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ORIGINAL ARTICLE

Spatial and Temporal Dengue Incidence in Banjarbaru, Indonesia: An Ecological Hotspot Analysis

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ABSTRACT

Introduction: Dengue is a vector-borne disease that is endemic in Banjarbaru with cases fluctuating every year. Spatial and temporal analysis with hotspot analysis is needed to map dengue transmission. **Materials and methods:** This study was conducted in Banjarbaru City, Indonesia. Monthly data for laboratory-confirmed dengue cases reported during 2016-2023 were obtained from the Banjarbaru Health Office. Decomposition analysis was conducted to determine the temporal incidence of dengue while Moran's I and Getis-Ord Gi* analysis to analyze the spatial distribution of hotspots. **Results:** The results of this study showed that the distribution of dengue cases in Banjarbaru did not show a significant spatial pattern from 2016 to 2023. Analysis using Moran's I test shows that the distribution of dengue cases is not spatially concentrated, with Moran's I values ranging from -0.237 to 0.079 and an insignificant p-value. This means that the distribution pattern of dengue cases in Banjarbaru is random and not clustered. However, the Getis-Ord Gi* analysis identified some areas that consistently became hotspots of dengue cases. For example, Guntung Manggis Village showed a significant p value in 2023, and Sungai Besar Village in 2018. **Conclusion:** This study concludes that although there are certain areas that are hotspots, overall, there is no significant spatial autocorrelation in the distribution of dengue cases in Banjarbaru during the study period. This study also emphasizes the importance of a better understanding of ecological factors and spatial-temporal patterns to design more effective prevention strategies.
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INTRODUCTION

Dengue fever is an infectious disease that is a major health problem in many tropical and subtropical countries, including Indonesia. Banjarbaru, a city located in South Kalimantan Province, is one of the areas that always experiences an increase in dengue cases every year. An effective response to the spread of this disease requires an in-depth understanding of the spatial and temporal dynamics of the distribution of dengue cases(1).

Spatial and temporal analysis is a very useful approach to understanding infectious disease transmission patterns (2,3). By using geographic and temporal data, we can identify areas where outbreaks are more likely to occur as well as specific time periods when dengue cases increase significantly (4,5). This approach can help in better targeting of prevention or control measures.

The ecological approach to disease analysis emphasizes the relationship between humans, the environment, and the causative agent. Factors such as population density, environmental conditions, climate change, or human behavior are factors that contribute to the occurrence/spread of dengue fever (6,7). On the other hand, hotspot analysis focuses on identifying areas with high concentrations of cases (8). By combining these two approaches, we can obtain a more comprehensive picture of the spread of dengue fever in Banjarbaru.

Several previous studies have been conducted to investigate the spread of dengue fever in various regions in Indonesia. Some studies have used spatial analysis to identify dengue hotspots in Jakarta (9), Medan(10), and Yogyakarta (11). The findings from these studies showed that areas with high population density and poor sanitation tended to show higher dengue incidence rates. In addition, research in Makassar found that climatic conditions such as temperature and rainfall were significantly correlated with an increase in dengue fever cases (12,13).

However, there has been no research that specifically focuses on spatial and temporal analysis using ecological and hotspot approaches in Banjarbaru. This is a research gap that needs to be filled to better understand the dynamics of dengue transmission in this region. There are not many studies that combine spatial and temporal analysis by means of hotspot ecology in dengue, although there have been many dengue studies in Indonesia. Most of them only focus on epidemiological aspects without any attention to ecological and spatial factors as a whole. Therefore, this study is intended to fill the gap by conducting a comprehensive analysis of the spread of dengue in Banjarbaru to provide more accurate and relevant information for disease prevention and control measures. By understanding the spatial and temporal patterns and ecological variables that influence the distribution of dengue in Banjarbaru, it is hoped that this study will be able to provide input in efforts to reduce the incidence of dengue for this area.

MATERIALS AND METHODS

Study area
Banjarbaru Regency is one of the thirteen regencies and the capital of South Kalimantan Province, Indonesia. Based on data from the Central Bureau of Statistics, the district has a population of 258,753 people. Its total area is approximately 371.38 km (37,130 ha). In general, Banjarbaru has a tropical climate, with an average rainfall of 2,584 mm/year, relative humidity ranging from 81-88% and temperatures ranging from 25.9-27°C. Banjarbaru is located in the western part of South Kalimantan province. The district ranges in elevation from 0 to >500 m above sea level and borders of Tanah Laut to the east and Banjarmasin to the north.

Data collection
In this study, the data collected is Dengue Incidence which is the number of dengue cases reported in Banjarbaru on a monthly and annual basis in the period 2016-2023. This data was used to identify areas with higher density of cases, which were then analyzed spatially and temporally to determine disease distribution patterns. All denguecases had to be reported by the Community Health Center to the Banjarbaru District Health Office through the national reporting system specifically for dengue. Community health workers (CHWs) at each Community Health Center compiled and sent monthly report forms to the provincial level for validation before being sent to the Ministry of Health.

Data analysis

Temporal analysis
Retrospective analysis was conducted on dengue notifications in Banjarbaru from 2019 to 2023. Boxplot analysis was conducted to categorize the data by year and month and to see the trend of case fluctuation. The analysis used SPSS version 21 (IBM, Armonk, NY, USA) [14]. Multiplicative seasonal decomposition analysis was performed using SPSS version 21 to decompose the monthly incidence of dengue (Yt) into a combined trend (Tt), seasonal component (St), and error or residual component (Et).18 The relationship between the different decomposition terms and the incidence of dengue is Yt = Tt + St + Et.

Examining spatial patterns and detecting hotspots
For spatial analysis and operational purposes, this study defined villages (if better spatial data were available) or Community Health Center work areas as the spatial unit of analysis. The analysis was limited to the mainland area of Banjarbaru, as dengue cases are mostly found in the mainland area. The center point (latitude and longitude) for each village was estimated using GIS software. dengue cases were associated with village polygon identifiers. Global spatial clustering of dengue incidence (API per 1000 population) was estimated using Moran's I statistics. Furthermore, to locate high-risk villages in mainland Banjarbaru, a Getis-Ord Gi* analysis was conducted to determine the spatial clustering of an area with its closest neighboring areas over a period of time.

Ethical Clearance
This research has received ethics approval from the Health Ethics Commission of the National Research and Innovation Agency, Indonesia with number No: 076/KE.03/SK/04/2024.

RESULTS

Dengue cases in Banjarbaru increased annually in 2019 and 2023, but decreased dramatically in 2021 and 2022 (Figure 1A), while monthly dengue cases increased at the beginning and end of the month, namely November - January each year, with the lowest cases between May - August (Figure 1B).

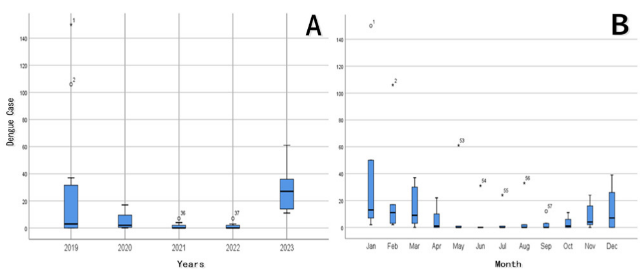

Figure 1: Boxplot of dengue cases in Banjarbaru City. A. Annual, B. Monthly

In the following figure there are additive decomposition plots. The first plot (Data) shows the actual data, the second plot (remainder) the additive decomposition of the random component, the third plot (seasonal) shows the additive decomposition of the seasonal component, the fourth plot (trend) shows the additive decomposition for the trend component (Figure 2).

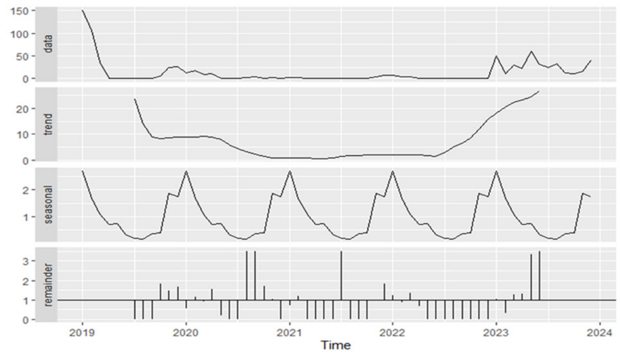

Figure 2: Time series decomposition of dengue cases in Banjarbaru from 2019-2023.

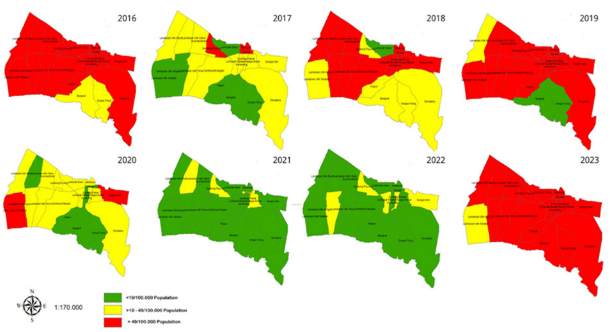

Figure 3: Incidence Rate of dengue cases in Banjarbaru City 2016-2023

The map of dengue case incidence rate in Banjarbaru for 2016-2023 shows a varied distribution of cases in different areas. During this period, several villages or sub-districts in Banjarbaru experienced fluctuations in dengue case incidence rates, with some areas showing a significant increase or decrease in cases. The years 2016, 2018, 2019 and 2023 show an increase in cases to an incidence rate >49/100,000 population (Figure 3).

Table I: Moran's Index Autocorrelation Test

Years	Moran's I	Z-Score	P-value	Result
2016	-0.019	0.428	0.669	dispersed
2017	0.079	1.046	0.296	dispersed
2018	0.042	0.831	0.406	dispersed
2019	-0.049	0.028	0.978	dispersed
2020	0.055	0.814	0.416	dispersed
2021	-0.075	-0.198	0.843	dispersed
2022	-0.237	-1.498	0.134	dispersed
2023	-0.088	-0.273	0.785	dispersed

Based on Table I, using a significance value of a=5% shows that the value of |Z_count |<Z_(a/2)=1.96 and the value of P_value>a then H_0 is accepted, meaning that there is no spatial relationship between locations in Banjarbaru in dengue fever cases. To see the distribution pattern between locations, the expected value or E(I) is used. The calculation of E(I) value can be seen as follows.

$$E(I)= -\frac{1}{n-1} = -\frac{1}{20-1} - 0.0526$$

Based on the table I it is known that the value of Moran's I in 2016 to 2020 shows that the value of Moran's I>E (I), which means that the value of I<E (I), then shows negative spatial autocorrelation where the pattern of the surrounding area has the same nature as each other or dispersed.

Based on Table II, the results of hotspot and coldspot analysis of dengue cases in Banjarbaru in 2016-2023 show significant spatial variation between villages. Guntung Manggis Village consistently showed a tendency to become a hotspot, especially in 2023 with a significant p-value of 0.092. In addition, Sungai Besar village became a significant hotspot in 2018 with a p-value of 0.023. Several other villages, such as Mentaos and Komet, also showed a tendency to become hotspots in certain years, although not always consistently. In contrast, Syamsudinnor Village was a coldspot in 2020 with a p-value of 0.039, indicating a decrease in dengue cases.

Figure 4 illustrates the incidence rate of dengue cases in Banjarbaru from 2016 to 2023. Spatial distribution of dengue cases in 2016 and 2017 with hotspots with 99% Confidence, in 2019 there were no hotspot or coldspot areas, but in 2020 there were coldspots with 90% Confidence, but in 2022 and 2023 hotspots with 90% Confidence were found again.

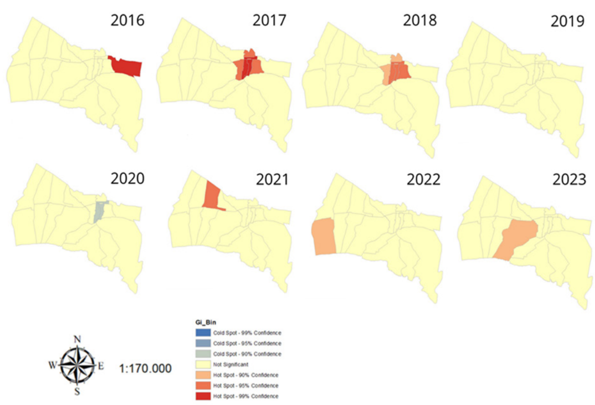

Figure 4: Hotspot and Cold spot distribution of dengue cases in Banjarbaru in 2016-2023.

Table II: Hotspot and Coldsopt analysis of dengue cases in Banjarbaru City in 2016-2023.

No	Village	P-Value							
		2016	2017	2018	2019	2020	2021	2022	2023
1	Guntung Manggis	0.737	0.565	0.852	0.465	0.884	0.588	0.518	**0.092***
2	Palam	0.396	0.169	0.500	0.752	0.170	0.416	0.312	0.739
3	Bangkal	0.281	0.162	0.255	0.144	0.125	0.444	0.337	0.557
4	Sungai Besar	0.100	0.014	**0.023***	0.880	0.630	0.694	0.752	0.560
5	Landasan Ulin Utara	0.769	0.509	0.575	0.356	0.696	0.745	0.228	0.325
6	Loktabat Utara	0.888	0.136	0.854	0.493	0.453	0.243	0.230	0.927
7	Mentaos	0.133	**0.027***	**0.078***	0.854	0.233	0.728	0.595	0.487
8	Komet	0.107	**0.006***	**0.024***	0.866	**0.093****	0.651	0.810	0.547
9	Loktabat Selatan	0.133	**0.027***	**0.024***	0.854	0.232	0.728	0.595	0.486
10	Kemuning	0.107	**0.006***	**0.078***	0.866	**0.093****	0.651	0.810	0.547
11	Guntung Paikat	0.108	**0.006***	**0.024***	0.866	**0.093****	0.651	0.810	0.547
12	Landasan Ulin Selatan	**0.396***	0.163	0.865	0.868	0.453	0.445	**0.088***	0.178
13	Landasan Ulin Timur	0.707	0.565	0.340	0.208	0.833	0.588	0.112	0.512
14	Guntung Payung	0.857	0.818	0.306	0.152	0.215	0.104	0.686	0.804
15	Syamsudinnor	0.991	0.611	0.448	0.279	0.867	**0.039***	0.686	0.427
16	Sungai Tiung	0.343	0.485	0.229	0.428	0.388	0.444	0.627	0.928
17	Cempaka	0.345	0.487	0.230	0.430	0.390	0.445	0.629	0.930
18	Sungai Ulin	**0.002***	0.712	0.970	0.740	0.150	0.404	0.696	0.840
19	Landasan Ulin Barat	0.989	0.477	0.512	0.342	0.735	0.995	0.339	0.466
20	Landasan Ulin Tengah	0.457	0.339	0.823	0.886	0.225	0.489	0.163	0.860

*Hotspot, **Coldspot

DISCUSSION

Dengue cases in Banjarbaru are endemic and fluctuating. Our analysis shows an annual increase in dengue cases in a span of 4 years. The increase in dengue cases every 3-5 years is due to a combination of factors, including the cyclical spread of four dengue virus serotypes, climate and environmental changes that favor the breeding of Aedes aegypti mosquitoes, urbanization and population density that exacerbate the spread of mosquitoes(14,15), as well as high population mobility between endemic and non-endemic areas(14). In addition, population immunity levels that increase after an outbreak may decline over time, allowing new outbreaks to emerge as immunity declines or as new susceptible populations emerge(16). Monthly dengue cases also appear when the beginning and end of the year are increasing. Dengue cases often increase at the end and beginning of the year because this period coincides with the rainy season in many tropical regions, including Indonesia. The rainy season creates ideal environmental conditions for the Aedes aegypti mosquito to breed, due to the large amount of standing water that serves as egg-laying sites for the mosquito. In addition, warmer temperatures at the end and beginning of the year also accelerate the life cycle of mosquitoes and the dengue virus in the mosquito's body, thus accelerating disease transmission. The combination of these environmental and climatic factors leads to an increase in dengue cases at that time (15,17).

At the beginning of the 2020 period there was a sharp decline in the number of dengue cases, which may be due to factors such as the effectiveness of public health interventions, changes in mosquito control policies, or better public awareness. The Coronavirus disease (COVID-19) pandemic also played a role in reducing dengue cases as lockdowns and mobility restrictions limited human-vector contact. After this period of decline, the trend stabilized at a lower number, indicating that dengue cases were successfully suppressed. However, towards 2023, the trend starts to increase again, which may be due to several factors, such as a decrease in the effectiveness of interventions, changes in community behavior, or the emergence of new viral serotypes that are not anticipated by the population's immune system(18). The seasonal graph shows a consistent pattern every year, with peak cases occurring at the beginning and end of the year. This corresponds to the seasonal pattern of dengue, where the rainy season often creates ideal conditions for the breeding of Aedes aegypti mosquitoes, the main vector of the disease (19). The rainy season usually occurs at the end and beginning of the year in many tropical regions, which explains the increase in cases during this period. The remainder component indicates fluctuations that cannot be explained by seasonal trends or patterns. This could indicate the presence of random events or extraordinary factors affecting dengue cases, such as local outbreaks, sudden climate change, or even temporary health policies (9,20).

The initial decline in cases may be related to effective public health interventions, such as mosquito control campaigns and community outreach. However, the increase in cases towards 2024 may indicate that these measures are starting to lose effectiveness or that the dengue virus is adapting. (21) A pattern of fluctuation in dengue case intensity, with periods of increase and decrease occurring every few years. This may be related to the epidemiological cycle of dengue disease, which tends to show a pattern of increasing cases every 3-5 years, as seen in 2016, 2019, and 2023. Increased dengue cases in those yearsDengue has a cyclical pattern, with an increase in cases occurring every few years. This may be due to a shift in the dominance of different dengue virus serotypes, affecting populations that lack immunity to the new dominant serotype (21,22). The effectiveness of Aedes aegypti mosquito control may fluctuate. In years with increased cases, there may be a failure or lack of effectiveness in vector control efforts. Favorable climatic conditions, such as high rainfall and warm temperatures, can increase mosquito populations and exacerbate the spread of dengue (23,24).

We found that dengue cases in Banjarbaru are spreading and this happens every year. This means that the distribution of dengue cases is not centered on a particular area and is more random. This condition indicates that dengue cases are not clustered geographically, which indicates that there is no consistent high risk area. (25) The results of the hotspot and coldspot analysis from 2016 to 2023 show significant spatial variation between villages, with some villages such as Guntung Manggis and Sungai Besar consistently becoming hotspots in certain years, indicating an increased risk of dengue spread in the area. Guntung Manggis village, for example, shows a tendency to become a hotspot especially in 2023. On the other hand, Syamsudinnor Village was a coldspot in 2020, indicating a decrease in dengue cases in this area. Syamsudinnor Village became a dengue cold spot in 2020 likely due to several factors, including the effectiveness of public health interventions such as structured fogging programs, improved environmental management, and increased community awareness regarding dengue prevention. Additionally, environmental conditions that were less favorable for Aedes aegypti mosquito breeding, such as a reduction in standing water and changes in land use that do not support mosquito habitats, contributed to the decreased risk of transmission. Furthermore, the implementation of focused and appropriate public health policies in the area played a key role in reducing dengue cases, making it a cold spot with a significant decline in incidence. A hotspot was found with a confidence level of up to 99%, while in 2020 a coldspot was found with a confidence level of up to 90%. This suggests that the pattern of dengue spread in Banjarbaru is dynamic, with some areas becoming more susceptible to increased cases in certain periods, requiring focused and adaptive public health interventions.

Thus, control strategies focused on specific areas may be less effective. Instead, a broader and more equitable approach is needed throughout the region, including interventions such as comprehensive vector control, increased public awareness, and environmental sanitation in every household(26). This random distribution also implies that non-spatial factors such as climate change, population mobility, and individual behavior may play a more significant role in the spread of dengue. It is important to note that the spatial distribution of dengue cases may not reflect the spatial distribution of the vectors, which is more critical for disease control activities. It can be considered that such factors in the control strategy, as well as ensuring flexibility and readiness in responding to changes in the spread pattern that may be unstable over time. More frequent monitoring and adaptive response will be key in reducing the impact of dengue outbreaks whose distribution is not tied to a specific geographical location.

This fluctuation in the distribution of dengue cases shows the importance of continuous monitoring and adaptation of control strategies, especially towards periods that historically show an increase in cases. In addition, a data-driven approach to predict trends and target interventions to high-risk areas is essential to reduce the impact of future outbreaks. The advantage of using spatial and temporal analysis, especially in the context of ecological and hotspot studies for diseases such as dengue, lies in its ability to reveal patterns of disease spread in space and time. Approaches to Identifying High Risk Areas, Understanding Temporal Trends, Dynamic Disease Control and Holistic Understanding of Ecological Factors. In the context of dengue control activities in Banjarbaru, these findings imply that localized interventions may not be sufficient. A broader, region-wide strategy incorporating continuous vector surveillance, public education, and adaptable control measures will be crucial in addressing the fluctuating nature of dengue transmission in the area. Moreover, these findings could be useful for dengue control activities in other parts of Indonesia and in countries with similar climates, where a comprehensive and adaptive approach may prove more effective than spatially limited interventions.

CONCLUSION

Dengue fever cases in Banjarbaru exhibited an overall upward trend from 2019 to 2023, with notable decreases in 2021 and 2022. Seasonal patterns reveal a peak in cases during November to January and a decrease between May and August. The additive decomposition analysis underscores distinct random, seasonal, and trend components in the data, providing insight into the underlying patterns of dengue incidence. Despite these trends, spatial analysis using Moran's I values indicated a negative spatial autocorrelation, suggesting that dengue cases are dispersed rather than clustered across the city. The spatial distribution of dengue cases varied significantly across different villages, with certain areas experiencing fluctuations in incidence rates. Notably, Guntung Manggis Village and Sungai Besar Village emerged as significant hotspots in 2023 and 2018, respectively. In contrast, Syamsudinnor Village was identified as a coldspot in 2020, reflecting a decrease in cases. The analysis of hotspots and coldspots over time highlights the need for targeted public health interventions and adaptive strategies that consider both temporal and spatial variability in dengue fever incidence.

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