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Spatial Analisys of Environmental Quality Variability with Dengue Fever (DHF) Cases in DKI Jakarta in 2018-2023

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KEYWORDS
Climate, Dengue, Population, Spatial Analysis, Vulnerability Index.

ABSTRACT
This study aims to determine the vulnerability index, spatial autocorrelation and the relationship of environmental factors to the incidence of DHF, environmental factor variables consist of climate (temperature, humidity, rainfall and wind speed), population and larvae Free Index (ABJ) in DKI Jakarta in 2018-2023. Secondary data were collected from the Surveillance of the DKI Jakarta Health Office, the Meteorology, Climatology and Geophysics Agency (BMKG), the Central Statistics Agency (BPS) of DKI Jakarta and the Silantor of the Ministry of Health. The ecological study design used in this study using ArchGIS and SPSS. The vulnerability index was calculated from each variable, spatial autocorrelation (Moran's I) was used to see spatial patterns and the Spearman test to determine the relationship between variables. Nine sub-districts showed a very high DHF vulnerability index (Koja, Tanjung Priok, Kalideres, Cengkareng, Tambora, Kebayoran Lama, Pasar Minggu, Jagakarsa, Duren Sawit and Cakung). The spatial pattern of population distribution and DHF cases were clustered and significant. Population density, DHF Incident Rate and Larvae Free Index (ABJ) showed a random and insignificant pattern. Three climate variables related to DHF cases were humidity, rainfall and wind speed, all climate variability was not related to the Incident Rate (IR). Population was strongly related to DHF cases and was not related to DHF IR. Population density and ABJ were not related to DHF cases and IR. Improvement of the early warning system, strengthening of mosquito nest eradication networks, especially in areas of very high vulnerability, and development of technology.

1. INTRODUCTION

Indonesia is a country with a high risk of dengue fever, there are still 13 provinces or 38.2% of provinces showing a CFR (Case Fatality Rate) above 1% (Kemenkes RI, 2022b). Meanwhile, nationally, DKI Jakarta is an area that has a DHF morbidity rate (Insidence Rate/IR) of 29 per 100,000 population, still above the national average (27 per 100,000 population) (Kemenkes RI, 2022a). It is possible that DHF cases in Jakarta can cause death and an increase in cases can even cause an Extraordinary Event (KLB).

Dengue Hemorrhagic Fever (DHF) is an acute viral infection caused by the dengue virus which can be accompanied by non-specific symptoms such as headaches, muscle and bone pain, skin rashes or pain behind the eyes. In the last 30 years, DHF cases will continue to rise and spread along with the increasing population, the increasing flow of people from villages to cities (urbanization) followed by increasing population movement activities (mobility) (Kemenkes RI, 2018). In addition, changes in weather and climate in the future such as increasing temperature, rainfall and humidity can increase

DHF infections (Direktorat Jenderal Pengendalian Penyakit dan Penyehatan Lingkungan Kementerian Kesehatan RI, 2017; Houtman et al., 2022; Tran et al., 2020).

There are many related studies to spatial analysis and the relationship between environmental factors with dengue fever cases, in the National Capital Region (NCR) Philippines, temporal analysis showed an increase in dengue fever cases from the Northwest to the Northeast (Pangilinan et al., 2017), in Northeast Malaysia showed a movement of dengue fever cases to adjacent areas (Masrani et al., 2022). in Singapore, the age of apartments and watertight buildings has a high risk of increasing dengue fever (Soh et al., 2022). On a city scale, altitude and minimum temperature are considered more relevant than rainfall related to the distribution environment of dengue cases and the number of Aedes larvae (Marceló-Díaz et al., 2023). Extreme heat in Singapore is related to a decrease in dengue fever (Seah et al., 2021). The increasing trend in the potential for a global dengue epidemic occurs in temperate climates, temperatures above 29oC can reduce this potential (Liu-Helmersson et al., 2014). Rainfall, temperature and humidity affect dengue fever transmission (Abdullah et al., 2022). Over the past four decades, dengue virus transmission has been caused by climate change, urbanization, and population growth (Nakase et al., 2024). Socio-economic and socio-cultural variables are highly correlated with the prevalence of Dengue Fever (Mysuru district India) (Ashwini et al., 2020). Population growth contributes up to 86% to dengue fever cases. while 14% is due to increased temperatures (Struchiner et al., 2015). Research related to climate, socio-economics and population growth was conducted to prevent an increase in dengue fever in the future (Messina et al., 2019). Research in Blitar showed that the Free Larvae Index did not show any relationship with dengue fever incidence (Nuranisa et al., 2022).

The ecological health framework was used to develop the Dengue Vulnerability Index (DVI) which describes the relationship between population, social and physical environment, and health to identify indicators of exposure, vulnerability, and adaptive capacity (Zafar et al., 2021). Dengue vulnerability assessment is adjusted to factors that influence vulnerability to infectious disease outbreaks such as population density, urbanization, medical care workforce, medical care infrastructure, public health delivery, clean water and sanitation and economic strength (Zulkifli et al., 2022). Dengue risk assessment through the concept of climate and environmental variable vulnerability uses a combined mapping and modeling approach (Pham et al., 2020). Previous research in DKI Jakarta grouped DHF-prone areas based on the variables of the number of dengue fever sufferers, the number of flood-prone RWs, area, population, temporary waste disposal sites and the number of green open spaces (Widyatami & Suryawan, 2021).

DKI Jakarta has the highest population density compared to other provinces, with a land area of 661.5 km2 and the 6th largest population after Banten, namely 10,679,951 people in 2022. The population density in DKI Jakarta is 16,145 people/km2 with quite high rainfall of 2394.6 mm/year. The trend of dengue fever incidents has been confirmed to increase coinciding with the peak rainfall levels, densely populated areas are also seen to be related to areas at high risk of dengue fever exposure (Fauzi et al., 2022). The author is interested in conducting research because there has not been much research related to the dengue fever vulnerability index in

DKI Jakarta to the sub-district level (Nandini et al., 2017) and there are still differences in theory with the results of previous studies regarding the relationship between climate and dengue fever cases (Nandini et al., 2017).

2. METHOD

The design used in this study is an ecological study, then spatial analysis, calculation of the vulnerability index, spatial autocorrelation and statistical tests are carried out to determine the strength and pattern of the relationship between independent variables (temperature, humidity, rainfall, wind speed, population density and the Free Larvae Index (ABJ) with the dependent variable (Dengue Hemorrhagic Fever cases) in DKI Jakarta Province in 2018-2023. The population is spatial data from 5 city areas and 42 sub-districts of DKI Jakarta Province while the sample is data on all research variables. Data grouping is adjusted to research needs, in the form of monthly data, data per sub-district, data per city area and data per year from each variable.

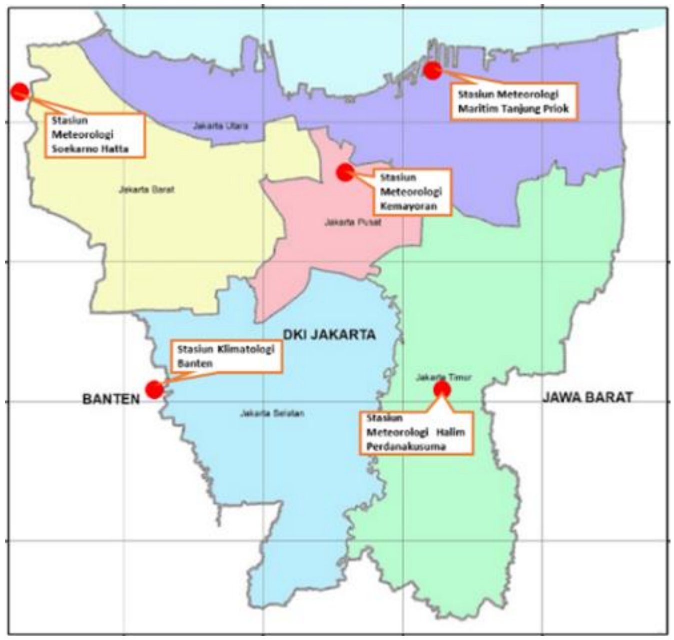

Figure 1. Map of the Distribution of Meteorology and Climatology Stations (BMKG) in DKI Jakarta Province and Banten Province in 2023.

All data are sourced from secondary data for the period 2018-2023, DHF case data from the DKI Jakarta Provincial Health Office (https://surveilans-dinkes. jakarta.go.id/), population data from the DKI Jakarta Provincial BPS (https://jakarta.bps.go.id). climate data from 5 BMKG stations are shown in Figure 1 (https:// dataonline.bmkg.go.id/data_iklim), ABJ data from the Indonesian Ministry of Health (https://silantor. kemkes.go.id/dashboard). Furthermore, the data is made into criteria/classification (table 1).

Table 1. Variables, Units, Weights, Criteria (Range) and Values in DKI Jakarta In 2018-2023

Variable (Unit) (Weight)	**Criteria (Range)**	**Values**
DHF Cases (people) (3)	Low (<148)	100
	Medium (148-455)	50
	High (>455)	0
Incident Rate	Low (<20)	100
	Medium (20-55)	50

(DHF case /100.000 people) (3)	High (>55)	0
Temperature (^{O}C) (2)	Not Optimal (<28 and >32) Optimal (28-32)	100 0
Humidity (%) (2)	Not Optimal (<60,5 and >88,7) Optimal (60,5-88,7)	100 0
Rainfall (mm) (4)	Low (0-100) Medium (100-300) High (300-500) Very high (>500)	100 75 50 0
Win speed (Km/jam) (2)	high (≥3) low (<3)	100 0
Population density (people /ha) (4)	Low (<150) Medium (150-200) High (201-400) Very high (>400)	100 75 50 0
Total Population (people) (4)	Low (<130.000) Medium (130.000-250.000) High (250.000-380.000) Very High (>380.000)	100 75 50 0

Univariate analysis using MS Excel 2013 to present and describe data in the form of tables and graphic images. ArcGis version 10.3 is used for spatial analysis in the form of maps of the distribution of DHF cases, population number and density and the number of free larvae. The Vulnerability Index consists of a combination of vulnerabilities from DHF incident variables (Cases and Incident Rate), Climate (temperature, humidity, rainfall, and wind speed), Population (population, population density) and Free Larvae Index (ABJ) in a 6-year period from 2018-2023. Through the rating scale method approach (Sugiyono, 2015), each variable is given a weight according to the number of previously determined criteria (based on government regulations, previous research and calculations of mean and standard deviation) and is given a value of 0-100, the weight will be multiplied by the value according to the criteria of each variable so that the final score is obtained for each sub-district and city, MS Excel is used as a formulation for calculating the final value for each sub-district and city. From the total value, the mean and standard deviation are then calculated to be divided into 4 vulnerability criteria (very high, high, medium and low). The Incident Rate variable consists of 3 criteria (table 1) so that it has a weight of 3, with a value of 100 for low criteria (IR = <20), a value of 50 for medium criteria (IR = 20-55) and a value of 0 for high criteria (IR => 55). For variables that have 2 criteria have a weight of 2 with a value of 100 and 0, variables that have 4 criteria have a weight of 4 with a range of values 100, 75, 50 and 0.

The ArcGis version 10.3 program is used for statistical tests of the Moran index, standard values (z-score), probability values (p-value) with a 95% confidence level. The Moran's I index has a range of -1 to 1, from which value Global Moran's I is able to identify the general characteristics of spatial patterns: clustered, random, and scattered. A value of 1 means a positive relationship with a clustered pattern. This means that attributes that have similar characteristics tend to be close together. Conversely, a value of -1 means a negative relationship with a distribution pattern (Figure 2). Attributes that have similar characteristics are far apart, or attributes that have different characteristics are grouped together.

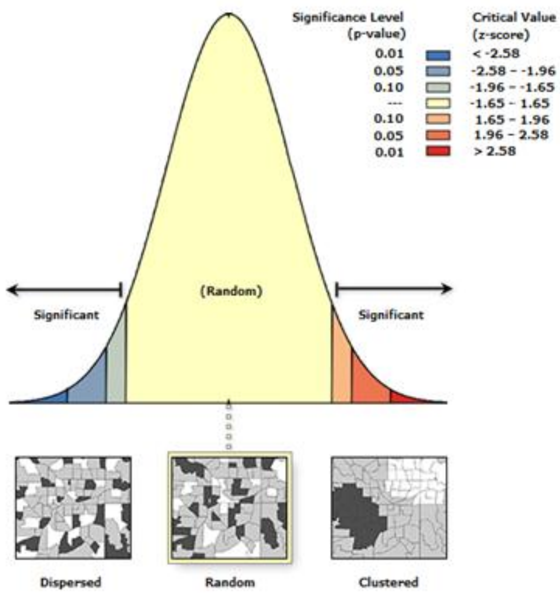

Figure 2. Morans-I Autocorrelation

Bivariate analysis using SPSS version. 25, aims to determine the relationship and strength of the relationship of each independent variable with the dependent variable, before testing the relationship between the two variables, the Komogorov Smirnov or Shapiro Wilk normality test is carried out. If the data is normally distributed, the Person test is then carried out, while if the data is not normally distributed, the Spearman relationship test is carried out. The p-value used in this study is 0.05 (α 5%) with the following calculation: H0 is rejected if the p-value ≤ 0.05, meaning that there is a relationship between the incidence of DHF and the variables of population, rainfall, temperature, humidity, wind speed and ABJ. H0 is accepted if the p-value> 0.05, meaning that there is no relationship between the incidence of DHF and the variables of population, rainfall, temperature, humidity, wind speed and ABJ.

This research has passed the ethical review No. 7/EA/KEPK-FKM/2024 from the Health Research Ethics Commission and is plagiarism-free with 5% similarity to other online sources through the results of the examination using the Turnitin application of the Faculty of Public Health, Diponegoro University.

3. RESULT AND DISCUSSION

Climate variables in DKI Jakarta in 2018-2023 show optimal conditions for the development of Aedes aegypti mosquitoes with an average temperature of 28.20C, humidity of 77.2%, rainfall of 186.6 mm/year and an average wind speed of 2.6 km/hour. In addition to climate factors, the population reaching >10 million and a density of 170 people/ha makes DHF cases reach a total of 78,373 cases with an average IR of 124 cases/100,000 population, indicating high criteria (Table 2).

Table 2. Average Figures Per Variable in DKI Jakarta Province In 2018-2023

Variable	**Average**
Incident Rate (IR)	124/100.000 people
DHF Cases*	71835
Temperature	28,2°C
Humidity	77,2%
Rainfall	186,6 mm
Win Speed	2,6 km/jam
Population Density	170 People/ha
Total Population**	10.643.577 people

Larvae Free Index (ABJ)	93%

*Total DHF cases in 2018-2023
**Total Population in 2018-2023

Figure 3 shows that Menteng Sub-district with the smallest population (76,232 people) has 106 DHF cases, the largest population is in Cakung Sub-district (563,182 people) with an average number of DHF cases of 484 cases. The pattern of increasing DHF cases is generally in line with the population, although several Sub-districts show an opposite pattern between DHF cases and population such as in Cilandak Sub-district and Kebon Jeruk Sub-district.

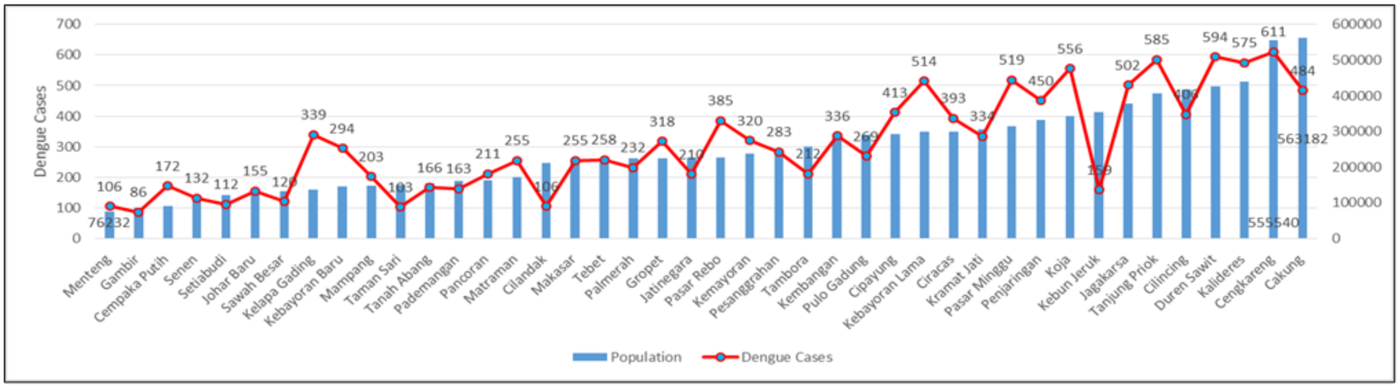

Figure 3. Lowest to Highest Population and Average Dengue Fever Cases per Sub-district in DKI Jakarta Province in 2018-2023

Figure 4a shows 7 sub-districts with the highest population (> 380,000 people), namely in Kalideres, Cengkareng, Cilincing, Tanjung Priok, Cakung, Duren Sawit and Jagakarsa Sub-districts. 11 sub-districts with high population criteria (250,001-380,000), 10 sub-districts with medium population (130,000-250,000) and 14 sub-districts with low population criteria (< 130,000).

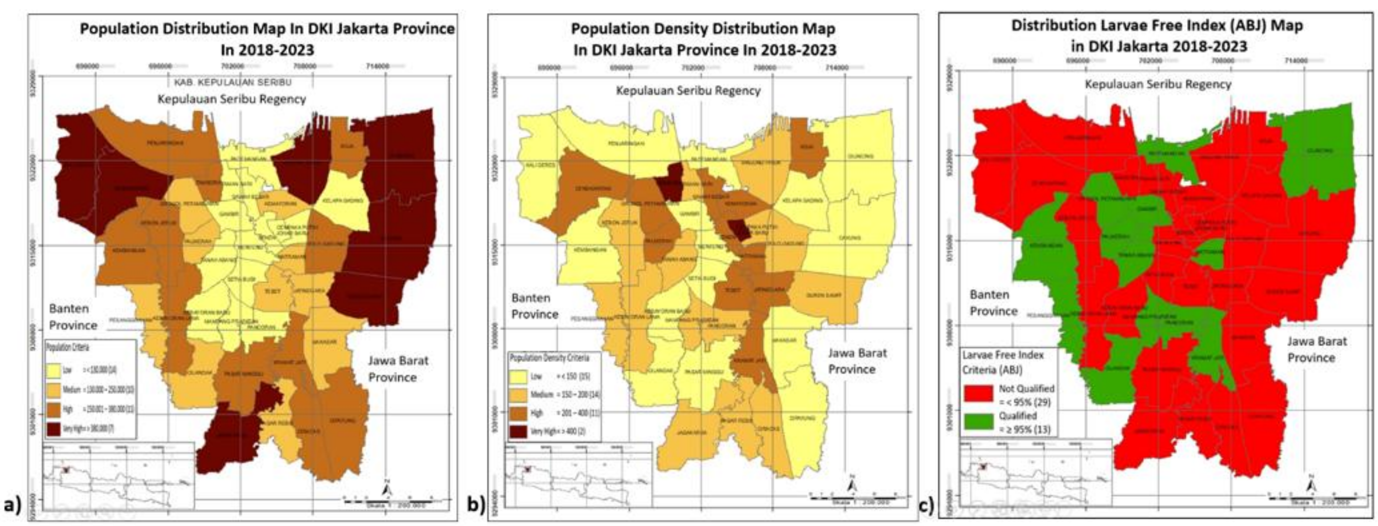

Figure 4. a) Population Distribuition Map; b) Population Density Distribution Map; c) Distirbution Larvae Free Index (ABJ) Map in DKI Jakarta In 2018-2023

Figure 4b shows Johar Baru and Tambora Sub-districts are sub-districts with very dense population density, namely> 400 people / ha. 11 Sub-districts with high population density (201-400 people/ha), namely Sawah Besar, Kemayoran, Senen, Koja, Cengkareng, Grogol Petamburan, Palmerah, Tebet, Kramat Jati and Jatinegara, 14 Sub-districts with medium population density (150-200) and 14 Sub-districts with low population density criteria (<150).

Figure 4c shows thirteen sub-districts show a Larvae Free Index (ABJ) that meets the requirements (≥ 95%) during 2018-2023, 4 sub-districts in the South Jakarta area (Pesanggrahan, Cilandak, Mampang Prapatan and Pancoran), 3 sub-districts in West Jakarta (kembangan, Petamburan and Palmeran), and 2 sub-districts each in North Jakarta (Cilincing and Pademangan), Central Jakarta (Gambir and Tanah Abang and East Jakarta (Kramat Jati and Matraman.

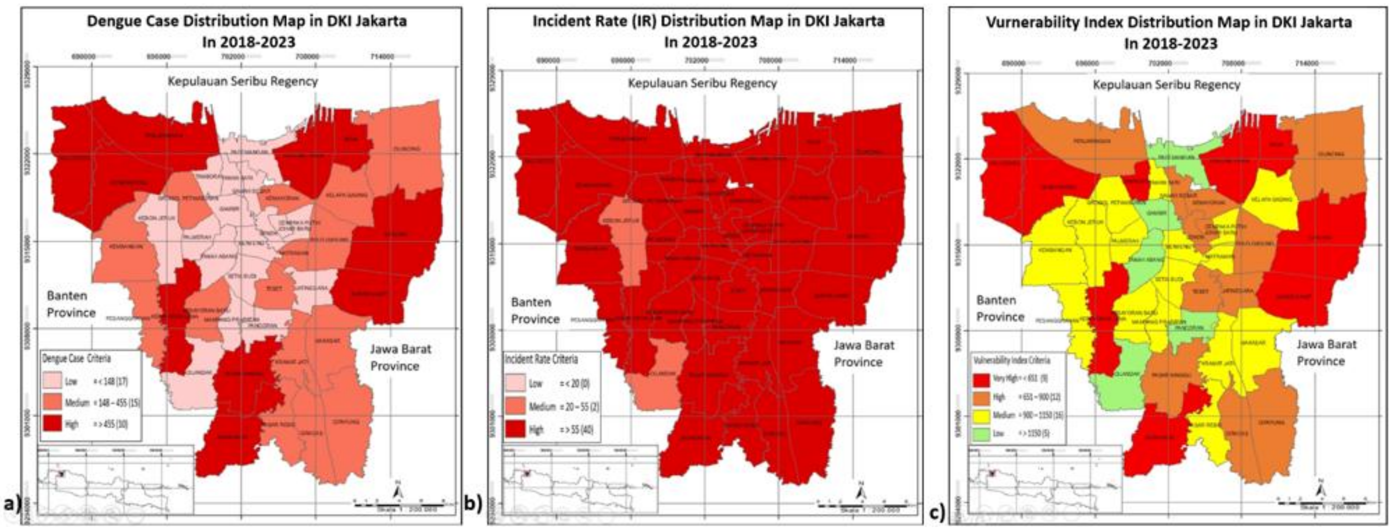

Figure 5. a) Dengue Case Distribution Map; b) Incident Rate (IR) Distribution Map; c) Vunerability Index Distribution Map in DKI Jakarta In 2018-2023

Figure 5a shows that in a 6-year period, the average DHF cases with high criteria (>455 cases) were found in 10 sub-districts spread across 4 city areas, 3 sub-districts in North Jakarta (Tanjung Priok, Koja and Penjaringan), 2 sub-districts in West Jakarta (Kalideres and Cengkareng), 3 sub-districts in South Jakarta (Kebayoran Lama, Pasar Minggu and Jagakarsa) and 2 sub-districts in East Jakarta (Duren Sawit and Cakung). For medium criteria (148-455 cases, 15 sub-districts showed moderate criteria, DHF cases with low criteria (<148 cases) as many as 17 sub-districts were seen in almost all areas of Central Jakarta except Kemayoran sub-district with moderate criteria. Figure 5b shows only 2 sub-districts with moderate IR (20-55 cases/100,000) while 40 sub-districts showed high IR criteria and were spread across 5 city areas.

Figure 5c shows that there are 9 sub-districts with very high vulnerability index criteria (<651), namely Koja, Tanjung Priok, Kalideres, Cengkareng, Tambora, Kebayoran Lama, Pasar Minggu, Jagakarsa, Duren Sawit and Cakung sub-districts, while the vulnerability index with low criteria is only 5 sub-districts (>1151), namely Gambir, Tanah Abang, Pademangan, Cilandak and Pancoran sub-districts. A total of 12 sub-districts show high criteria (651-100) and

16 sub-districts show moderate criteria (900-1150).

Table 3. Moran's I Autospatial Data Results in DKI Jakarta In 2018-2023

Variable	z-score	p-value
Population	4,658007	0,00000
Population Density	0,816419	0,41426
DHF Cases	3,584654	0,00033
Incident Rate (IR)	0,06226	0,95035
Larvae Free Index (ABJ)	1,07570	0,28206

The results of spatial autocorrelation (Moran's Index) of population distribution from 2018-2023 show z-core> 2.58 and p-value <0.01, meaning that the spatial pattern of the population is clustered/grouped and significant. In contrast to the distribution of population, for population density after spatial autocorrelation (Moran's Index) from 2018-2023, a z-core of -0.047 to 1.39 and a p-value> 0.1 were obtained, meaning that the spatial pattern of population density was random and insignificant (table 4.3). The average dengue fever case showed a z-core = 3.6 and p-value = 0.00, meaning that the spatial pattern of dengue fever cases was clustered and significant. For dengue fever IR during the period 2018-2023, a z-core value of 0.06 and a p-value of 0.95 were obtained, meaning that during that period the spatial pattern of dengue fever IR was random and insignificant. ABJ during a 6-year period and Spatial Autocorrelation (Moran'I Index) was carried out, the z-core value was 1.67 and the p-value was 0.28, meaning that during this period the spatial pattern of ABJ was random and insignificant (Table 3).

Table 4. Bivariate Test Results (Rank Spearman) in DKI Jakarta In 2018-2023

Variable	r	p-value
Climate with Dengue Cases		
Temparatture	-0,04	0,76
Humidity	0,45	0,00
Rainfall	0,31	0,01
Win speed	-0,35	0,00
Climate with Incident Rate		
Temparatture	0,07	0,90
Humidity	0,03	0,95
Rainfall	-0,11	0,83
Win speed	-0,73	0,10
Population with Dengue Cases		
Population	0,83	0,00
Density	-0,14	0,37
Population with Incident Rate		
Population	-0,03	0,85
Density	-0,09	0,55
ABJ with Dengue Cases	-0,08	0,60
ABJ with Incident Rate	-0,21	0,17

Table 4 shows the results of the Komogorov Smirnov normality test, all pairs of data variables are not normally distributed, so a Spearman relationship test was carried out. The relationship between temperature and dengue cases shows a value of r = -004 and p-value = 0.76, meaning there is no relationship between temperature and dengue cases, for humidity and dengue cases shows r> 0.45 and p-value = 0.00, meaning that during the period 2018-2023 humidity in DKI Jakarta has a relationship with dengue fever cases, the strength of the relationship is strong with a positive direction, the same thing can be seen in the relationship between rainfall and dengue fever cases shows a value of r = 031 and p-value = 0.01, meaning there is a relationship between rainfall and dengue fever cases with a strong relationship strength and positive direction. While for wind speed shows a value of r = -035 and p-value = 0.00, meaning there is a relationship between wind speed and dengue fever cases with a strong relationship strength and negative direction. The test results on climate variability (temperature, humidity, rainfall and wind speed) with Incident Rate (IR) show a p-value> 0.05 so that H0 is accepted, meaning there is no relationship between climate variability and Incident Rate (IR), for the test results of the relationship between population and DHF cases show a p-value = 0.00 and r = 0.70 - 0.89, meaning there is a relationship between population and DHF cases with a positive relationship direction with a very strong relationship strength level. Population density with DHF cases, population with IR, population density with DHF IR, ABJ with DHF cases and ABJ with DHF IR show a p-value> 0.05, meaning that the variables above are not related to DHF cases or DHF IR in DKI Jakarta in 2018 - 2023.

Discussion

Dengue fever is found in tropical and subtropical climates throughout the world, mostly in urban and semi-urban areas (WHO, 2024). The number of people at risk of contracting dengue virus is increasing due to climate factors and population growth (Messina et al., 2019; Nakase et al., 2024). A large-scale study elucidated the relationship between entomological (using ovitraps to reflect the size of the Aedes mosquito population), epidemiological (dengue cases over five consecutive years) and environmental (rainfall, humidity, temperature and air pollution index) factors contributing to dengue outbreaks in Selayang and Bandar Baru Bangi (Malaysia) (Ahmad et al., 2018). Dengue virus epidemics may increase with increasing temperatures, not only because of more infections per generation but also because of faster generation cycles (Siraj et al., 2017). The lowest temperature threshold for Aedes aegypti to develop is 16 °C and the highest is 34 °C (Reinhold et al., 2018). An increase in average temperature to 29 °C increases the potential for dengue epidemics, but temperatures above 29 °C reduce this potential (Liu-Helmersson et al., 2014). Temperature plays an important role in the development and survival of Aedes mosquitoes, the optimal temperature range for their development is 25 °C-30 °C. When the temperature exceeds 40°C, adult mosquitoes die, and eggs and larvae fail to develop (Liu et al., 2023). Air humidity below 60% can shorten the lifespan of mosquitoes, because when humidity is low, more fluids in the mosquito's body will evaporate so that the mosquitoes will experience drought (Amelinda et al., 2022). Small rainfall over a long period of time can increase mosquito breeding sites and increase their population (Maretha et al., 2022). The impact of heavy rain delayed by 24–55 days is associated with an increased risk of dengue fever when previous water availability is low, with the largest incidence rate ratio (IRR) of 1.37 (Cheng et al., 2023). Wind speed can affect the number of Aedes mosquitoes, and wind speed can also make it difficult for mosquitoes to fly (Adeleke et al., 2022). High wind speeds contribute to reduced interaction with hosts and the possibility of exposure to dengue infection is reduced (Cheong et al., 2013). Open areas with high wind speeds are barrier zones for mosquitoes to enter the human environment (Verdonschot & Besse-Lototskaya, 2014). DHF cases decrease when wind speeds increase (3 km/hour – 3.9 km/hour) (Handiny et al., 2021).

There is no specific standard for measuring the DHF disease vulnerability index. To measure the DHF vulnerability index in DKI Jakarta, research variables are used as the basis for calculating the vulnerability value. Temperature, humidity, rainfall and wind speed in almost all of DKI Jakarta are included in the vulnerable category, while the population, population density, Free Larvae Index (ABJ), Dengue Fever (DHF) Cases and DHF Incident Rate (IR) have different levels of vulnerability in each District. Other studies have grouped DHF-prone areas based on the variables of the number of dengue fever sufferers, the number of flood-prone RWs, area, population, temporary disposal sites and the number of green open spaces for dengue, the number of flood-prone RWs, area, population, temporary disposal sites and the number of green open spaces (Handiny et al., 2021). Weighting of DHF disease vulnerability indicators in Semarang City was carried out using Principal Component Analysis, resulting in a classification of temperature and flooding for the exposure component; population density and DHF cases for the sensitivity component; number of health service facilities, number of health workers, clean and healthy living behavior programs, and healthy homes for the adaptive capacity component (Azhar & Veridona, 2019).

Jakarta is a metropolitan city with a higher density and population than cities or districts outside Jakarta, so the results of spatial autocorrelation are different, such as in Kandangan sub-district, Temanggung district, the population pattern is spread out and not significant (Yuningrum & Daulay, 2024). The distribution of the population in DKI Jakarta in 2018-2023 after spatial autocorrelation (Moran'I Index) showed that the population was clustered/grouped and significant, having the same pattern as Bandung (Hernawati & Ardiansyah, 2017) and Madurai City India (Balaji & Saravanabavan, 2021). Meanwhile, in Section 7 Syeh Alam, Malaysia, the pattern of DHF cases showed a random pattern (Hasim et al., 2018). The indicator for achieving the Larvae Free Index (ABJ) which meets the requirements is ≥ 95% and is used as the national vector control quality standard for dengue and is a benchmark for the success of the PSN 3M Plus activities (Kemenkes RI, 2021), In theory, with a low ABJ, DHF cases should also be high (Delita & Nurhayati, 2022). In Tasikmalaya City, DHF cases tend to follow the Larvae Free Index (ABJ) low (Ruliansyah et al., 2017). In Lahat Regency, South Sumatra, larval density showed a correlation between the incidence of DHF (Maretha et al., 2022). Several studies showed results that differed from the theory, in Jambi City, namely that low ABJ did not affect the high incidence of DHF (Chandra & Hamid, 2019), in Cirebon City, research results from 2014-2018 showed that there was no relationship between the ABJ variable and the incidence of DHF (Latifah & Fitria, 2021).

4. CONCLUSION

DKI Jakarta is one of the endemic areas of dengue fever in Indonesia because it has a fairly large climate and population. The dengue fever vulnerability index in DKI Jakarta in 2018-2023 shows 9 sub-districts with a very high level of vulnerability, namely Koja, Tanjung Priok, Kalideres, Cengkareng, Tambora, Kebayoran Lama, Pasar Minggu, Jagakarsa, Duren Sawit and Cakung sub-districts. While 5 sub-districts show a low level of vulnerability, namely Pademangan, Gambir, Tanah Abang, Pancoran and Cilandak sub-districts. This study proves the theory that climate has a relationship with dengue fever cases, the results of the Spearman test show the results of humidity (r = p-value =); rainfall (r = p-value =); and wind speed (r = p-value =). the temperature variable shows a weak relationship with dengue fever cases in the direction of a negative relationship (r = p-value =). In addition, the population factor shows a very strong relationship with the incidence of DHF in the direction of a positive relationship (r = p-value =), for the number of residents does not show any relationship with IR DHF and population density does not show any relationship with DHF cases and IR DHF. The Larvae Free Index (ABJ) does not show a relationship with DHF cases and IR DHF. The results of spatial autocorrelation show that the number of residents and DHF cases have a clustered and significant grouping pattern, while IR DHF and ABJ show a random and insignificant pattern.

Prevention efforts are needed through the improvement of an early warning system that is more integrated with all related sectors and informed to areas or communities that are vulnerable to dengue fever, in addition to strengthening the mosquito nest eradication network simultaneously for all levels of society as well as the development of technology and ongoing research for a sustainable dengue fever control program.

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