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Environmental potential of Aedes Aegypti Mosquitoes for Dengue haemorrhagic fever in Pekanbaru, Indonesia

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Abstract

Dengue fever is frequently considered a common fever, and this misconception carries the highest risk of fatality. Dengue haemorrhagic fever is still one of Riau Province's unsolved diseases. This is one of the reasons why this study is necessary to identify prospective mosquito environmental zones with major significance for understanding epidemic transmission in the Pekanbaru City area. The bivariate statistical approach was employed in this research. The aim is to link environmental physical factors to data on the occurrence of dengue haemorrhagic fever in Pekanbaru City. The area under the curve for the correlation between the environment and the distribution of dengue haemorrhagic fever was 0.76 for the rainfall parameter, with 0.68 for the area under the curve derived from the air humidity parameter. The establishment of six environmental indicators resulted in a weight of evidence value of 10,467 to -35,693 for the mosquito's environmental potential. Meanwhile, the most favourable potential zone, which encompasses 5,935 ha, accounts for 9.18% of the overall area. Areas with the highest risk of spreading Aedes aegypti mosquitoes were found around the city center, both residential and office areas. The risk of dengue haemorrhagic fever transmission in this zone is higher than in the other three zones. By taking earlier events into account, this knowledge can be one of the early preventions in understanding the environmental structure of the Aedes aegypti mosquito habitat.
Keywords: *environment, surveillance, sustainability, Pekanbaru City*

Introduction

Infectious diseases with endemic infection of dengue haemorrhagic fever originating from the *Aedes aegypti* mosquito can be spread through bites and transmitted from person to person. Other species in the distribution of this disease include *Ae. albopictus*, *Ae. polynesiensis*, *Ae. scutelaris* and *Ae. Niveus* as a secondary vector (Alam & Haque, 2021). Species from secondary vectors have a limited distribution space with a distribution rate of epidemic vectors that is less efficient than primary epidemic vectors despite having excellent host capabilities for the dengue virus (Louis et al., 2014). The flight range of the *Aedes aegypti* mosquito is as far as 40 meters with a height of up to 1,000 meters above sea level (Verdonschot & Besse-Lototskaya, 2014). The virus can be transmitted by the *Aedes aegypti* mosquito, causing individuals to get infected during the acute fever phase and facilitating transmission even after the onset of fever (Nunthavichitra et al., 2020). The virus becomes infective about 8-12 days after the mosquito sucks the blood of a patient who is viraemic and remains infective after a period of salivary gland viremia where the mosquito bites and secretes saliva into the bite wound into another person's body (Her et al., 2017). The next stage is the occurrence of an incubation period in the human body for 3-14 days with sudden onset of symptoms of the disease (Firdous et al., 2017). It is unknown whether the case reported in the sub-district was locally acquired or imported from a neighbouring sub-district because information about the source of infection is not obtained by the surveillance system (Wangdi et al., 2020; Tsheten, Clements, Gray, & Wangdi, 2021). In some places, it is vital to update the identification of possible dengue virus or other mosquito-borne disease vectors, which has substantial consequences for disease occurrence (Naish et al., 2014; Salim et al., 2021). Dengue fever is sometimes confused with a common fever which increases the risk of death significantly (Koyadun, Butraporn, & Kittayapong, 2012; Zambrano et al., 2017).

Currently, there is a need for the identification of potential vector of the dengue virus or other mosquito-borne diseases in specific areas to be updated, in order to better understand the development of disease incidence. The symptoms of the condition are divided into three phases: fever, shock, and recovery, which is characterized by headaches, muscular aches, and bone pain (Hnusuwan, Kajornkasirat, & Puttinaovarat, 2020). Various epidemiological transmissions of infectious diseases, such as diarrhea, typhoid, malaria, and dengue fever, can be approximated using spatial models by enhancing the effectiveness of treatments that will lead to improved results (Phanitchat et al., 2019). A study in Kaohsiung City, Southern Taiwan, looked at the association between climatic conditions and the dengue outbreak and discovered that humidity and bite rates were substantially connected with cases of dengue disease (Cheng et al., 2020).

The purpose of using geographic information systems for studies is often used as a predictive model, for example, several layers of data indicating vector disease may be combined spatially to predict vector disease prevention as an output map (Pineda Cortel, Clemente, & Nga, 2019). Many studies have applied a probabilistic model (Phung et al., 2015), this model is important before entering other statistical models to gain a better understanding of the spatial extent of dengue outbreaks, especially in certain areas so that they can be planned specifically (Mutheneni, Mopuri, Naish, Gunti, & Upadhyayula, 2018). Several studies on disease geography are categorized into three classes related to the ecological environment, disease clusters, and disease distribution (Murad & Khashoggi, 2020). Geographical information system-based disease mapping information depends on the interests of researchers in sharpening the research area (Sekarrini et al., 2021). Dengue haemorrhagic fever symptoms are still one of Indonesia's unsolved diseases (Faridah et al., 2021). According to the Riau Provincial Health Office, 3,375 cases of dengue haemorrhagic fever were reported, with as many as 27 deaths. Bengkalis Regency had the most dengue fever cases, with 956 cases, followed by Pekanbaru City with 400 cases, and Dumai City with 378 cases, out of the 12 regencies/cities (Frislida, 2020). Pekanbaru City has a unique situation, since the average dengue haemorrhagic fever case per sub-district is not in line with population density, except for Sukajadi District, which has a fairly high average dengue haemorrhagic fever case, specifically in 2015–2018 (Juwita, Purwitasari, & Masnarivan, 2020).

The development of dengue environmental studies using satellite-based climate data, in conjunction with geospatial data, allows for a reduction in the dependence on time-consuming field data (Kesetyaningsih, Andarini, Sudarto, & Pramoedyo, 2018). This, in turn, facilitates the minimization of delays in predictions through the application of appropriate statistical analysis. The existence of bias often results from the inappropriate use of methods in a problem (Mala & Jat, 2019). Characterization is accomplished by applying quantitative values that directly describe the actual conditions of *Aedes aegypti* mosquito presence. The information on the prospective spread of the *Aedes aegypti* mosquito in the Pekanbaru City region is still limited and incomplete, particularly when it comes to the environmental dispersion of the *Aedes aegypti* mosquito, which is important for early prevention (Giofandi & Umar, 2021). One strategy to combat the problem of dengue haemorrhagic fever is to eliminate or limit the presence of the *Aedes aegypti* mosquito (Riyanto et al., 2020). The presence of bias is generally one of the disadvantages of utilizing the approach in a problem; however, in the environmental needs of the *Aedes aegypti* mosquito, a class criteria value limit is given to eliminate this bias (Maula et al., 2018; Majid et al., 2019). These characteristics are determined using a bivariate statistical approach that employs quantitative values to directly characterize the current state of the *Aedes aegypti* mosquito's existence. The physical parameters of Pekanbaru City distinguish this study from earlier research. As a result, the goal of this study was to establish the *Aedes aegypti* mosquito's environmental potential in limiting dengue fever transmission by forming a cluster of environmental potential levels in Pekanbaru City.

Study area

The study area is delineated by the plains surrounding the urban area of Pekanbaru City (0.5333ºN and 101.45ºE), situated in Riau Province, serving as the capital of the province with an area of 402.32 km^2 (Fig. 1).

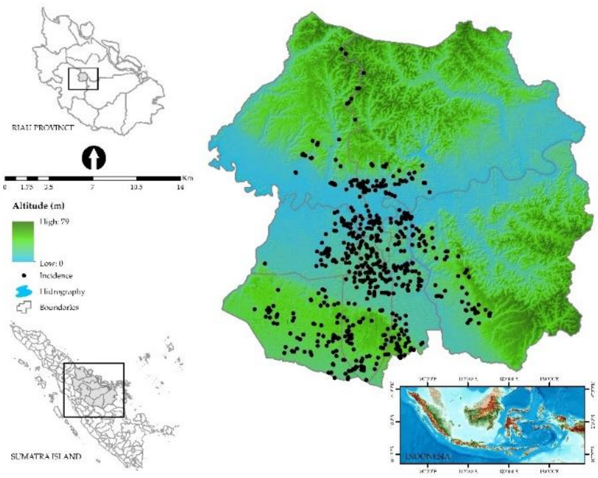

Figure 1. The geographical location of the study area

Pekanbaru City is positioned on an alluvial plain, where most of the area is characterized by wetlands, with some areas also designated as peatlands. Climatological conditions in this area include an annual average temperature of 26.76ºC, an average humidity of around 84.8%, and an average monthly rainfall of 286.5 mm^3. The area is encompassed by the Siak watershed, covering an area of 1,124 km^2, which also includes surrounding districts and provinces. Currently, land use and land cover (LULC) in Pekanbaru City are predominantly influenced by plantation vegetation, built-up land, shrubs, and mixed gardens (Giofandi & Sekarjati, 2020). The socio-demographic aspect of this urban area is represented by 1,117.54 people, with a population density of 1,800 people/km^2. Meanwhile, a population growth rate of 1.30% is observed, and the poverty rate is 3.06% of the total population in Pekanbaru City. Based on the growth of the gross regional domestic product in Pekanbaru City, it was recorded at 6.78%, surpassing that of other regions within Riau Province. In terms of health, an increase in dengue fever cases is observed in the area, along with limited information on the potential transmission of Aedes aegypti mosquitoes. This information is deemed essential for the formulation of prevention strategies based on the environmental characteristics of Pekanbaru City.

Materials and Methods

This study uses a statistical model that considers bivariate statistical analysis approaches to determine the probability class of dengue haemorrhagic fever for the study area. The Dengue Haemorrhagic Fever incidence database is a compilation of surveillance calculations carried out from January to December 2020 by the Pekanbaru City Health Office. The data is recorded by name and address, including latitude and longitude coordinates.

Table 1. Database structure

No	Name of Data Basis	Type	Resolution	Attribute	Acquisition
1	Occurrence	Vector	1:5.000	Address	Primary (from Health Ministry, 2021)
2	Land Use	Vector	1:25.000	Usage Type	Primary (from Ministry of Public Work and Public Housing, 2021)
3	Elevation	Raster	8m	Height Value (m)	Model (from GIA, 2021)
4	Rainfall	Raster	10m	Rainfall Value (mm/year)	Model (from MCGA, 2021)
5	Humidity	Raster	10m	Humidity Value (%)	Model (from MCGA, 2021)
6	Vegetation Density	Raster	10m	Density Value	Secondary (from Sentinel Image-2A, 2021)
7	Surface Temperature	Raster	30m	Value of Surface Temperature (°C)	Secondary (from image of Landsat OLI 8, 2021)

The dependent variable for ascertaining the causal statistical effect is dengue fever data, with trigger coefficients (land use, elevation, rainfall, humidity, vegetation density, and surface temperature) serving as representations of the independent variables (Table 1 and Table 2). The inclusion of these coordinates is essential for the evaluation of potential Dengue Haemorrhagic Fever outbreak transmissions, ensuring the accuracy of the data. This method of analysis accurately describes the results of prior studies for various area sizes. The statistical model is proposed to be implemented using a geographic analysis model technique that has the result by creating a spatial database, digital vector, raster, and adapting the requirements of the domestic Aedes aegypti mosquito's environmental potential model (Kirkwood & Sterne, 2003).

It was decided to use the average spatial scale used in the spatial analysis modelling in identifying the potential environment for the *Aedes aegypti* mosquito as a support for the 1:50,000 scale map in the realization of the vector database, taking earlier events into account the average spatial scale used in the spatial analysis modelling in identifying the potential environment for the *Aedes aegypti* mosquito. The Ministry of Public Works and Public Housing and the National Digital Elevation Model with a scale of 1:25,000 are used to get land use and elevation parameters indirectly. Mosquito communities with a higher diversity of disease vector species in urban areas are significantly contributed to by land use that reflects anthropogenic activities (Steiger, Ritchie, & Laurance, 2016). The presence of built-up land in peri-urban areas, characterized by small village buildings, introduces a weakness in the categorization of land use classification. Generally, land cover characteristics, such as vegetation and water bodies (e.g., forest, plantation, bush, mixed plantation, field, open space, lake, river, and aquaculture), should not be associated with dengue fever incidence. However, a higher number of incidents than built-up land is observed in the study area. This is influenced by vegetation cover (e.g., fields, shrubs, and plantations), which should be able to provide information on the built-up land below a certain height. Furthermore, uses like rivers, even with relatively small buildings, are often generalized into vegetation or water bodies, influencing the overall discussion. One of the main considerations in the utilization of land use data is the unavailability of high-resolution raw image data and the absence of other land use databases that can provide more detailed information. Since the data is officially available from the relevant agencies and is fully taken into consideration and incorporated in the spatial modelling study, the usage of database parameters with varied scales was chosen.

One of the most important databases used in modelling the spatial analysis of the *Aedes aegypti* mosquito's environment is rainfall and surface temperature identified in the study area, the parameters obtained with a 30-meter resolution raster data format based on geographic coordinates. The event database is divided into two usage structures in spatial modelling of the *Aedes aegypti* mosquito environment, namely, the structure represented by the point of the incident location that will be used as a calculation of the bivariate statistical probability value and the event point structure is used as a step in calculating the final result validation value based on Weights of Evidence (WoE) and Area Under Curve (AUC) event characteristics.

Table 2. The environmental assessment parameters for *Aedes aegypti* mosquitoes

Variable	Class	Area (Km²)	Percentage (%)
Rainfall	1571.41 - 1499.00	94	14.42
(mm/year)	1549.00 - 1363.44	188	28.83
	1363.44 - 1269.05	181	27.76
	1269.05 - 1055.96	189	28.99
Air	88.21 - 85.44	198	30.37
Humidity	85.44 - 84.29	182	27.91
(%)	84.29 - 82.94	148	22.7
	82.94 - 81.55	124	19.02
Vegetation	-0.80 – 0.25	151	23.16
Density	0.25 – 0.50	222	34.05
	0.50 – 0.70	242	37.12
	0.70 – 0.90	37	5.67
Elevation	79 - 43	68	10.43
(masl)	43 - 28	155	23.77
	28 - 14	172	26.38
	14 - 0	257	39.42
Surface	30 - 28	8	1.23
Temperature	28 - 24	158	24.23
(°C)	24 - 21	322	49.39
	21 - 17	164	25.15
Land Use	Forest	37	5.67
	Plantation	242	37.12
	Bush	122	18.71
	Mixed Plantation	85	13.04
	Field	15	2.3
	Open Space	22	3.37
	Residence	119	18.25
	Lake	2	0.31
	River	6	0.92
	Aquaculture	2	0.31

The Weights of Evidence (WoE) statistical model belongs to the category of bivariate approaches based on the probability of being predicted by some binary patterns to predict other binary patterns. According (Bonham-Carter, 1994), the Weights of Evidence statistical model is calculated using the formula:

$$\mathrm{W}^{+} = \mathrm{In}\left[\frac{\mathrm{P}\{\mathrm{B}|\mathrm{A}\}}{\mathrm{P}\{\mathrm{B}|\mathrm{A}\}}\right] (1)$$

$$\mathrm{W}^{-} = \mathrm{In}\left[\frac{\mathrm{P}\{\underline{\mathrm{B}}|\mathrm{A}\}}{\mathrm{P}\{\underline{\mathrm{B}}|\bar{\mathrm{A}}\}}\right] (2)$$

The description of *W+* and *W-* explains that the value of *P* is the probability and In is the natural logarithm, with *B* and $\underline{B}$ indicating the presence or absence of side conditions in each factor, and *A* and $\bar{A}$ reflecting the presence or absence of dengue haemorrhagic fever incidence in each variable. After the WoE calculation is executed, the dengue haemorrhagic fever incidence data is tested to determine the AUC value, resulting in a comparison graph depicting the percentage of the total area of the parameter class. If the Area Under Curve value for the environmental parameters influencing the

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incidence is >0.6, then it is considered that a parameter is affecting the incidence.

The database is built as a core model as part of a larger model (climate, topography, and vegetation) to identify the mosquito's living environment using spatial analysis as the foundation for development. Regarding the related vector/raster derivative databases (topography, settlements, vegetated land), the same resolution was chosen to maintain the raster value against the spatial scale and obtain a high overall accuracy value.

Results

The equation is used to calculate the correlation coefficient between the incidence of dengue haemorrhagic fever and each environmental parameter used. The results of the Area Under Curve of each parameter that is thought to affect the occurrence of dengue haemorrhagic fever in 2020 in Pekanbaru City are presented in Figure 2.

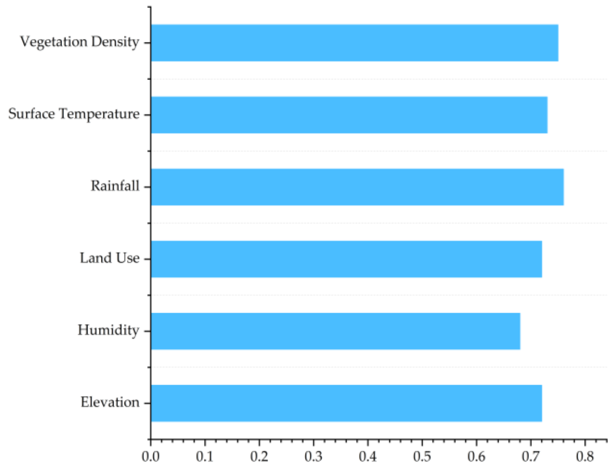

Figure 2. The value of the area under the curve of environmental parameters

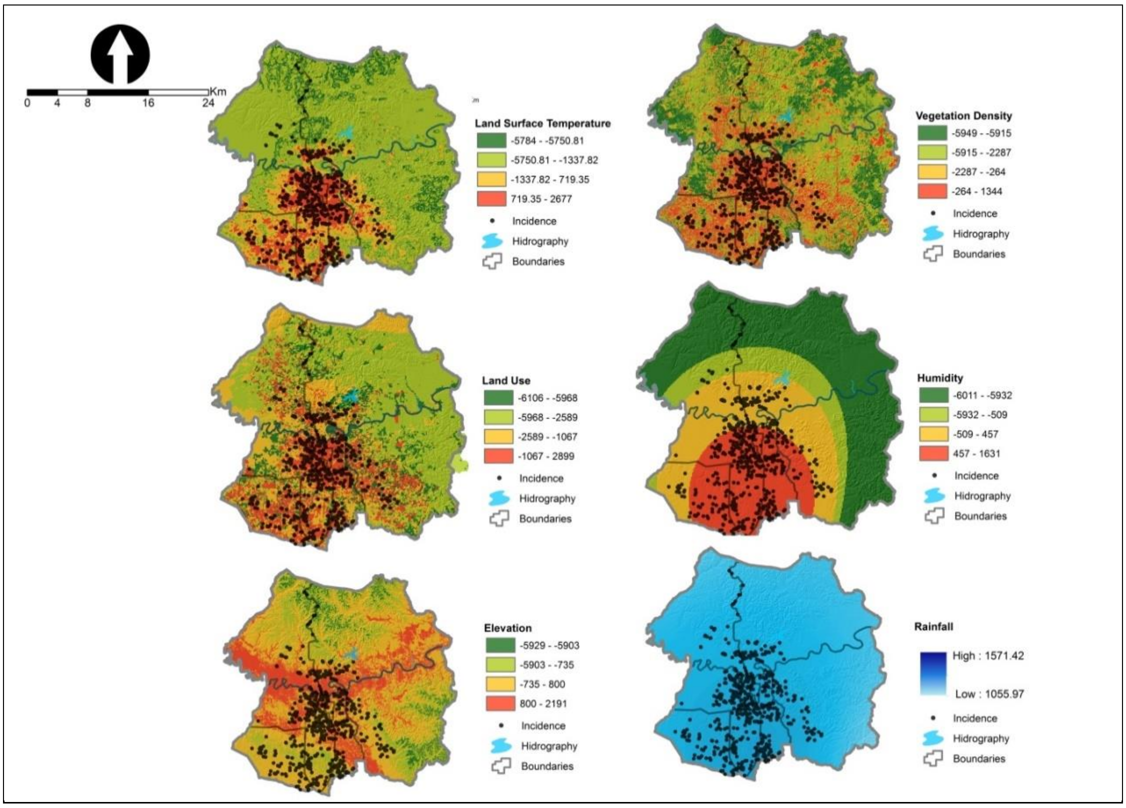

Figure 3. Map-based on bivariate statistical values

The findings related to the relationship between the environment and the distribution of dengue haemorrhagic fever from 6 environmental parameters resulted in different under curve area values as follows: rainfall (0.76), vegetation density (0.75), surface temperature (0.73), elevation (0.72), land use (0.72), humidity (0.68). The value of the area under the curve is used to determine the level of relationship between each parameter with 611 cases of dengue haemorrhagic fever. According to the value obtained from the area under the curve, it is known that the binary logistic regression model has a high predictive performance. This value indicates that the value of the frequency ratio between the location of the incident and environmental variables shows their respective effects in responding to the symptoms of dengue haemorrhagic fever. The geographic distribution and temporal patterns of dengue incidence are primarily influenced by rainfall, with a crucial role played in outbreak intensity by temperature (Arcari, Tapper, & Pfueller, 2007). Air humidity in the range of 70% to 90% at intervals of 10-18 weeks positively affects dengue incidence, while negative impacts are observed at air humidity below 70% at intervals of 4-9 weeks (Talagala, 2015). Additionally, a significant association is found between dengue and the estimated normalized difference vegetation index (NDVI) (Acharya et al., 2018). This underscores the significance of certain land use factors, exhibiting a statistically significant positive correlation with the number of dengue cases. The amplification of disease transmission is further facilitated by the interplay between these factors and human elements (Chen et al., 2019). The main advantage of using logistic regression is that it allows the application of a binary dependent variable type in effect probability for environment-based mapping, shown in Figure 3.

Table 3. Bivariate statistical values for the overall parameter index

Variable	Category Potential	Interval	Area (Km^2)	Percentage (%)
Rainfall (mm/year)	High	1674 – 415	187	28.68
	Medium	415 – (-2300)	128	19.63
	Low	(-2300) – (-5841)	82	12.58
	Very Low	(-5841) – (-5916)	255	39.11
Air Humidity (%)	High	1631 – 457	139	21.32
	Medium	457 – (-509)	166	25.46
	Low	(-509) – (-5932)	79	12.12
	Very Low	(-5932) – (-6011)	268	41.1
Vegetation Density	High	1344 – (-264)	169	25.92
	Medium	(-264) – (-2287)	116	17.79
	Low	(-2287) – (-5915)	243	37.27
	Very Low	(-5915) – (-5949)	124	19.02
Elevation (masl)	High	2191 – 800	91	13.96
	Medium	800 – (-735)	97	14.88
	Low	(-735) – (-5903)	398	61.04
	Very Low	(-5903) – (-5929)	66	10.12
Surface Temperature (°C)	High	2677 - 719.35	97	14.88
	Medium	719.35 – (-1337.82)	97	14.88
	Low	(-1337.82) – (-5750.81)	393	60.28
	Very Low	(-5750.81) – (-5784)	65	9.97
Land Use	High	2899 – (-1067)	141	21.63
	Medium	(-1067) – (-2589)	158	24.23
	Low	(-2589) – (-5968)	266	40.8
	Very Low	(-5968) – (-6106)	87	13.34

Source: Analysis, 2021

The environmental potential of mosquitoes, categorized as having a very low potential level, was assessed with a Weight of Evidence (WoE) value ranging from -35,693 to -5,713 (Table 3). A low environmental potential level is indicated by a WoE range of -5,713 to 3,099, while a moderate environmental potential is determined within a WoE range of 3,099 to 5,343. A high environmental potential is denoted by a WoE value between 5,343 and 10,467. Pekanbaru City is classified in the category of very low environmental potential, with a WoE value ranging from -35,693 to -5,713, encompassing 62.24% of the total area, equivalent to 40,232 hectares. Areas of finding low environmental potential are scattered in almost all sub-districts. The low environmental potential has a WoE value of -5,713 to 3,099 and covers 22.80% with an area of 14,736 hectares. Additionally, areas of moderate environmental potential are also spread across nearly all sub-districts. The medium environmental potential has a WoE value of 3,099 to 5,343 which includes 5.78% with an area of 3,733 hectares. Furthermore, areas of high environmental potential were found in almost all sub-districts except for Tenayan Raya, Rumbai, Rumbai Pesisir, and Tampan sub-districts resulting in a WoE value of 5,343 to 10,467 covering 9.18% with an area of exposure of 5,935 hectares.

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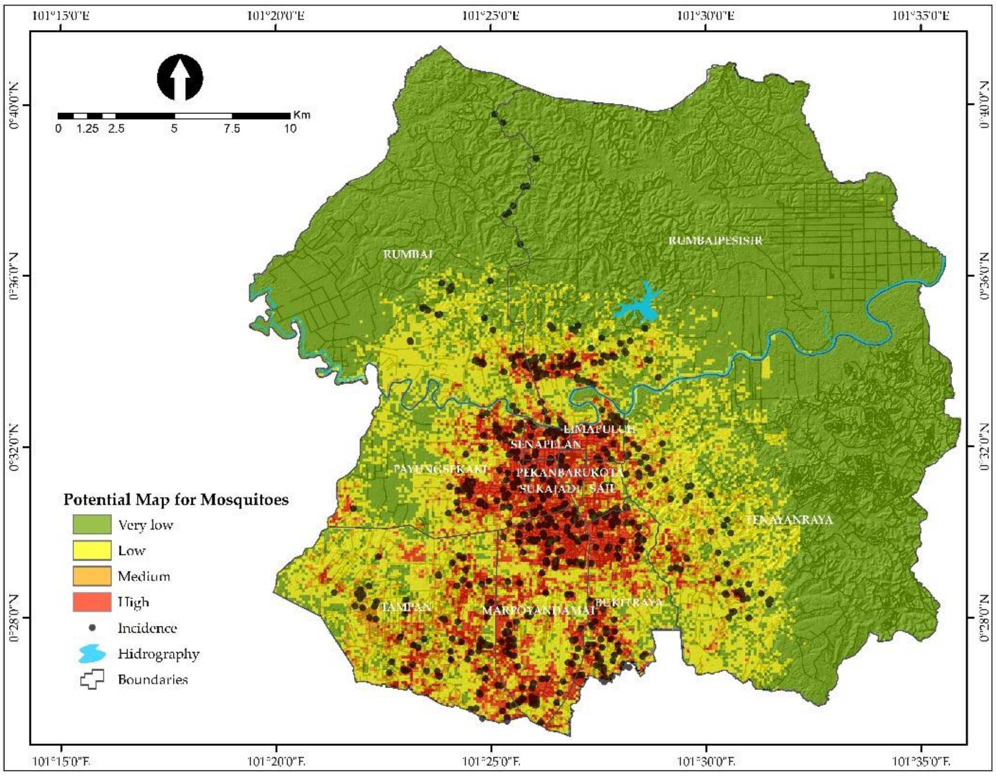

Figure 4. Mosquito environmental potential map

Table 4. The potential mosquito breeding areas in each sub-district in Pekanbaru City

Category	District	Area (Ha)	Category	District	Area (Ha)
Very Low	Tampan	736	**Medium**	Bukit Raya	356
	Marpoyan Damai	59		Sail	57
	Bukit Raya	216		Sukajadi	15
	Sail	12		Pekanbaru Kota	19
	Lima Puluh	58		Senapelan	19
	Payung Sekaki	1.162		Lima Puluh	81
	Tenayan Raya	11.921		Payung Sekaki	394
	Rumbai Pesisir	16.696		Tenayan Raya	626
	Rumbai	9.288		Rumbai Pesisir	198
Low	Tampan	2.905		Rumbai	138
	Marpoyan Damai	1.171	**High**	Tampan	870
	Bukit Raya	877		Marpoyan Damai	1.420
	Sail	105		Bukit Raya	865
	Sukajadi	8		Sail	254
	Pekanbaru Kota	18		Sukajadi	370
	Senapelan	11		Pekanbaru Kota	169
	Lima Puluh	107		Senapelan	247
	Payung Sekaki	1.748		Lima Puluh	279
	Tenayan Raya	4.190		Payung Sekaki	864
	Rumbai Pesisir	1.576		Tenayan Raya	229
	Rumbai	2.007		Rumbai Pesisir	235
Medium	Tampan	1.118		Rumbai	131
	Marpoyan Damai	433			

The results of the assessment of mosquito potential environmental categories were compiled to determine the potential for transmission in the study area (Figure 4 and Table 4). The level of environmental potential of mosquitoes from all parameters in the study area can be explained as follows (a) a very low level of potential for the environment is observed, with humidity values ranging from 83 to 88%. This value is in line with the climatological process which assumes the value of humidity is inversely proportional to rainfall. In other words, when the humidity value is high, the rainfall value will be lower which is indicated by the rainfall value ranging from 1387 to 1055 mm/year. If viewed from other parameters, the existence of a very low category through the interpretation of land use outside the built-up area is in line with the vegetation density value which is close to 0.91. This value describes land uses such as fields, shrubs, mixed gardens, plantations, and forests. The very low presence of *Aedes aegypti* mosquitoes and the low probability of transmission of dengue outbreaks are explained by the finding on the surface temperature parameter, around <20°C. At this level of potential, there are 27 cases. The findings suggest that the presence of undetected built-up land in the land use generation and dense vegetation cover constitutes barriers to the detection of anthropogenic activities. The very low potential category includes the sub-districts of Tampan, Marpoyan Damai, Bukit Raya, Sail, Lima Puluh, Payung Sekaki, Tenayan Raya, and Rumbai. Additionally, the Rumbai Pesisir sub-district is encompassed as the largest area in the 'very low potential' category, comprising 16,696 hectare/ 167 km^2.

Furthermore, (b) low environmental potential level means the mosquito environmental potential level is low based on findings in the form of 15 cases of dengue haemorrhagic fever. If viewed from other parameters, the annual rainfall is found to be in the range of 1387 to 1431.61 mm/year. In terms of land use parameters, the low potential level is located on the outskirts of the city with built-up land exposed to low zones around shrubs, mixed gardens, and fields. At the low potential level, 133 cases were identified. This was reinforced by the density of vegetation and rainfall around the location, resulting in a description of low potential. The presence of Aedes aegypti mosquitoes is indicated, although not as numerous as in the medium and high potential levels. The Tenayan Raya sub-district is encompassed as a large area within the low potential category, covering 4,190 hectares or 41.9 km^2. Additionally, the low potential category can be observed in the sub-districts of Tampan, Marpoyan Damai, Bukit Raya, Sail, Sukajadi, Pekanbaru Kota, Senapelan, Lima Puluh, Payung Sekaki, Rumbai, Rumbai Pesisir, and Tenayan Raya.

However, (c) the moderate level of environmental potential overlaps the area where the level of environmental potential for mosquitoes is low based on information obtained from several parameters such as land-use zoning with moderate potential in built-up land. Rainfall conditions range from 1138.7 to 1571.4 mm/year and the surface temperature listed is 24°C to 29°C. This climatological value informs that many mosquito habitats are starting to be found, so dengue fever cases are common in this area. In terms of dengue haemorrhagic fever incidence, 97 incidents were recorded at the high potential level, with the Tenayan Raya sub-district having the largest area, reaching 626 hectares/ 6.26 km^2 compared to other sub-districts. The distribution of this medium potential category can be found in the sub-districts of Tampan, Marpoyan Damai, Bukit Raya, Sail, Sukajadi, Pekanbaru Kota, Senapelan, Lima Puluh, Rumbai Pesisir, Rumbai, and Payung Sekaki. Overall, a significant relationship was observed for all variables in associating the mosquito living environment with incidence in 2020.

Finally, (d) high level of environmental potential. In this case, the potential level of the mosquito environment is high when viewed based on cases that occurred in 2020 where almost all cases occurred in the zone. Climatic factors play a major role in determining the habitat of the *Aedes aegypti* mosquito, ranging from land use such as built-up land and surface temperatures that reach 24°C to 32°C. This is in line with research (Sarfraz, Tripathi, Faruque, & Bajwa, 2014) which explains that the ideal surface temperature ranges from 24°C to 28°C for the habitat of the *Aedes aegypti* mosquito. Rainfall which reaches 1387.47 to 1571.41 mm/year also has similarities to research (Santos et al., 2019) which found that 1500 – 3670 mm/year of rainfall is suitable for the survival of mosquitoes. The vegetation density in this area is close to -0.168 which indicates that this area is not vegetated or land is built up. This density value is in line with research (Nejati et al., 2017) which says that the smaller the vegetation or close to 0 – 0.25, the more high presence of mosquitoes in the area. At the high potential level, there were 344 cases of dengue haemorrhagic fever, with many found in the sub-districts of Tampan, Marpoyan Damai, Sail, Sukajadi, Pekanbaru Kota, Senapelan, Lima Puluh, Payung Sekaki, Tenayan Raya, Rumbai, Rumbai Pesisir, and Bukit Raya. The largest area of high mosquito potential is covered by Marpoyan Damai sub-district, comprising 1,420 hectares or around 14.2 km^2.

Discussion

This study assesses the relationship between physical factors and incidence cases to examine potential zones of dengue haemorrhagic fever in Pekanbaru City, Riau Province. The application of geographic information system technology to map the presence of disease, density, and the root cause of the source of disease infection can be determined. The findings of the spatial analysis shown in the research results add to the explanation that there is interference from human activities to form new mosquito habitats, both from household activities and urban industry. Furthermore, when viewed in suburban areas, these areas are experiencing increased growth thus making them limited by non-standard sanitation facilities which add to the potential immediate impact throughout the peri-urban area. Generally, the growth and development of dengue vectors depend on the climatological conditions of the surrounding environment. Because dengue is a vector-borne disease, the occurrence of dengue infection depends on the presence and density of vectors (Ramachandran, Roy, Das, Mogha, & Bansal, 2016). Several studies that have been conducted around the world explain that climatological factors such as temperature, humidity, and rainfall are the most important factors due to seasonal variations in the presence of the *Aedes aegypti* vector (Servadio et al., 2018; Lubinda et al., 2019; Estallo et al., 2020; Nuraini et al., 2021).

Some public health experts are shifting their focus away from disease etiology models that are based on individual risk factors and toward more complicated models that include the impacts of the physical and social environment (Geanuracos et al., 2007; Sekarrini, Sumarmi, Bachri, Taryana, & Giofandi, 2022). Areas with a poor socioeconomic class and a high number of slum homes are important criteria to consider when doing epidemiological research to see if disease clustering exists, starting with a rational interpretation of the population at risk (Ernst et al., 2013; Gillam & Charles, 2019; Wamukoya et al., 2020). Spatial grouping is one method for identifying possible groupings for the transmission of an outbreak. Furthermore, the amount of public concern, which can range from a few persons to a huge group, must be taken into account when conducting health research and developing epidemic management plans. Through exploratory analysis and periodic studies, public health surveillance is anticipated to contribute to the discovery of variables and causes of health problems. Because *Aedes aegypti* has a small flight range and is unlikely to transmit over large distances, the migration of persons infected with dengue must also be taken into account (Spitzen et al., 2017; Menda et al., 2019).

Our study has a lot of limitations, ranging from data collecting that only provides information on the total number of cases to annual data that combines all causes, making it impossible to analyse cases, particularly for their reasons. The majority of dengue fever cases reported to the Pekanbaru City Health Office are the result of epidemiological surveillance investigations involving moderate or severe cases. As a result, mild dengue fever cases have not been counted by researchers. People in Indonesia can simply buy drugs from any pharmacy to treat themselves without having to go to the hospital, however, the data collected from hospital admissions or public health institutions are utilized to offer serious and more reliable data measures. The last one, this research is limited in analysing sensitivity to several socio-demographic factors such as hygiene behaviour, household, economic status, and sanitation. Better data collection mechanisms and rigorous monitoring of case determination are also required, as well as elucidation of the role of confounding factors and potential modifiers in the observed connections.

Another issue that must be considered when modelling is the use of spatial-temporal analysis scales. The spatial structure and temporal characteristics can provide useful information related to risk assessments that will be used either in a national program or by residents (DeRoeck et al., 2003; Pollett et al., 2018; Rahman et al., 2021). Dengue control through preparation and response to dengue epidemics is sensitive to regional and global landscape conditions. Therefore, we suggest developing a model at the level of detail and local scale that will increase the predictive capacity, by adding the local factors that most significantly affect the transmission of dengue fever.

Conclusion

The study's findings were generated from data on the dengue haemorrhagic fever monitoring population and mosquito environmental factors, which included elements such as surface temperature, rainfall, humidity, land use, plant density, and surface elevation. In the regional scale of Pekanbaru City, the findings reveal a major zoning structure with four distributions of the predicted habitat of the *Aedes aegypti* mosquito. Some of the shortcomings that we identified include other variables such as social, sanitation, and environmental hygiene in the community that we did not include in the study. The estimated risk of spreading *Aedes aegypti* mosquitoes was discovered around the city centre, both residential and office areas, according to this study. This zone has a higher risk of dengue haemorrhagic fever transmission than the other three. By taking earlier events into account earlier events, this knowledge can be one of the early preventions in understanding the environmental structure of the *Aedes aegypti* mosquito habitat. This establishes a relationship between the impact of the urban landscape on the *Aedes aegypti* mosquito's habitat in the Pekanbaru City region as preventive knowledge in the management of dengue haemorrhagic fever transmission.

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Author contribution

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Conflicts of interest

The authors declare no conflict of interest.

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