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RESEARCH ARTICLE

Distribution modelling of *Aedes aegypti* in three dengue-endemic areas in Sumatera, Indonesia

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ABSTRACT

Ae. aegypti is a dengue virus vector and a public health threat in Indonesia. Furthermore, the Dengue Haemoragic Fever (DHF) has spread to all cities in the country, including Bandar Lampung. A species distribution model, Maximum Entropy (MaxEnt), was used to predict the geographic distribution of this vector in three dengue-endemic areas, namely Sukarame, Kemiling, and Tanjung Seneng. Previously, surveillance was conducted to determine the presence of *Ae. aegypti*. Therefore, this study suggested that environmental variables such as rainfall, temperature, land cover, and population density have influenced the widespread of *Ae. aegypti* and facilitate its proliferation in the study areas. The influence of the environmental variables was analyzed using a response curve. The model performance was measured by percent contribution, the importance of permutations, and the jackknife test. This study's evaluation indicates that the certainty models for the presence of *Ae. aegypti* in Sukarame, Kemiling, and Tanjung Seneng were developed extremely well, with respective values of 0.989, 0.993, and 0.969. The results showed that *Ae. aegypti* is widespread in the three endemic areas. The high population density and land conversion into settlements are influential environmental variables essential in determining the distribution of the vector in three areas of Bandar Lampung. Climatic factors such as rainfall and temperature are supporting aspects in maintaining the habitat of *Ae. aegypti* in the area. Mapping areas at risk of this dengue vector can aid in planning disease management strategies and identifying priority locations for entomological surveys to control epidemics.

Keywords: *Ae. aegypti*; dengue; distribution; MaxEnt; vector-borne disease.

INTRODUCTION

Mosquitoes are vectors of dengue, malaria, chikungunya, filariasis, yellow fever, and others (CDC, 2018). Dengue is a viral disease transmitted by the bite of *Ae. aegypti* and *Ae. albopictus* mosquitoes (Christophers, 1960). *Ae. aegypti* is the principal vector of dengue fever in urban and rural locations around the world because of urbanization, the expansion of rural water supply systems and the enhancement of transportation infrastructure (Burkett-Cadena *et al*., 2013; Brown *et al*., 2014). The spread of this disease is influenced by many factors, including vectors, environmental conditions, population mobility, population density, artificial or natural shelters around the home environment, landfills or other waste, and community behavior (Harrington *et al*., 2014). The high population density results in the utilization of several artificial water reservoirs, causing the availability of mosquito breeding habitats in the house. Furthermore, it supports high mobilization, thereby speeding up the spread of disease. Climatic factors such as rainfall, temperature, and humidity also affect the spread of the dengue virus (Misslin *et al*., 2016). The climatic factors contributed to the high cases of dengue were high precipitation, humidity, and hot temperatures. The precipitation and high humidity create many water reservoirs outside the house, increasing mosquito breeding grounds. Meanwhile, the high temperature helps accelerate mosquito breeding in their habitat.

Dengue fever is a public health problem in Indonesia with increasing spread and sufferers. Its cases were first reported in Surabaya and DKI Jakarta in 1968. At that time, the number of carriers was 58, of which 24 died (Moh, 2018; Harapan *et al*., 2019). Furthermore, in 1988 dengue fever began to spread in Indonesia, with the number of sufferers reaching 13.45 per 100,000 (Moh, 2018; Harapan *et al*., 2019). The infection has spread evenly in all

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provinces in Indonesia, and Bandar Lampung is one of the leading cities that has become the growth centre of Southern Sumatra. The dengue cases in Bandar Lampung from 2016-to 2020 are increasing and often become extraordinary, with its high number reaching 1061 cases by 2020, which is a severe problem (BLCHO, 2018).

By using dynamic physical growth factors in dengue-endemic areas, the distribution of *Ae. aegypti* can be modelled temporally and geographically through the species distribution model (SDM) (Phillips *et al*., 2006; Diuk-Wasser *et al*., 2006). This helps integrate mathematical models of mosquito distribution with the factors that influence it to predict the spread of disease in an area. The objective was to understand the population of the vector with the possible geographic range of these mosquitoes based on environmental suitability in the dengue-endemic area in Bandar Lampung. Monitoring vector population helps detect species distribution, density fluctuations changes, and permits programe evaluation. Furthermore, the Program can inform and improve strategies and vector control to reduce cases in dengue-endemic areas. The information obtained from these maps is beneficial to local health authorities in effectively implementing control and preventive measures to combat the principal vector of the dengue virus. Additionally, community engagement could potentially improve the local residents' awareness of forestall outbreaks and dengue cases.

MATERIALS AND METHODS

Study areas and species sample records

The distribution of *Ae. aegypti* was modelled for three sub-districts in Bandar Lampung, namely Sukarame, Kemiling, and Tanjung Seneng (Figure 1). These regions have the highest dengue cases in 5 years (2016-2020), hence, they are categorized as dengue-endemic areas in Bandar Lampung. Sukarame and Tanjung Seneng are urban areas with a reasonably high population density, while Kemiling is a sub-urban region bordered by several rubber forests and hills.

Between January and July 2021, sampling was conducted on 300 houses in three sample areas, each containing 100 homes. This was based on the entomology survey program run by the Ministry of Health of Indonesia (2010) to obtain the entomological index value. The survey was conducted once to determine the density, habitat characteristics, and spatial distribution (WHO, 2011). The selected house sample was located within a radius of 100 m from the dengue sufferers recorded in 2021. The survey was performed in the morning inside and outside the house by observing each container as a potential breeding site for mosquitoes. Containers containing 70% alcohol are used to collect up to 1-3 mosquito larvae samples, which are then examined under the microscope. This study is limited to seeing *Ae. aegypti* spatial distribution predictions in the sample areas. Finally, the coordinates of each house were taken using a Garmin Montana 680 GPS.

Environmental covariates

The environmental variables, such as temperature, precipitation, land cover, and human population density, were selected to determine the distribution of *Ae. aegypti*. Temperature and precipitation data were derived from bioclimatic variables with a spatial resolution of 1 km. Land-cover data was derived from Landsat 8 – OLI imagery for the third area with a spatial resolution of 30 m. Meanwhile, population density data derived from WorldPop at

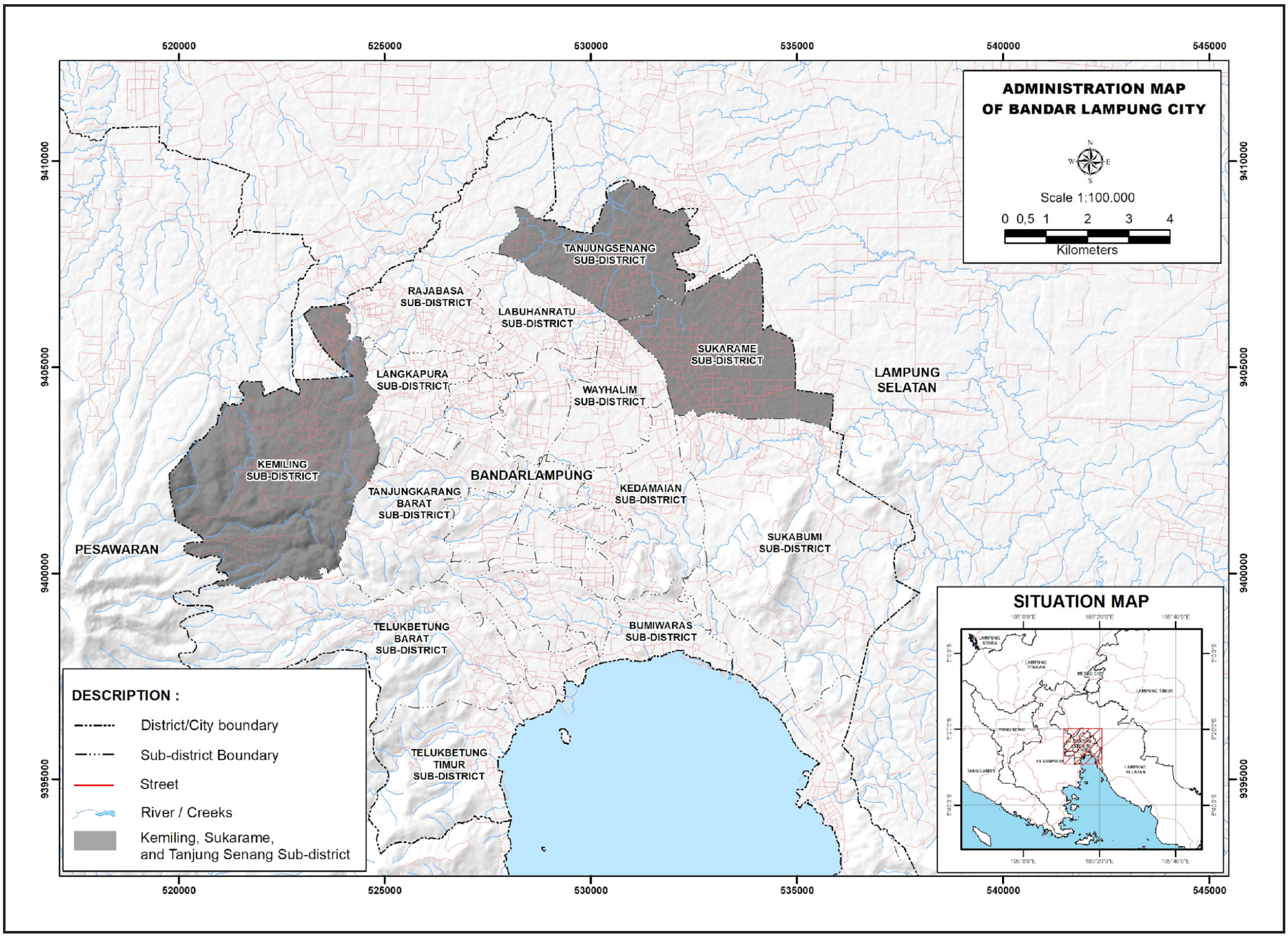

Figure 1. Location of the study Area. Three sub-district on Bandar Lampung (Sumatera, Indonesia); a. Sukarame, b. Kemiling, c. Tanjung Seneng.

30 m. Finally, the spatial resolutions of the variables were resampled to 30 m using the tool in 'ArcMap 10.1' (Fatima *et al*., 2016).

Evaluation of model performance

Maximum Entropy (MaxEnt), which is a method that can predict the geographical distribution of *Ae. aegypti,* was used. It is an application with a simple and precise mathematical formulation and has several aspects, such that it can model the geographical distribution of the vector. MaxEnt should avoid making assumptions that are not supported by the data when analyzing the environmental conditions in which a species is seen (Phillips *et al*., 2006).

The use of MaxEnt to predict *Ae. aegypti* should be subject to the limitations imposed by the available information regarding the distribution of the observed species and the environmental conditions in the study area. This technique does not require missing data in modelling the vector distribution but uses environmental data as a background for the entire study area. Figure 2 shows the method for producing habitat suitability maps for the presence of *Ae. aegypti*.

The model was evaluated using the Receiver Operating Characteristic (ROC) based on sensitivity and specificity (Baldwin, 2009). It was used to assess the overall model fit or accuracy. Low AUC values show model performance, where 0.5-0.7 is deemed acceptable, 0.7-0.9 is considered useful, and greater than 0.9 indicates a high level of accuracy in determining attendance and absence (Manel *et al*., 2001).

Three measures of variable contribution were used to determine how each variable impacts the experience of *Ae. aegypti*. These include the percent contribution used to determine environmental variables on the model results. This indicates the higher the PC value, the greater the contribution of these variables to the habitat of the modelled species. A permutation describes the importance of a variable to the running model. The jackknife test was used to determine which variables provided unique information that was not shown by others. Meanwhile, the response curve was used to determine the model changes through inclusion, exclusion and permutation in each variable.

RESULTS

Predictive distribution of *Ae. aegypti*

The results showed that the distribution of *Ae. aegypti* has spread in Bandar Lampung, specifically in the three sample areas. Between January and July 2022, sampling was conducted on 300 houses in the regions. It was done through an entomological survey to determine mosquito larvae density, habitat characteristics, and spatial distribution. Out of the 300 houses sampled, it was recorded that 87 houses contained *Ae. aegypti*, and from 1996 containers examined, 179 of them were positive for the vector, as shown in Table 1. Figures 8, 9, and 10 illustrate the predicted distribution of *Ae. aegypti* in three dengue-endemic regions.

Evaluation of model performance result

Evaluation of the model revealed the probability model for the presence of *Ae. aegypti* in Sukarame, Kemiling, and Tanjung Seneng was highly accurate. This was performed based on the AUC value, where 0.6 to 0.7, 0.7 to 0.8, 0.8 to 0.9, and greater than 0.9 indicates low, moderate, good, and high accuracy value in measuring the presence and absent substances (Elith *et al*., 2011). Figure 3 shows the AUC value for *Ae. aegypti* in Sukarame, Kemiling and Tanjung Seneng. The red and blue lines show the mean AUC and average standard deviation values, respectively. It can be stated that the closer the red line to the left (closer to the value of 1) and the smaller the standard deviation value, the better the model's performance (Johnson *et al*., 2017).

The results of the jackknife test on AUC, as presented in Figure 4, showed that environmental variables have an effect individually or without variables. This test was conducted on the model's performance to evaluate the predictive model. The relationship between the probability of the presence of *Ae. aegypti* with environmental variables can be seen in the response curve generated by MaxEnt. These curves show how highly environmental variables affect the prediction of *Ae. aegypti* in three endemic areas. In general, the response to the presence of the vector to interconnected environmental variables (non-linear) is above the median value of 0.5.

In Sukarame, the environmental variables play a significant role in the model results by observing the Percent contribution (PC) value of rainfall (PC=38.4%) and population density (PC=29.2%). Furthermore, the Permutation Important (PI) value at 5% rainfall indicates that the overall model performance decrease without this variable, while it is invariable for the population density. In Kemiling, the environmental variables that play a significant role are land cover (PC = 50.9%) and temperature (PC = 29.4%). They have a value above 5% that affects the overall model performance. Meanwhile, in Tanjung Seneng, the significant environmental variables are population density (PC=57.7) and land cover (PC=38.8).

Environmental variables result

The response curves for environmental variables are shown in Figures 5, 6 and 7. The distribution of *Ae. aegypti* in the three sample areas is closely related to human population density. Although all three places are urban, Kemiling has a lesser population than Sukarame and Tanjung Seneng due to its location on the city's

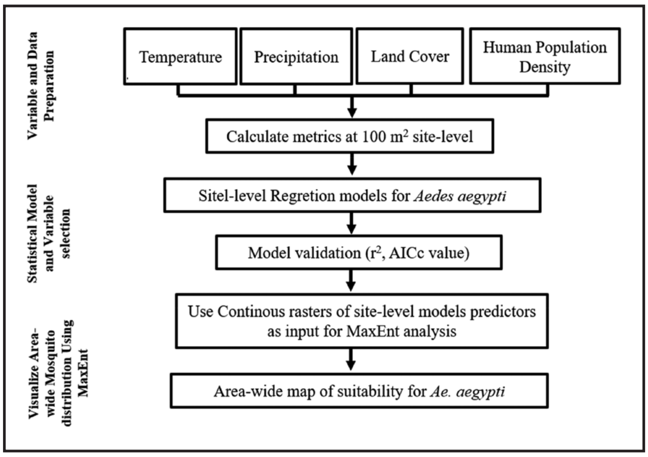

Figure 2. Methodological work flow to produce habitat suitability maps for the presence of *Ae. aegypti*.

Table 1. Distribution of *Ae. aegypti* Larvae in Endemic Area in Bandar Lampung

Variable	Sukarame			Kemiling			Tanjung Seneng		
	–	+	%	–	+	%	–	+	%
House	100	41	41	100	38	12,67	100	32	10,67
Ae. aegypti		36	12,00		26	8,67		25	8,33
Container	749	105	14,02	640	77	12,03	607	60	9,88
Ae. aegypti		86	11,48		45	7,03		49	8,07

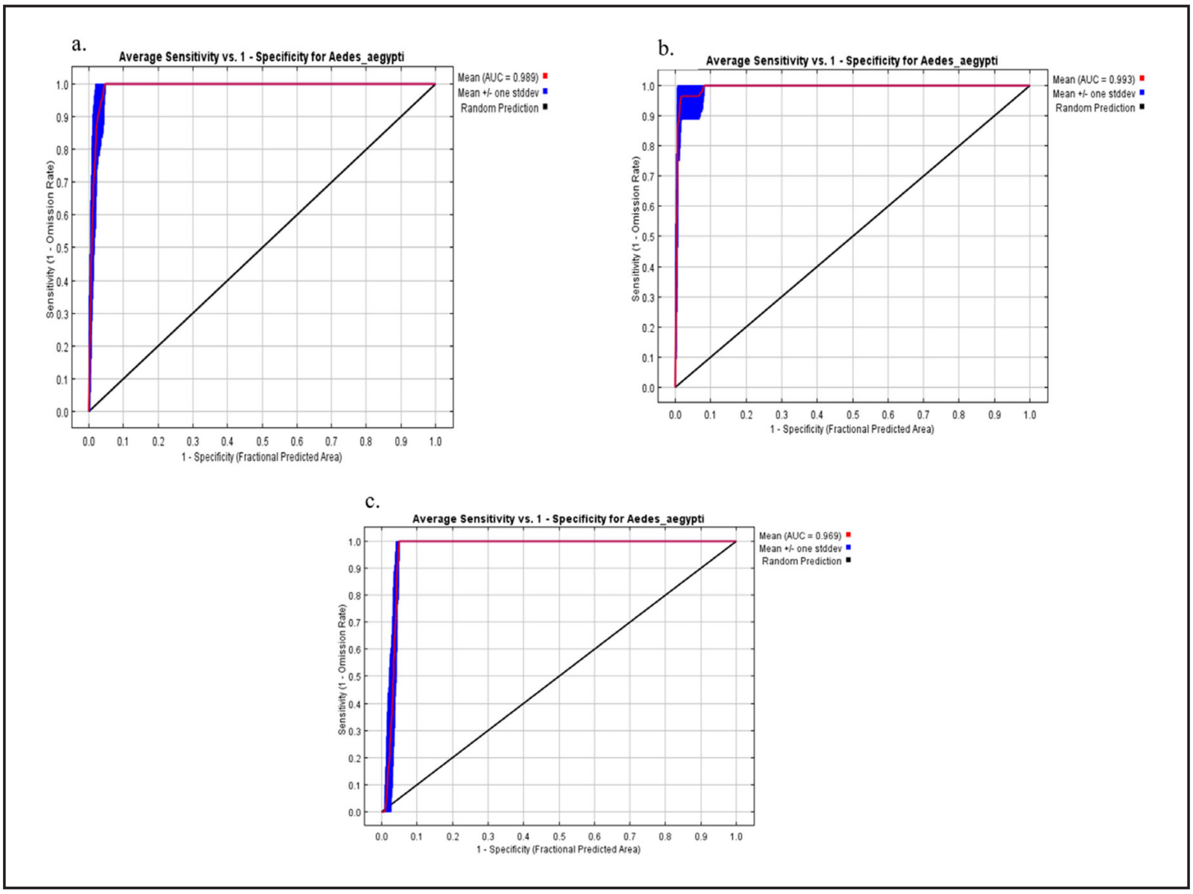

Figure 3. Sensitivity and specificity curve of prediction modelled of three areas (a. Sukarame, b. Kemiling, c. Tanjung Seneng).

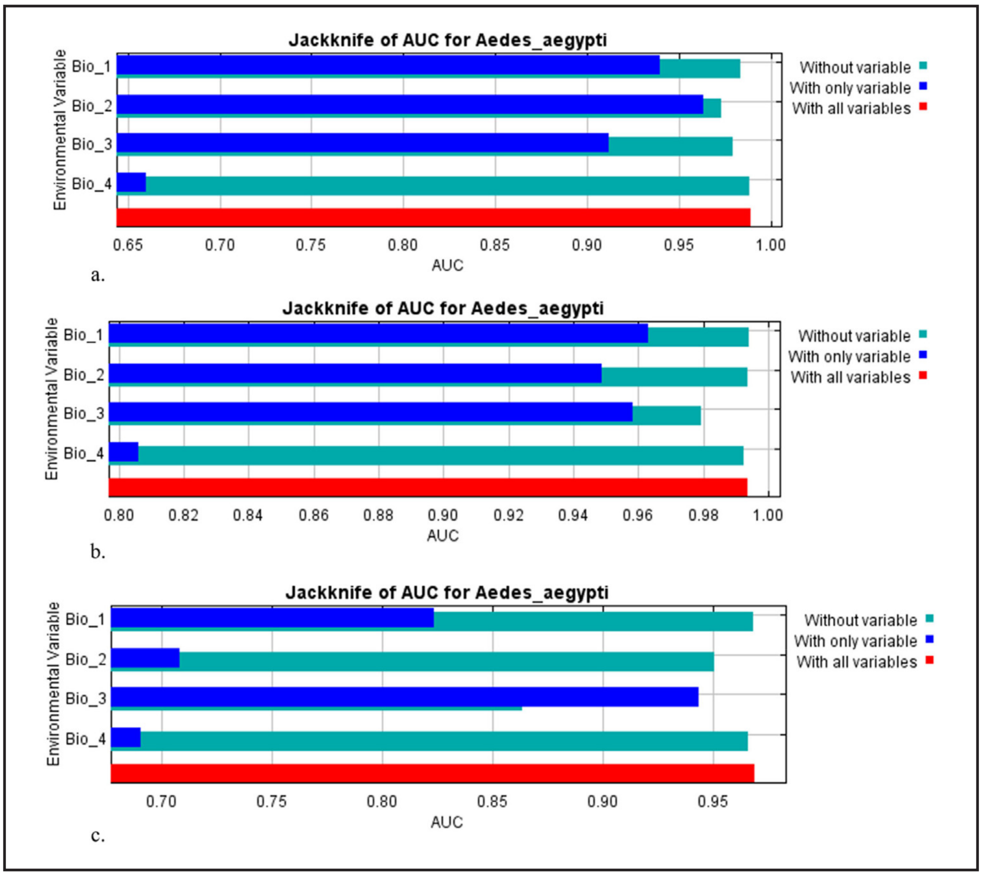

Figure 4. The results of the jackknife test on the AUC for the presence of *Ae. aegypti* (a. Sukarame, b. Kemiling, c. Tanjung Seneng).

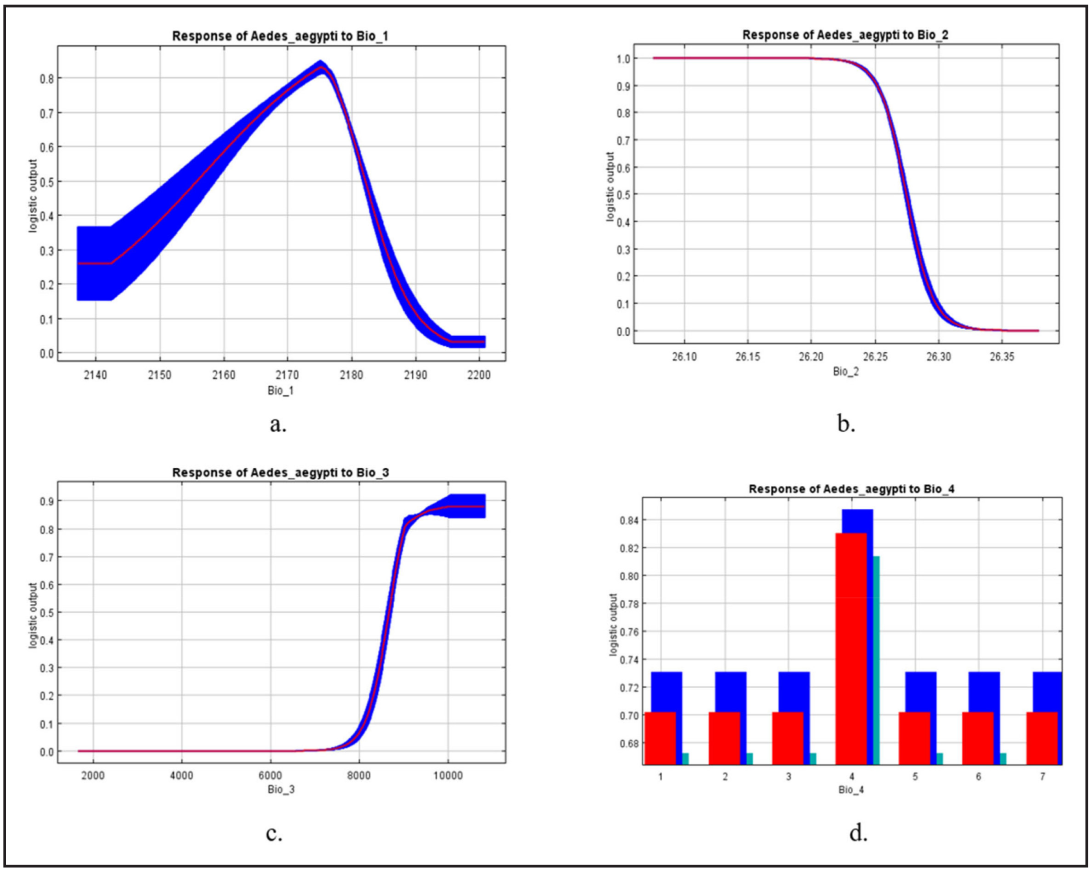

Figure 5. Model response curve for the presence of *Ae. aegypti* larvae in relation to all environmental factors in Sukarame (a. Precipitation; b, temperature; c. human density; d. land cover).

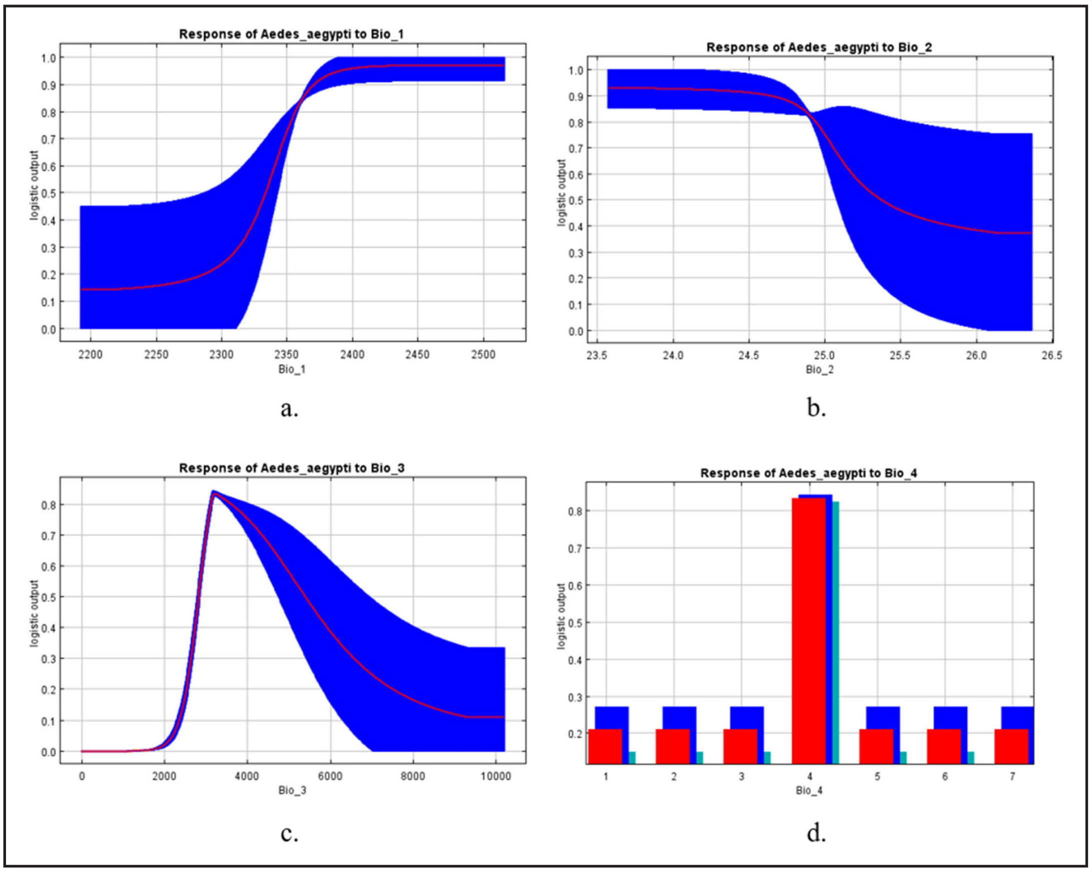

Figure 6. Model response curve for the presence of Ae. aegypti larvae in relation to all environmental factors in Kemiling (a. Precipitation; b, temperature; c. human density; d. land cover).

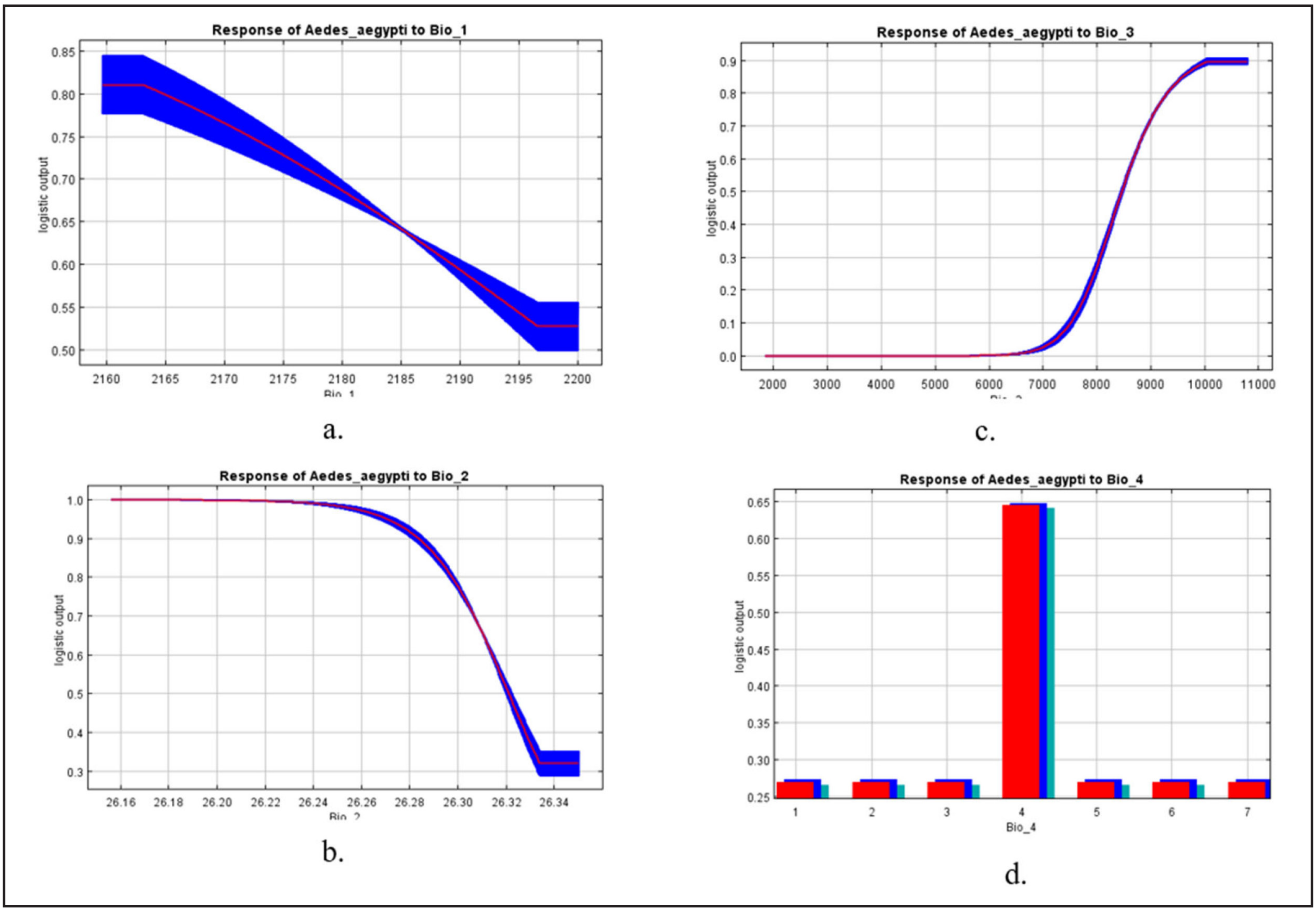

Figure 7. Model response curve for the presence of *Ae. aegypti* larvae in relation to all environmental factors in Tanjung Seneng (a. Precipitation; b, temperature; c. human density; d. land cover).

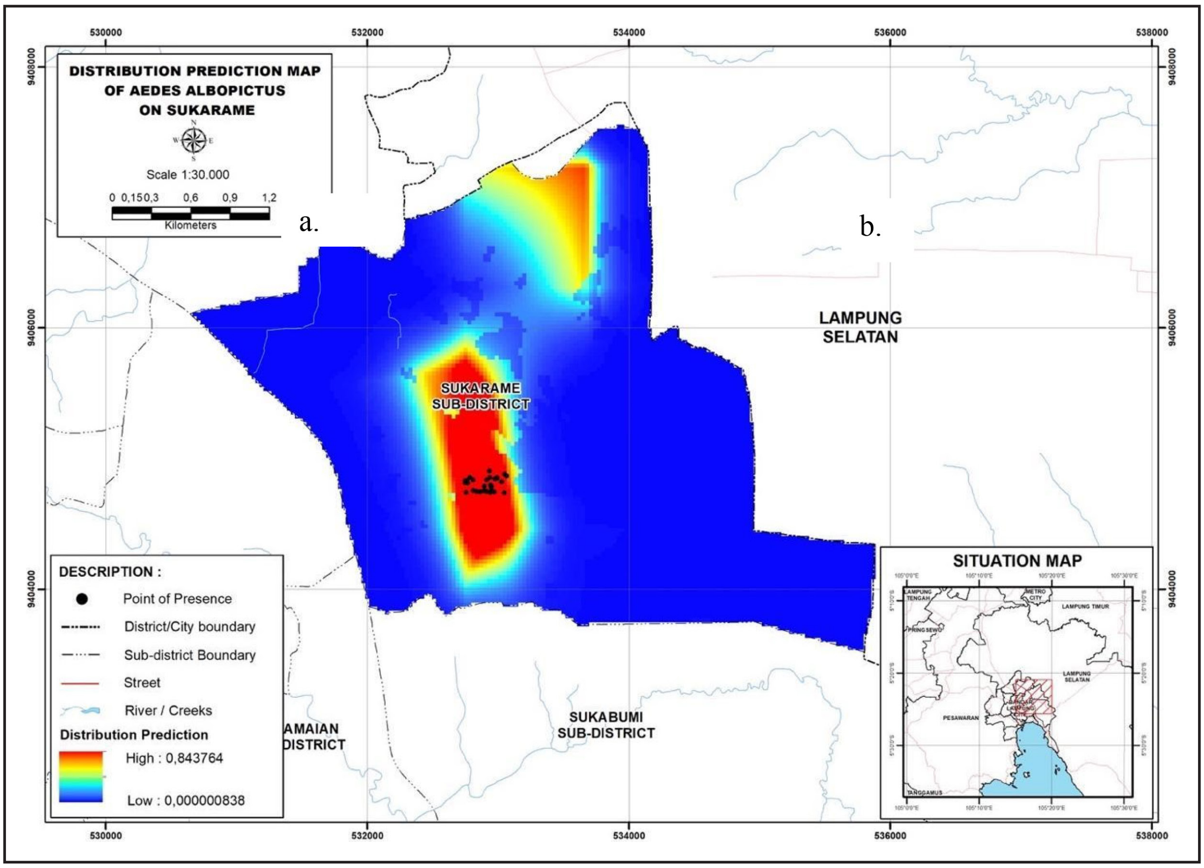

Figure 8. Prediction Distribution Map of *Ae. aegypti* in Sukarame.

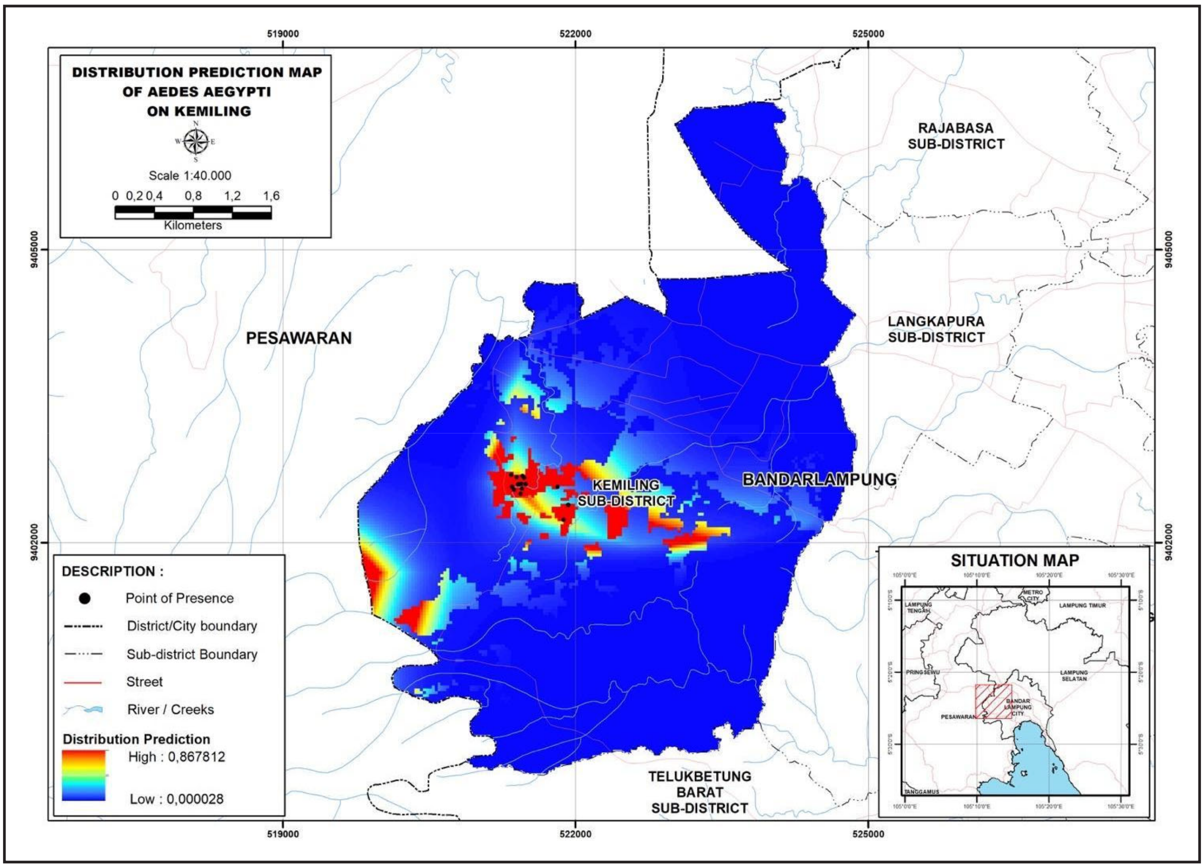

Figure 9. Prediction Distribution Map of *Ae. aegypti* in Kemiling.

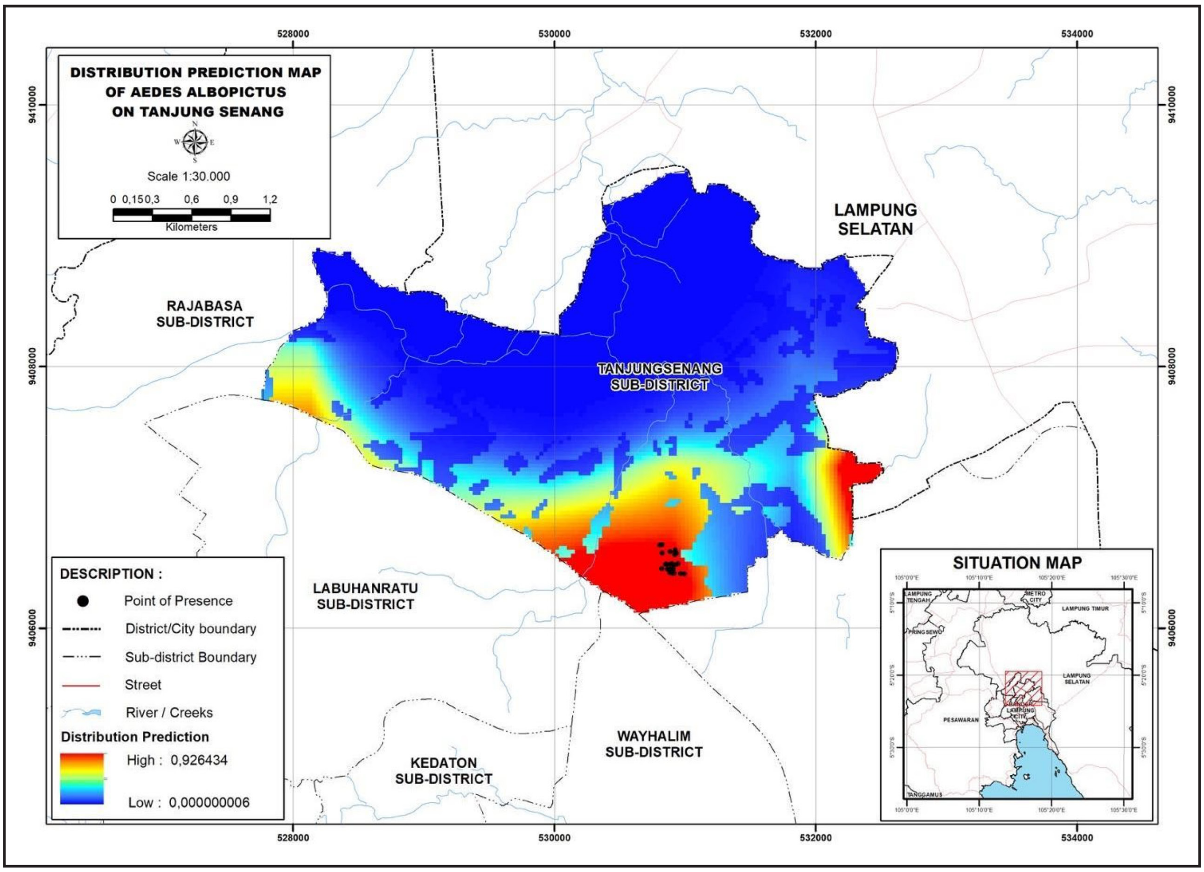

Figure 10. Prediction Distribution Map of *Ae. aegypti* in Tanjung Seneng.

outskirts bordering the district, primarily surrounded by rubber trees and farms. The effect of rainfall on *Ae. aegypti* has a significant influence on the model in Sukarame, but not in Kemiling and Tanjung Seneng. The variability in the three regions indicates that *Ae. aegypti* responds quite well to variations in rainfall ranging from 21.6 – 21.8 mm/day. Temperature also affects the presence of the vector in the three sample areas. Sukarame and Tanjung Seneng have an optimum temperature range of 26°C, while Kemiling is lower at 23-25°C and affects the presence of the vector.

The land cover also contributed to the probability of the presence of *Ae. aegypti*. Furthermore, the variables observed were water bodies, forests, open land, settlements, dry land agriculture, rice fields, and shrubs. As a result of the land cover response curve, the type of settlement provides a strong correlation to the presence of *Ae. aegypti*. The factor is closely related to the nature of anthropophilic mosquitoes, indicating the more settlements, the higher the population. This will provide great potential to increase the mosquito population in an area. Figures 11, 12, and 13 depict the habitat suitability map of *Ae. aegypti*.

DISCUSSION

Bandar Lampung is a large city located at the tip of the Indonesian island of Sumatra, which has a very strategic location. The natural potential, the population, and the potential of the surrounding area, Bandar Lampung will lead to future development. The mobilization and population growth in this area are relatively high. It has a destructive impact, including vector-borne diseases such as dengue, which are easy to develop. Environmental factors also significantly affect the spread of this fever, specifically in the development of *Ae. aegypti*, a virus vector (Higa, 2011; Wijayanti *et al*., 2016). In the case of the spread of a highly complex disease, a tool is needed to explain the occurring phenomena in a visual, schematic, and diagrammatic way (Cianci *et al*., 2015; Estallo *et al*., 2018). Maximum Entropy (MaxEnt) becomes a very suitable method to explain the probability distribution of species in an area. Dengue, a vector-borne disease, easily shows the probability of the case spreading through the vector distribution.

The results indicate that human population density and infrastructure have a significant role in influencing *Ae. aegypti*'s existence, success, and spread. According to Figure 4, the jackknife tests at three locations indicate that human population dynamics was an essential factor in the existence of this vector (Stewart Ibarra *et al*., 2013; Obenauer *et al*., 2017). Sukarame and Tanjung Seneng are urban areas with a reasonably high population density. Meanwhile, Kemiling site is a sub-urban bordered by several rubber forests and hills with a moderate population density (Rochlin *et al*., 2016). Based on the habitat suitability map (Figures 11, 12, 13), the results showed that the three areas have good suitability for *Ae. aegypti* development. The evolution of the distribution, which initially came from sylvatic areas, and the encroachment of forests into agricultural land and settlements was the beginning of the spread of this species to rural regions (Rey *et al*., 2006). The residential area has been more extensive, resulting in an urban region where *Ae. aegypti* has been closely selected for human life. This relationship is related to the mosquito life cycle that requires water in the immature stage. The selection of the species, specifically by laying their eggs in numerous artificial water reservoirs utilized in human life, has resulted in the availability of breeding habitats in the home (Getachew *et al*., 2015). Due to the presence of *Ae. aegypti*

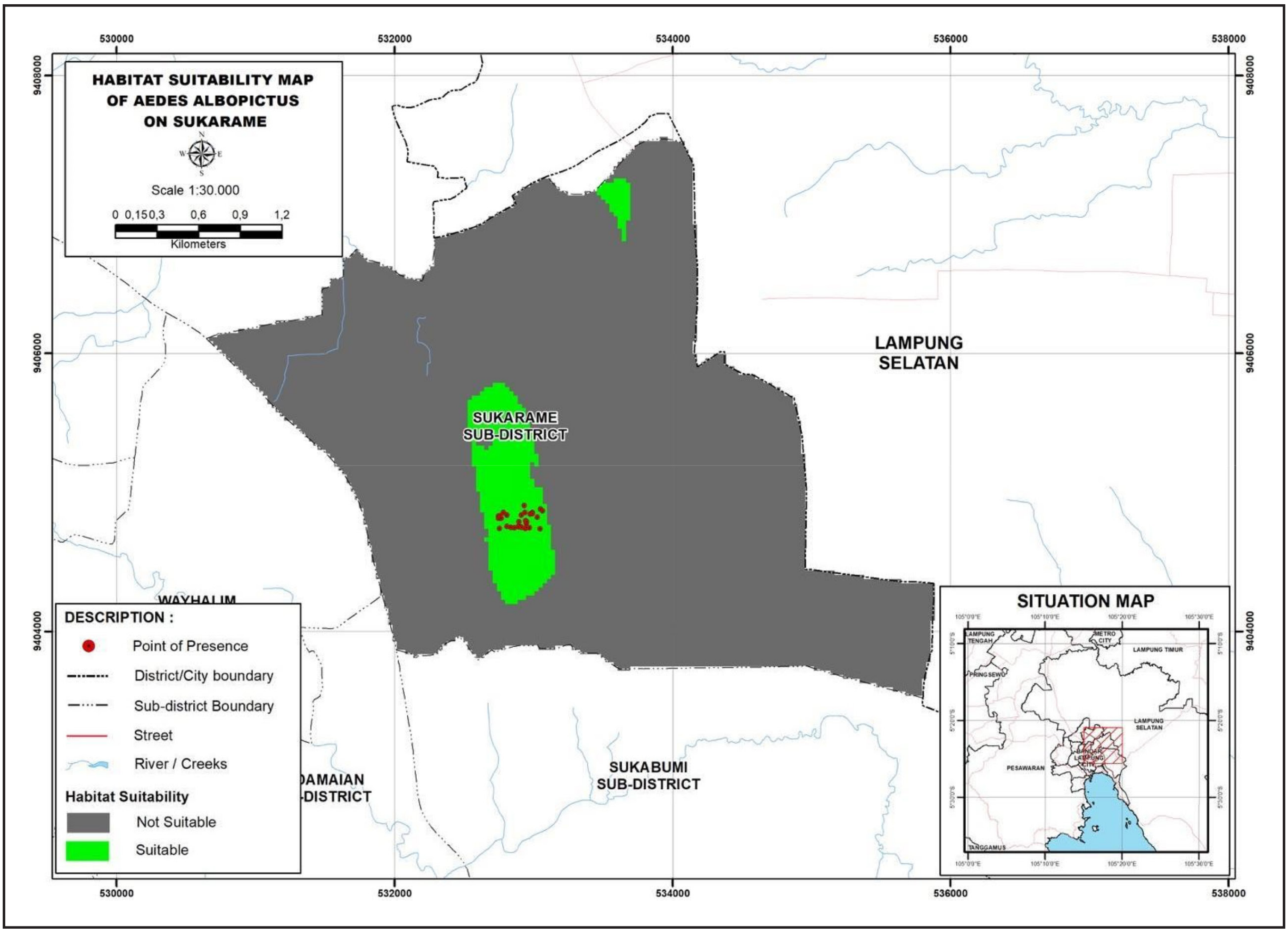

Figure 11. Habitat suitability map of *Ae. aegypti* for Sukarame with Jackknife test. Yellow marks indicate the species presence records.

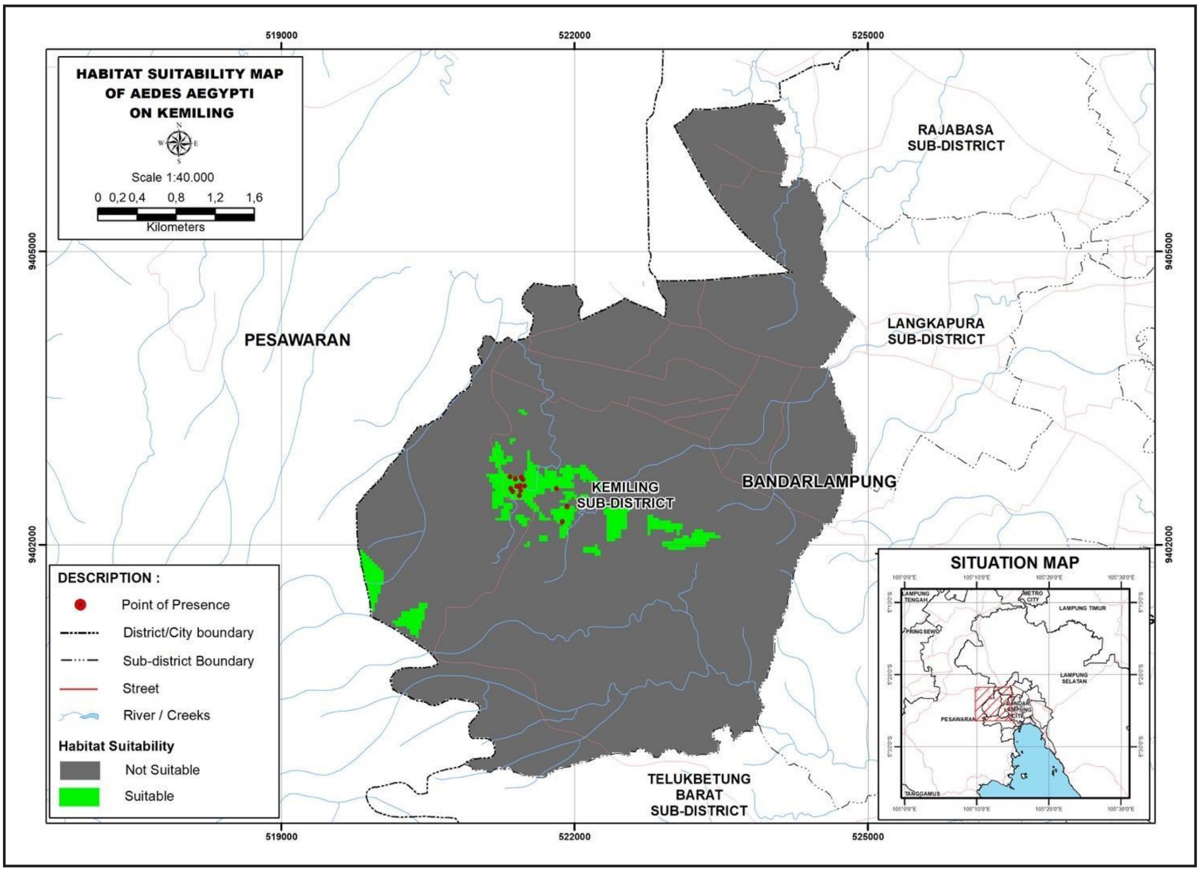

Figure 12. Habitat suitability map of *Ae. aegypti* for Kemiling with Jackknife test. Red point indicate the species presence records.

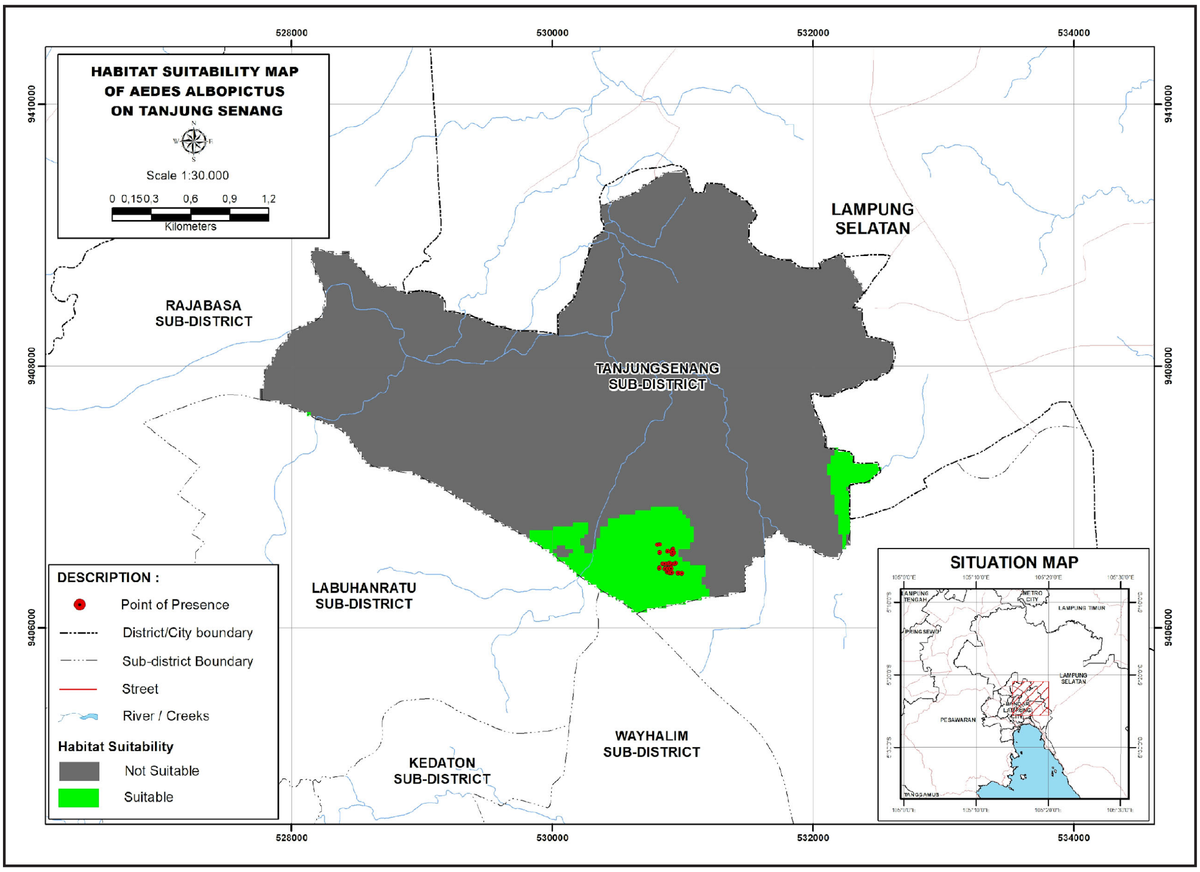

Figure 13. Habitat suitability map of *Ae. aegypti* for Tanjung Seneng with Jackknife test. Yellow marks indicate the species presence records.

Table 2. Comparison of the three Area in accuracy, variable importance and contribution

Area	Accuracy AUC test	Variables	Percent contribution (%)	Permutation importance (%)
Sukarame	0,989	Precipitation	38,4	5,0
		Human Density	29,2	0,8
		Temperature	18,4	26,8
		Land Cover	14,0	67,4
Kemiling	0,993	Land Cover	50,9	12,5
		Temperature	29,4	16,3
		Human Density	18,1	52,6
		Precipitation	1,6	18,6
Tanjug Seneng	0,969	Human Density	57,7	82,3
		Land Cover	38,8	5,2
		Temperature	3,3	9,7
		Precipitation	0,2	2,9

are anthropophilic (exclusively feeding on humans) and endophagic (feeding within the home) (Harrington *et al*., 2014).

The result also showed that precipitation and temperature were other important factors contributing to the high number of dengue cases in the three regions. Moderate rainfall but with sufficient daily intensity creates many air shelters outside the house which also increase the breeding ground for mosquitoes (Leisnham & Juliano, 2012). Variations in rainfall facilitate this vector's habitat availability, essential in increasing the species' population. The result is supported by discovering many positive containers for *Ae. aegypti* larvae (Burkett-cadena *et al*., 2013). Even though it does not directly affect the presence of mosquitoes, high temperatures can support the breeding cycle in their habitat (Liu *et al*., 2019). According to the mosquito data, the three regions provide observed variables: population density, residential area, temperature, and rainfall. This result is in line with Nurjanah *et al*. (2021), which stated that *Ae. aegypti* has a high density.

The high AUC value (Table 2) implies the increased distribution of *Ae. aegypti* in the three endemic regions was predicted. According to the distribution map of the virus, the sampling area has a high species distribution (Figures 8, 9, 10). The modelling results for *Ae. aegypti* can help plan disease control strategies, discover diseases that may be the site of previous dengue spread, and determine the central locations for which entomological surveys are conducted for epidemic control (Kraemer *et al*., 2015; Ding *et al*., 2018). The species distribution model help determines disease control timing to select mosquito sampling and surveillance areas.

The errors and uncertainties that often occur in MaxEnt modellings were overcome (Elith *et al*., 2011), using known and standardized sampling methods for mosquito data collection, reducing the number of variables in the model to avoid overfitting and limiting the study to representative areas of mosquito sampling locations, and conducting collinearity testing. The sampling was conducted directly in areas with confirmed cases of dengue fever which were high enough to obtain accurate confirmation and the absence of *Ae. aegypti*. Because of the limited time and sampling area, it is challenging to develop a regional distribution for the entire city of Bandar Lampung. Repeated sampling from year to year with a sufficiently representative area will significantly improve the model's accuracy, making the spread of dengue cases more visible (Peterson, 2006; Lounibos & Juliano, 2018).

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Conflicts of interest

The authors declared that there are no potential conflicts of interest with respect to this study, authorship, and publication.

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