sugiarto et al., 2010). Full protection was provided to maleo even before the wide-ranging Natural Resources Law of 1990 (UU no. 5), but this law is rarely enforced; egg hunting is commonplace, and local extinctions have been numerous with many historic nesting sites are now empty of maleos (Dekker, 1990; Argeloo, 1994; Butchart & Baker, 2000; Gorog et al., 2005; Summers et al., 2023).

Species distribution models (SDMs) offer a powerful tool for predicting distribution patterns of species diversity (Khwarahm, 2020; Li et al., 2020). SDM has undergone many developments to measure the relationship between records of species occurrence and environmental variables and predict the potential distribution of species, such as genetic algorithms for rule-defined production (GARP) (Padalia et al., 2014), bioclimatic modeling (BIOCLIM) (Booth, 2018), climex and dymex (CLIMEX) (Kriticos et al., 2017), ecological niche factor analysis (ENFA) (Rosas et al., 2023), Maximum entropy (MaxEnt) (Ngarega et al., 2024) and so on. MaxEnt is widely used given its accuracy and strong performance (Ghareghan et al., 2020) in estimating the maximum entropy probability distribution function to predict optimal distributions based on the presence of known species along with environmental variables (Phillips et al., 2006; Dudik et al., 2007; Aldiansyah & Risna, 2023). MaxEnt is rated superior in the following ways: (i) high success rate and statistical significance with small sample size, (ii) can handle environmental variables both continuous and categorical data, (iii) can produce continuous probabilistic output that is easy to interpret (Pearson et al., 2007; Elith et al., 2011; Li et al., 2020; Cao et al., 2022; Aldiansyah & Risna, 2023). The impact of climate change on biodiversity has been evident in the distribution of a large number of species (Varga et al., 2019; Tarnian et al., 2021). MaxEnt is also conducive to identifying potential threats to biodiversity and formulating positive response strategies for biodiversity conservation (Khwarahm, 2020; Aldiansyah & Risna, 2023).

Current and future species distributions can be modeled accurately using only bioclimatic data, either partially or completely (Booth, 2018; Morales-Barbero and Vega-Álvarez, 2019; Ahmed et al., 2020; Aldiansyah & Wahid, 2023; Ke et al., 2024). Many regression or machine learning algorithms have been intensively developed to understand biodiversity distribution patterns from climate data, such as Generalized linear model (GLM), Random Forest (RF), and Support Vector Machine (SVM). The algorithm indicates those are quite better to predict the potential current and future distribution pattern of endemic species (Yudaputra et al., 2019; Mohammady et al., 2021; Aldiansyah & Wahid, 2023). GLM was adopted to predict species distribution in Australia and produced good performance compared to other models (Shabani et al., 2016). SVM is a reasonable model for modeling SDMs when sample information is limited (Drake et al., 2006). In a recent study modeling the spatial distribution of Guettarda speciose in Indonesia, the average AUC and Kappa values (measures of model fit and predictive capacity) of SVM were much higher compared to BIOCLIM and DOMAIN (Yudaputra et al., 2019). As the most commonly used algorithm, RF is very accurate compared to simple decision trees and other models (Valavi et al., 2023). Recent studies show that RF is the best prediction model compared to GLM and SVM (Aldiansyah & Wahid, 2023).

Studies on Maleo have been carried out specifically in an area with a relatively narrow area

(Laban, 2007; Gazi, 2008; Ambagau, 2010). However, the study was limited to the research area, exploration outside the natural habitat, and time and cost. This research aims to model the current and future potential distribution of Maleo Macrocephalon due to climate change outside its natural habitat. Several famous regression and machine learning models GLM, SVM, and RF were also compared and evaluated with one another to obtain an accurate model of the distribution of the Maleo endemic.

2. Materials and methods

2.1. Data acquisition

This research uses WorldClim version 1.4, Climate Model Intercomparison Project version 5 (CMIP5) data, and the presence of species in situ. The WorldClim data used is the average climate for the years 1970–2000 with a spatial resolution of 1 km (WorldClim, 2020). CMIP5 data is data that predicts future climatic conditions for the year 2080–2100 (Navarro-Racines et al., 2020) and is considered good enough for geographic distribution and temperature modeling (Kamruzzaman et al., 2021). The use of climate data is based on the findings of Leclerc et al. (2020) that Sulawesi is very vulnerable to climate change. WorldClim data is provided in the form of monthly average rainfall, maximum temperature, minimum temperature, average temperature, and topographic data. There are 19 bioclimatic variables used (Worldclim, 2020). Maleo presence data was obtained from the open data access source Global Biodiversity Information Facility (GBIF) (Fig. 1).

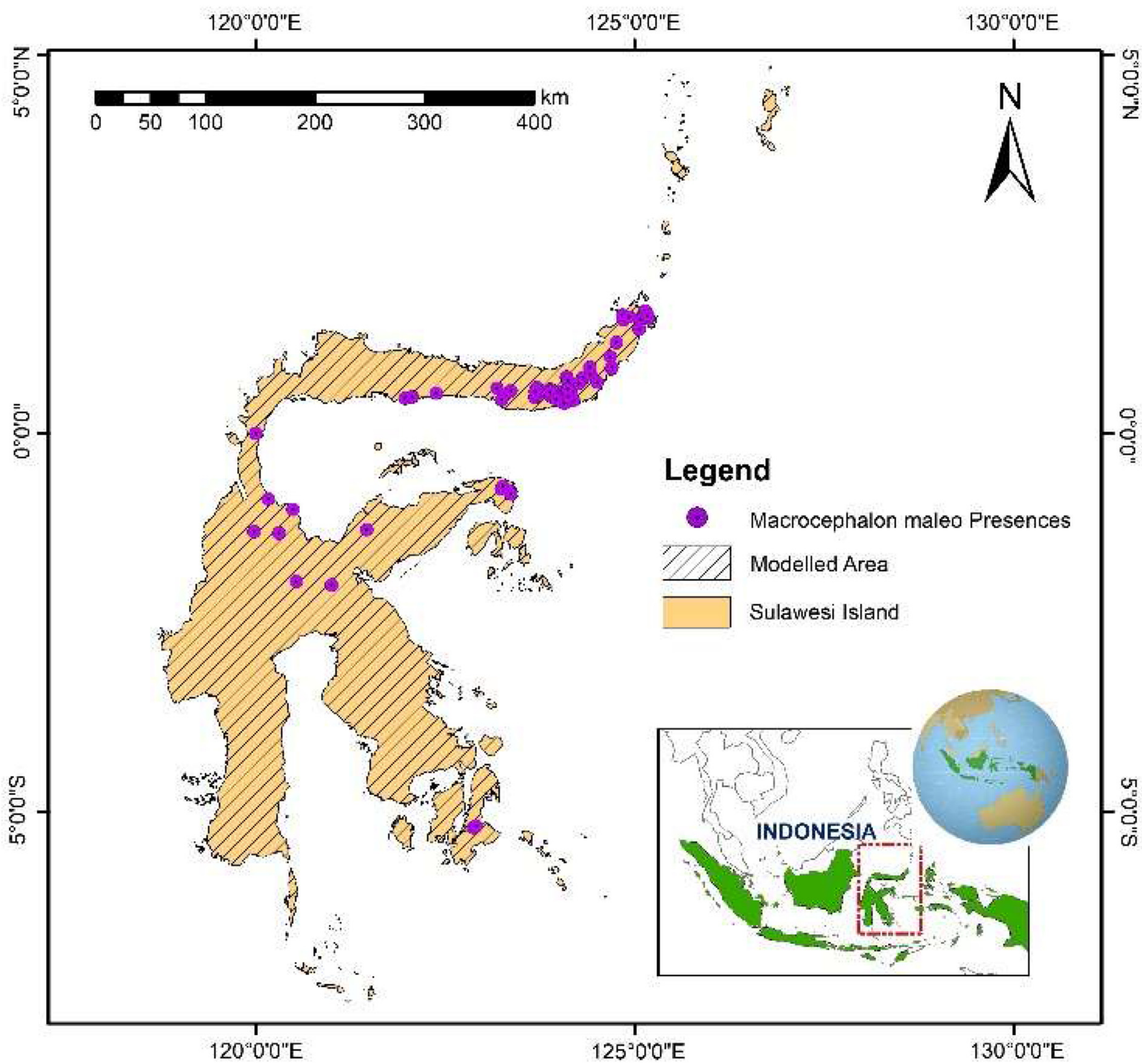

Fig. 1. The occurrence records of Macrocephalon Maleo in Sulawesi.

2.2. Data preprocessing and feature selection

Modeling the distribution of species is carried out using the MaxEnt on R software for all of Sulawesi (Phillips et al., 2006). There are two stages, namely: setting data model and modeling. In ecological niche modeling, collinearity between the explanatory variables (predictors) causes instability in the model performance which results in uncertain prediction (Dormann et al., 2013) Therefore, it is recommended that highly correlated variables should not be included in the model fitting to have a robust result (Naimi et al., 2014). To address the collinearity issue, we used the Variance Inflation Factor (VIF). A total of 19 bioclimatic variables were selected using the VIF value to eliminate the presence of high spatial correlation between variables. The VIF reflects how much the standard errors are inflated as a result of the multicollinearity of the variables included in the model. We used the 'vifstep' function in the 'usdm' package in R to compute the VIF for the variables. The correlation threshold was set at 0.7 (Table 1). The spatial resolution of both modeling results is reduced to 2.5 km according to the standard factor approach (Walton et al., 2015). In future modeling, we use the Representative Concentration Pathways (RCP) 8.5 scenario (high scenario) adopted from The Intergovernmental Panel on Climate Change (IPCC). RCP 8.5 refers to the concentration of carbon that delivers global warming at an average of 8.5 W per square meter across the earth. The RCP 8.5 pathway delivers a temperature increase of about 4.3 °C by 2100, relative to pre-industrial temperatures. The model setting is used to see the distribution of species (latitude & longitude) using the "sdmData" function with a "biom" predictor. Modeling is done by entering the algorithms using the "sdm" package for fitting the species distribution. The resulting model is referred to as "m".

There were 464 presence data provided, but only 330 presence data were used after ignoring duplicate data, coordinate errors and data that did not have coordinates. All data samples were used in building the model. This data is observational results from 1840 to 2020 (GBIF.org, 2022). Extraction of geographic data (latitude and longitude) of species was carried out based on the name of the species. It is assumed that each presence of data represents 1 species. Background = 100 (default) is used to determine the points outside the random existing point as "d". Distribution modeling is carried out based on "biom" and "m" data.

2.3. Model training

Three different SDMs algorithms were applied to understand the current and future distribution patterns of maleo. These models include GLM, SVM, and RF. GLM is a linear regression (Friedman et al., 2010). We trained GLM subsampled the entire dataset by randomly selecting the presence and the absence locations, trained a GLM, and produced a species distribution probability surface. We reiterated this process 100 times with replacement and produced the final species distribution probability

Table 1. Bioclimatic variables and their computed variance inflation factor (VIF) obtained from the Worldclim database for modeling the potential distribution of Macrocephalon Maleo.

Bioclimatic variable	Variable description	Unit	VIF
Bio1	Annual mean temperature	°C	282.29
Bio2	**Mean diurnal range [mean of monthly (maximum temp − minimum temp)]**	**°C**	**1.38**
Bio3	Isothermality (Bio2/Bio7) (× 100)	°C	12.43
Bio4	Temperature seasonality (standard deviation × 100)	°C	31.65
Bio5	Maximum temperature of the warmest month	°C	21.12
Bio6	Minimum temperature of the coldest month	°C	18.83
Bio7	Temperature annual range (Bio5−Bio6)	°C	46.27
Bio8	**Mean temperature of wettest quarter**	**°C**	**1.45**
Bio9	**Mean temperature of driest quarter**	**°C**	**19.77**
Bio10	Mean temperature of warmest quarter	°C	401.01
Bio11	Mean temperature of coldest quarter	°C	70.41
Bio12	Annual precipitation	mm	39.94
Bio13	Precipitation of wettest month	mm	92.83
Bio14	**Precipitation of driest month**	**mm**	**2.02**
Bio15	**Precipitation seasonality (coefficient of variation)**	**mm**	**2.64**
Bio16	Precipitation of wettest quarter	mm	170.08
Bio17	Precipitation of driest quarter	mm	214.17
Bio18	**Precipitation of warmest quarter**	**mm**	**2.44**
Bio19	**Precipitation of coldest quarter**	**mm**	**1.66**

Note: The variables in bold text are those that were selected based on VIF for predicting the potential distribution of Macrocephalon Maleo.

surfaces by averaging the 100 probability surfaces, independently for each felid. SVM is a machine learning technique that is based on a simple linear algorithm and applies presence and background data, (Karatzoglou et al., 2006 Our model settings for the SVM analyses were 10% hold out for testing, degree = 3, Nu = 0.05, and cost = 1. RF is a machine learning based on a decision tree that uses presence and background data (Breiman, 2001). Similar to the GLM approach, Each RF was produced by bagging the training data, a procedure automatically implemented in the algorithm to reduce the variance that might otherwise characterize decision trees. Therefore, by bootstrapping also the training data of each RF, we implemented a two-stage bagging procedure. Table 1 provides a brief description of the SDMs. The "sdm" library is used to run several SDMs algorithms and their corresponding syntax codes are presented in Table 2. The species distribution model is then processed into ArcMap 10.4.1 software by dividing the distribution model class into 2 classes (50% probability) to see the extent of suitability of climatic conditions for this species.

2.4. Model evaluation

The model is evaluated by looking at the value of the Receiver Operating Characteristics - Area Under Curve (ROC-AUC) (Hao et al., 2020), Correlation (COR), True Skill Statistics (TSS) (Wunderlich et al., 2019), and Deviance (Agresti, 2018). The AUC value is used to evaluate the degree of separation between positive and negative values in the variables and presence data. The AUC value has a range of 0–1, a good AUC value if the value is >0.7 (Shabani et al., 2018; Hao et al., 2020). The strength of the relationship between climate variables and attendance data was evaluated through the COR value. The TSS value is used to see the strength of the relationship between observations and predictions. The TSS values range between −1 and +1, the closer the TSS value +1, the stronger the relationship between the two variables (Shabani et al., 2018; Wunderlich et al., 2019). The deviance value represents the error rate with an interval of 0–1, the closer the value to 0 is, the lower the error rate (Agresti, 2018). ROC-AUC, COR, TSS, and Deviance are calculated using the following equations:

$$AUC = \sum \mathrm{TP} + \sum \mathrm{TN} \ / \ (P + N)$$

where TP and TN are considered the rate of pixels classified correctly as presence and absence, and P and N are the total numbers of presence and absence, respectively.

$$COR = \frac{\sum_{i=1}^{n} (SOI - \overline{SOI})\ (SSI - \overline{SSI})}{\sqrt{\sum_{i=1}^{n} (SOI - \overline{\overline{SOI}})^2} \sqrt{\sum_{i=1}^{n} (SSI - \overline{SSI})^2}}$$

where SOI indicates species presence (LOI = 1) or absence (LOI = 0), while SSI indicates sensitivity to species predicted by the model. Sensitivity refers to the known species pixels that were modeled as potential distribution areas. Specificity, however, is the known absence of pixels that were labeled as potential distribution areas by the model.

$$TSS = \frac{ad - bc}{(a+c)(b+d)} = Sensitivity + Specificity - 1$$

Where the number of true positive (a), false positive (b), false negative (c), and true negative (d) cases predicted by the model.

$$D = 2 \sum_{i=1}^{n} \left(y_i \, ln\left(\frac{y_i}{\mu_i}\right) + (1 - y_i) ln\left(\frac{1 - y_i}{1 - \mu_i}\right) \right)$$

where $y_i = \mu_i$ for all future observations, the D value is zero. If $y_i \neq \mu_i$ is always true, the value of D is infinite (Kwon, 2017).

Evaluation was also carried out on the distribution model that had been classified using the results of observations from Mustari (2021). In addition, the prediction of the distribution of Macrocephalon Maleo from BirdLife International (2021) was used as well as published by IUCN. The research flow is presented in Fig. 2.

Table 2. Brief descriptions of three applied SDMs.

Algorithm			Syntax code in "sdm" package	Data	Reference
Type	Full name/abbreviation	R Package used			
Machine learning	Support Vector Machine (SVM)	e1071	svm	Presence and Absence	Fukuda et al. (2013)
	Random Forest (RF)	randomForest	rf	Presence and Absence	Reiss et al. (2011)
Regression	Generalized linear models (GLM)	glm2	glm	Presence and Absence	Dicko et al. (2014)

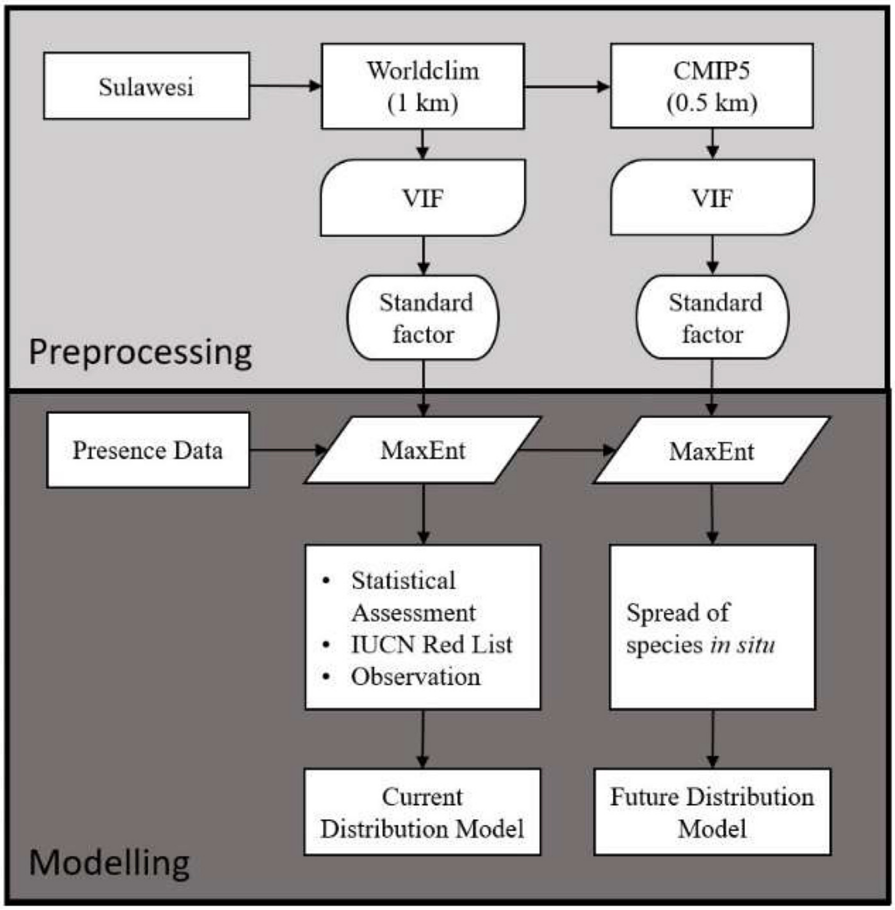

Fig. 2. Flowchart of study.

3. Result and discussion

3.1. Maleo distribution model

The Maleo distribution model shows a different pattern. This model is a distribution prediction model based only on the presence of pixels. Some models have a high level of sensitivity to topographical structures. The SVM model is only sensitive to the point of attendance and ignores areas that have the same characteristics as the location of the presence data. This model also makes an error in classifying the expanse of rice fields on the north side of the capital city of South Sulawesi Province as a highly distributed area. The western part of West Sulawesi is classified as a low distribution, this is in contrast to the IUCN data which shows that most of this area is a distribution area. The GLM model generalizes several areas that are not habitats for this species, such as in some built-up areas that are centers of human activity and areas for agriculture/plantation/ponds. This is in contrast to the RF model which is quite sensitive in classifying urban areas as low distributed areas (blue color). The distribution model highlights several important distribution areas of this species with high distribution such as Bogani Nani Wartabone National Park (BNWNP), Rawa Aopa Watumohai National Park (RAWNP), Lore Lindu National Park (LLNP), Tanjung Matop Wildlife Sanctuary, Morowali Nature Reserve, Taman Mangolo Nature Tourism, Around Lake Towuti in Maluku, and Buton Island. This location was also identified by recent research (Gusmawan et al., 2018; Froese & Mustari, 2019; Santrio, 2022; Karim et al., 2023).

The Bogani landscape around BNWNP plus the Tanjung Dako and Tanjung Matop areas along the coast in North Sulawesi are the main areas for the largest proportion of the maleo population (Argeloo, 1994; Butchart & Baker, 2000; Gorog et al., 2005). Meanwhile, in Central Sulawesi, the main locations are TNLL (Butchart & Baker, 2000), Morowali Nature Reserve, and the nearby Bosu River, and three locations to the east of the peninsula (Bakiriang, Libuun, and Pintu Kubur) in Central Sulawesi (Butchart & Baker, 2000). The distribution of Maleo in Sulawesi is quite wide, especially in Central Sulawesi, North Sulawesi, Southeast Sulawesi, and South Sulawesi (Gusmawan et al., 2018).

The level of importance of the variables in Fig. 3 shows a correlation to the variables Mean Diurnal Range/bio2 (0.245), Precipitation of Warmest Quarter/bio18 (0.19), Mean Temperature of Driest Quarter/bio9 (0.18), Precipitation of Driest Month/bio14 (0.15), Precipitation of Coldest Quarter/bio19 (0.14), Mean Temperature of Wettest Quarter/bio8 (0.128), and Precipitation Seasonality/bio15 (0.092). Our results are in line with previous research showing that temperature and precipitation have a significant influence on maleo population abundance under field conditions (Jamili and Rudia, 2015; Karim et al., 2023). These results show that Maleo can only live in a tropical climate, where there is a gap between the hottest and coldest temperatures in 24 h. The constant temperature range affects Maleo reproduction in nature. Ospina et al. (2018) reported that temperature is one of the most important factors in determining or influencing embryo development, hatchability, and growth of offspring after hatching. If the temperature is not constant it will produce weak and unable to survive. The heat conditions of Maleo bird nesting come from the temperature of the soil. Soil temperature is strongly influenced by weather conditions (such as the length of solar irradiation and rainfall) (Karim et al., 2023). Maleo nests are usually made in open sandy soil and exposed to direct sunlight throughout the day. Heat conductivity will be higher in sandy soil compared to other types of soil (Bockheim et al., 2020). The sand has a warm temperature to soak the eggs because the sun's heat can be directly absorbed into the soil, and then the soil stores this heat (geothermal heat) which can be tolerated by maleo bird eggs (Jamili et al., 2015).

The resulting accuracy values are in the range of AUC training = 0.99–1.0, AUC test = 0.98–0.99, COR = 0.93–0.96, TSS = 0.96–0.99, and Deviance = 0.13–0.68 (Table 3). The SVM and RF models have perfect AUC values. Meanwhile, the lowest performance was shown by GLM. When viewed from the observation points at important distribution locations referring to Mustari (2021), RF is quite good in modeling the distribution of this species. This model is also very sensitive to the topographical structure of the area, where ecologically Macrocephalon Maleo reproduces by laying eggs on a flat elevation and sandy soil structure (Mustari, 2021). Several studies have reported good performance of RF in studying species distributions. RF was able to study the invasion of Euphorbia escula and Centaurea moculosa in Montana based on hyperspectral HySpex images with 86% and 84% accuracy, respectively (Lawrence et al., 2006). Another study proved the ability of RF to identify two grassland species Molinia caerulea and Calamagrostis epigejos in the Silesian plateau in Poland with the highest kappa of 0.89 and 0.85, respectively (Marcinkowska-Ochtyra et al., 2018). RF has been generally available for more than 20 years and has been known to perform extremely well in ecological predictions (Mi et al., 2017). However, although its application continues to increase, its potential remains underutilized in conservation efforts, ecological (spatial) applications, and inference.

There are many reasons such as pixel size, number of samples, and study area. The limitation of this research can be different pixel resolutions so the

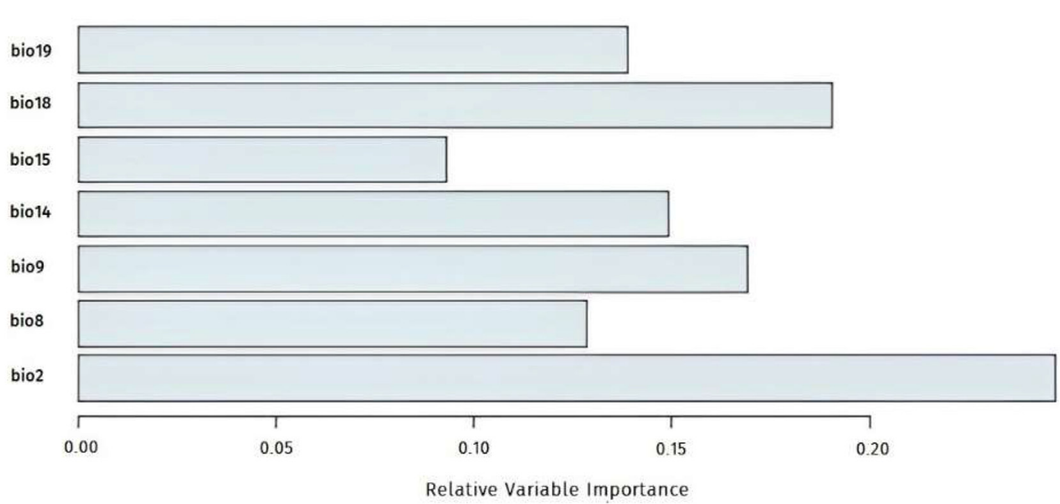

Fig. 3. Relative variable importance of Macrocephalon Maleo.

Table 3. Evaluation of each algorithm to predict the potential distribution of Macrocephalon Maleo.

Algorithm	AUC Training	AUC test	COR	TSS	Deviance
Support Vector Machine (SVM)	1.0	0.99	0.96	0.99	0.13
Random Forest (RF)	1.0	0.99	0.96	0.99	0.14
Generalized linear models (GLM)	0.99	0.98	0.93	0.96	0.68

standard factor approach needs to be adjusted. The algorithm used is also limited to the GLM, SVM, and RF algorithms. Other factors such as human interference were not considered. This aspect is a serious threat to this species (Dekker, 1990; Butchart and Baker, 2000; Gorog et al., 2005; Mustari, 2021). Nevertheless, our results show that it informs ecological and biogeographic theory and is suitable for conservation applications in global climate change scenarios, especially over a relatively large study area and many unknown locations. Distribution of unrecorded in situ species in West Sulawesi and Southeast Sulawesi. This method helps save time and effort in model selection and enables robust and rapid assessment and decision making for efficient conservation.

3.2. New distribution model

The results of the new distribution model based on bioclimatic variables and in situ species presence data give quite promising results on a scale of 1:60,000. Fig. 4a is a map of the distribution species with a grouping of at least 50% probability. This area covers 156,597.76 km^2 (88%) of the total area of Sulawesi. There were 92.31% matched areas with the presence of Macrocephalon Maleo (Fig. 7). This model is considered valid because it has a value of AUC = 1. Although the AUC value shows strong results, when viewed from the point of distribution it is important. The distribution area of the Tanjuk Matop Wildlife Reserve was not identified after the classification system was applied.

Patterns generated by BirdLife International (2021) show similar patterns and regions. However, the resulting pattern is very similar to BirdLife International (2016) without highlighting the Muna Island and the Kabaena island. Although in the southern part of Sulawesi, there is a very wide distribution. The Quarles mountain range which stretches from West Sulawesi to South Sulawesi is also no longer designated as a distribution area in the IUCN predictions after the status of this species became critical. Macrocephalon Maleo is estimated to inhabit 110,033.17 km^2. This area is smaller than this study estimated.

The predicted distribution model has a corridor connecting West Sulawesi to Southeast Sulawesi, between North Central Sulawesi to Gorontalo and North Sulawesi, and between Southeast Sulawesi which is separated from the Tanjung Peropa Wildlife Sanctuary and Tanjung Batikolo Wildlife Sanctuary which is an important distribution of this species (Mustari, 2021). This finding did not exist in previous studies. Data released by IUCN show this corridor was not predictable but could be identified in this

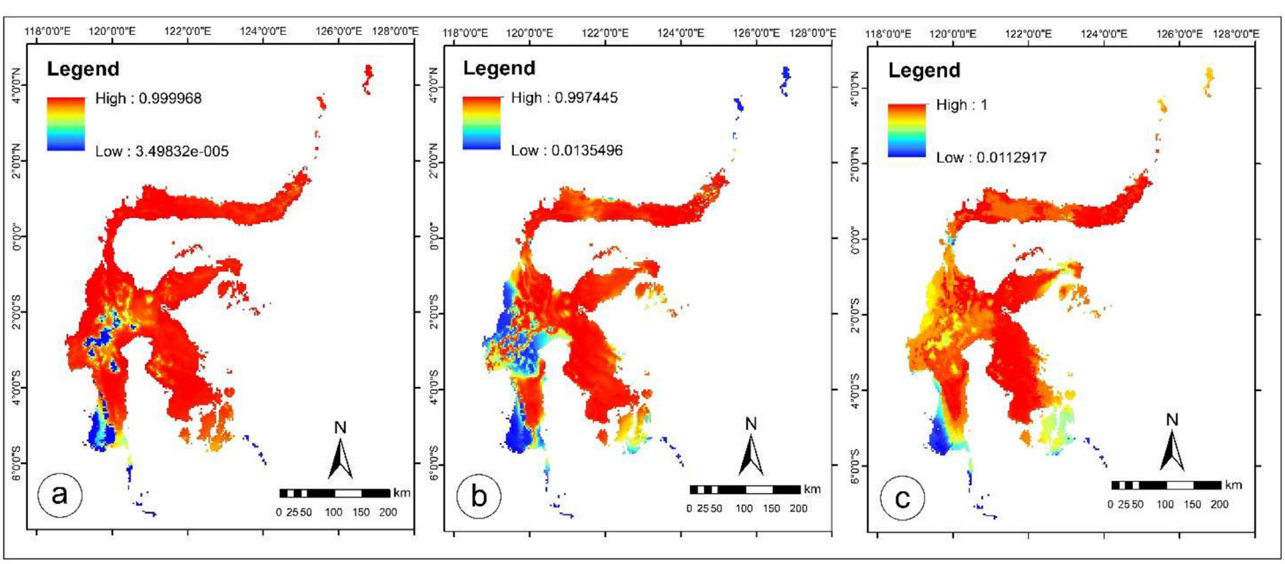

Fig. 4. Distribution Model of Macrocephalon Maleo: GLM Model (a). SVM model (b). RF models (c).

study (Fig. 5a and b). The existence of this corridor makes it possible to connect nesting sites with non-breeding areas. Restoring or protecting habitat in degraded Maleo corridors can help maintain and increase populations. Maleo are reported to be shy towards humans and mostly walk (Collar et al., 2001), so open areas and high levels of human activity are the main obstacles, and this cannot be negotiated by maleo. Therefore, inhibiting, preventing, and minimizing these developments is considered important. Replanting open areas to increase forest cover and encourage the success of native forests, including trees for roosting, is also considered to improve the quality of corridors.

The maleo's important distribution area (Mustari, 2021) has been included in the new distribution model. Areas confirmed as habitat for Macrocephalon Maleo include Bogani Nani Wartabone National Park (1), Panua Nature Reserve (2), Lore Lindu National Park (4), Morowali Nature Reserve (5), Rawa Aopa Watumohai National Park (6), Tanjung Peropa Wildlife Sanctuary (7), Tanjung Batikolo Wildlife Sanctuary (8), Mangolo Nature Park (9), North Buton Nature Reserve (10), Lambusango Wildlife Sanctuary (11), Lake Towuti on the East Side (12), and Dua Saudara Nature Reserve (13) (Fig. 6).

3.3. Future maleo distribution scenarios

Macrocephalon Maleo is predicted to survive in most parts of Sulawesi in the future. Around 149,601.22 km^2 (84%) of Sulawesi's area is still suitable for this species. There is 4% of the distribution area lost in 70 years. An area that is not suitable as a habitat for Macrocephalon Maleo is the Lambusango Wildlife Sanctuary (11) due to climate change (Fig. 7). This is in line with Leclerc et al. (2020) that the southern side of Sulawesi is very vulnerable to climate change which will affect the number of species populations in nature. Sulawesi has never been identified as a megapode (Foden et al., 2013).

This species only lays 8−12 eggs/year in its habitat and is monogamous (Mustari, 2021). Small numbers and high survival abilities are needed by maleo chicks (Mustari, 2021) to avoid predators, regardless of parental care. Maleo egg conservation has also been carried out in situ and ex-situ (Hafsah et al., 2008; Tasirin et al., 2021). However, ex-situ hatchery efforts are also considered to continue to decline and are less promising (Butchart and Baker, 2000; Hafsah et al., 2008). Many nesting sites were found empty without eggs in their natural habitat (Gorog et al., 2005; Bashari et al., 2021; Mustari, 2021). This number continues to decline in several locations (Summers et al., 2023). Generally, these events are associated with forest fragmentation, primary forest habitat degradation, and uncontrolled egg collection (Dekker, 1990; Butchart and Baker, 2000; Mustari, 2021; Summers et al., 2023).

The corridor connecting the central and northern parts of Sulawesi in 2092 is expected to be reconnected (Fig. 7). This climate change could allow for

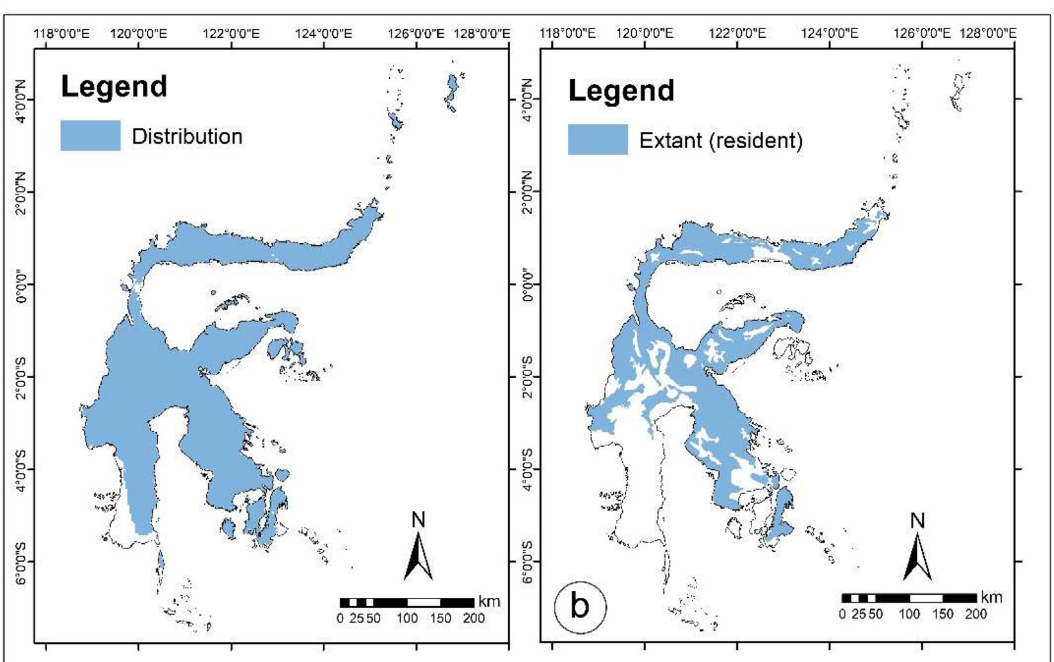

Fig. 5. Maleo prediction: New model (a). Predictions from BirdLife International (2021) (b).

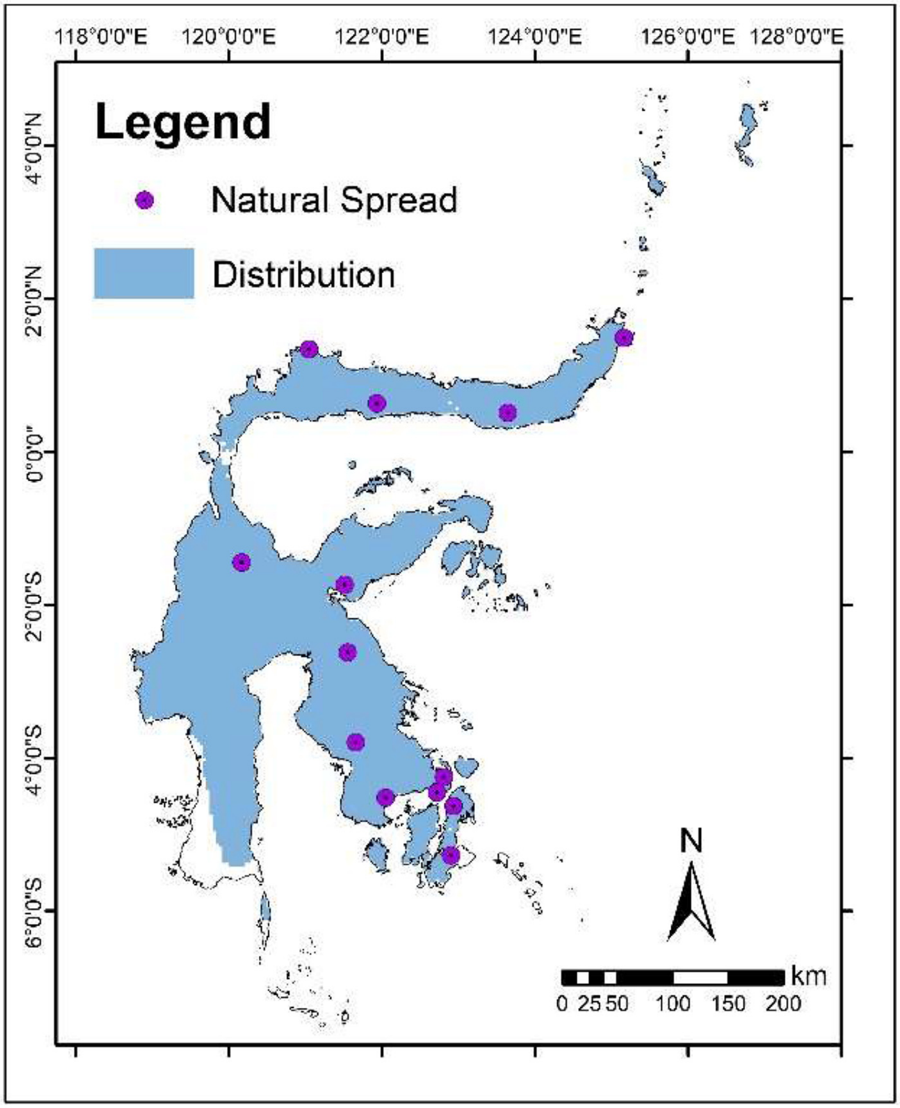

Fig. 6. Maleo's predictions overlap with the results of observations by Mustari (2021) in Sulawesi.

the migration of species between these areas and serve as a starting point for conservation efforts in their natural habitats. Reforestation between forest areas and nesting sites as well as minimizing human disturbance (BirdLife International, 2021) can be used for forest restoration which may be a corridor for the exchange of the largest Maleo individuals on mainland Sulawesi.

Large-scale connectivity conservation initiatives are already underway on all continents, including national efforts such as the Yellowstone to Yukon initiative, transnational conservation areas in the Greater Virunga landscape in Central Africa and the establishment of biological corridors such as the MesoAmerican Biological Corridor (Worboys et al., 2010) are clear evidence. New protected areas and land use mosaics are designed to build ecological corridors in Mexico and the Vilacamba-Amboro region of the Andes in Colombia, Venezuela, Ecuador, and Peru (World Bank, 2010). In South Africa, large nature reserves in the Greater Cederberg region and elsewhere in the Cape Floristic Region include government-designated protected areas, as well as public and private lands under sustainable stewardship and management arrangements to create biological corridors from the mountains to the sea (Sandwith et al., 2010). Governments in several parts of the world are also proposing a continent-wide connectivity conservation approach, combining the goals of biodiversity conservation and resilience to climate change through National Wildlife Corridor Plans. Nonetheless, further studies of this species including biophysical variables, distribution aspects, human

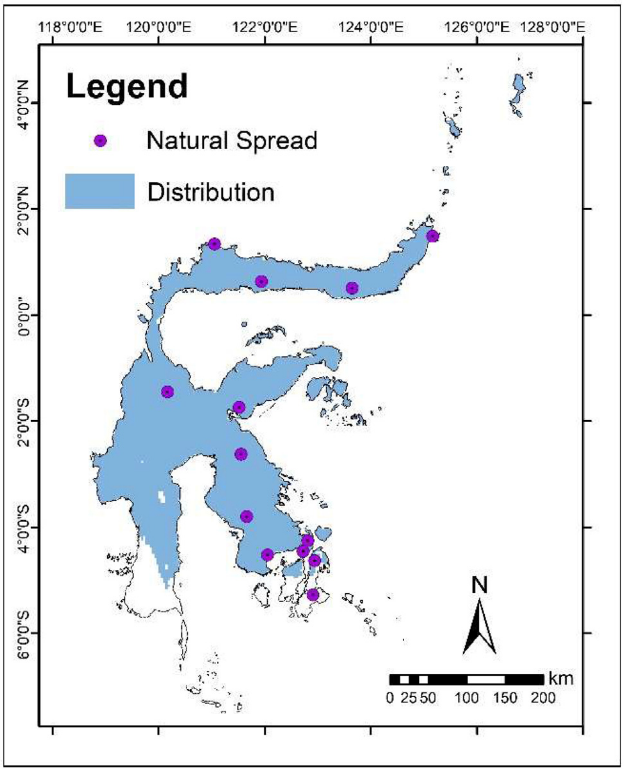

Fig. 7. Distribution prediction of Macrocephalon Maleo (2092).

activities, and site habitat history are needed to provide important tools for management and conservation.

4. Conclusions

The three models can visualize the Maleo distribution using only bioclimatic variables and attendance data. A fairly good model is shown by Random Farest which is sensitive to the topographic structure and distribution of the presence data. The variables bio2, bio8, bio9, bio14, bio15, bio18, and bio19 are highly correlated with future climate and climate data. These results indicate that maleo live at ideal temperatures, where the temperature range tends to be constant because it will affect maleo reproduction in nature.

The model shows that there is a corridor connecting the Macrocephalon Maleo, namely between West Sulawesi to Southeast Sulawesi and between North Central Sulawesi to Gorontalo and North Sulawesi. Ex-situ conservation actions can be carried out on this species because most of the Sulawesi area has a suitable habitat from the climate aspect. However, along with climate change. Lambusango Wildlife Sanctuary, which is the habitat of this species, is becoming more vulnerable and is predicted to have environmental incompatibility in the future.

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Authors' contributions

SA and KAW designed this study. SA collected data from GBIF and WorldClim. SA processes data. All authors analyzed the data. KAW approved the last version of the script.

Declaration of Generative AI and AI-assisted technologies in the writing process

We declare that no Artificial Intelligence (AI) technologies or AI-assisted tools were utilized in any capacity during the writing and preparation of this article.

Conflict of interest

The authors declare that they have no conflict of interest.

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