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Spatial Analysis on the Spread of Dengue Hemorrhagic Fever in Baubau, Southeast Sulawesi, Indonesia

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Abstract

We studied the spatial patterns of Dengue Hemorrhagic Fever (DHF) transmission in Baubau, a city in Southeast Sulawesi, Indonesia. DHF is a serious disease caused by the dengue virus and spread by Aedes mosquitoes. We used Moran's Index, a spatial analysis tool, to create a DHF spread map for Baubau's sub-districts. We found different patterns of DHF risk, such as: cold spots, Betoambari and Batupoaro had lower DHF cases, but they were vulnerable to infection from nearby areas; hot spot, Murhum had higher DHF cases and could transmit the disease to neighboring areas; and low risk, Bungi had the lowest DHF risk and was resilient to infection. Our findings suggest that preventive measures should be tailored to the specific risk level of each sub-district. Our study also provides useful guidance for controlling DHF transmission in Baubau and beyond. Our research is a beacon of hope for a safer and healthier future.

Keywords: *dengue hemorrhagic fever, thematic map, Moran's I, spatial analysis, Aedes mosquitos*

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1. Introduction

Dengue Hemorrhagic Fever (DHF) is a severe illness resulting from the dengue virus, and its transmission occurs through Aedes aegypti and Aedes albopictus mosquitoes. It typically manifests as a sudden fever lasting two to seven days, accompanied by symptoms such as headaches, nausea, and various bleeding manifestations. According to the World Health Organization (2023), it is now endemic to more than 100 countries with Americas, South-East Asia and Western Pacific regions as seriously affected. In fact, Asia represents 70% of the serious cases globally.

In Indonesia, Aedes mosquitoes are prevalent throughout most regions of the country. Hence, dengue fever remains a persistent public health concern, particularly in densely populated urban areas (Halide & Ridd, 2008). The study of Harapan et al. (2019) showed an increasing trend of DHF in the country over the past 50 years while fatality decrease by half every decade. The incidence rates (IR) of DHF from 2018 to 2020 were 65,602, 138,127, and 108,303, respectively (Badan Pusat Statistik, 2021). However, Triastuti (2022) found a decrease in both IR and number of deaths due to DHF in 2022 as compared to the recorded cases in 2021. Majority of the conducted studies in various regions of the country exhibited an increasing trend of DHF cases (i.e. Mochamad Rizal Maulana et al., 2023; Faridah et al., 2023; Dewi et al., 2021; Pasaribu et al., 2021; Nainggolan et al., 2023; Fuadzy et al., 2020; Suryadi et al., 2021; Hasana & Susanna, 2019; Rakhmani et al., 2018; Setiawati, 2019; Utama et al., 2019; Sasmono et al., 2020; Haryanto, 2018; O'Reilly et al., 2019; Harapan et al., 2019; Maula et al., 2018; Wahyono et al., 2017). Hence, it remains a serious social issue not only by the medical practitioners but by different sectors of the society.

Numerous authors have proposed various approaches to address the challenges posed by Dengue Hemorrhagic Fever (DHF). While it is given that the majority of the strategies are medical in nature (i.e. Cavany et al., 2023; Smith, 2021; Saputra & Oktaviannoor, 2017; Indriani et al., 2023; Sulistyawati, 2020; Sulistyawati et al., 2023; Utama et al., 2019; Kurniawan et al., 2021; Sulistyawati et al., 2019; Utarini et al., 2021; Brady et al., 2020; Suwantika et al., 2020), there are breakthrough studies to control the spread of the disease through modeling techniques (i.e. Ramadona et al., 2023; Bannister-Tyrrell et al., 2023; Eryando et al., 2013; Nirwantono et al., 2022), profiling (Chew et al., 2019; Indriani et al., 2018; Adrizain et al., 2018) and spatial analysis (Dhewantara et al., 2019; Syukri &

Wardiah, 2023). For instance, Halide and Ridd (2008) developed a statistical model capable of forecasting DHF outbreaks up to six months in advance, utilizing current DHF cases, climate variables, and weather conditions. Similarly, Camargo et al. (2022) devised a mathematical model that illustrates how infants born to mothers with immunity to certain dengue serotypes can still contract DHF, particularly during periods of elevated monocyte infection and dengue virus levels. In addition to these contributions, Nuraini and Tasman (2012), Gonçalves et al. (2012), Bente and Rico-Hesse (2006), Tolinggi and Dengo (2019), Derouich et al. (2003), and Esteva and Vargas (1999), have also explored modeling dengue transmission within the human population. Despite the substantial number of studies on this field, the cases of DHF continues to pose challenges and evolve.

Several factors have been implicated in the persistence of DHF cases, including the lack of comprehensive information regarding the timing, location, and total number of incidents in an integrated manner. According to Kusairi and Yulia (2020), the use of Geographic Information Systems (GIS) helps facilitate the reduction of cases. The use of map as proposed by Mukhsar at al. (2021), Sani et al. (2023), and Mukhsar at al. (2023) could provide information on the spread of DHF among neighboring areas. However, there is still no specific study or published research on the distribution and vulnerability mapping (spatial aspects) of dengue cases in Baubau, a prominent city in Southeast Sulawesi Province situated on Buton Island, which was consistently been labeled as an endemic area for DHF. This is substantiated by the annual detection of a relatively high number of cases. For instance, in the years 2018, 2019, and 2020, there were 98, 160, and 74 recorded cases, respectively (Badan Pusat Statistik, 2021). With the population of 159,248 people based on 2020 census, the IR were 62, 100, and 46 cases in every 100,000 people, while the global IR is 50. The fatality rates were 0%, 1.27%, and 1.20%, respectively. These statistics underline the ongoing challenge in effectively curtailing DHF within Baubau City.

Understanding the regional dynamics is crucial, as each area varies in population behavior, density, and type. A geographic distribution map would be invaluable in empirically investigating the relationship between geographic factors and the disease, aiding in prevention efforts. Hence, this article aims to analyze the pattern of spatial distribution of DHF using spatial autocorrelation and to create a map of DHF vulnerability in Baubau City in 2018-2020.

2. Theoretical Background

2.1. Spatial autocorrelation

Spatial data refers to georeferenced information wherein different attributes are associated with distinct spatial units. In the context of GIS, the data can be categorized into two primary types: spatial data and attribute data. Spatial data pertains to information intrinsically linked to spatial locations, whereas attribute data encompasses non-spatial details designed to elucidate the characteristics of various objects within the spatial dataset (Smith, 2020; Griffith, 2020). According to Lee and Wong (2001), it is a method for identifying spatial patterns by considering the values of locations and their attributes. Spatial patterns can be described into three parts, namely *clustered*, *dispersed*, and *random*. Spatial autocorrelation has positive value if the spatial data pattern tends to be clustered, it has a negative value if the pattern tends to spread out, and it is said to have no spatial autocorrelation if the pattern is random (Anselin, 1995; Lee & Wong, 2001; Griffith, 2020).

2.2. Spatial weights matrix

A spatial weights matrix serves as a mathematical construct designed to capture and quantify the inherent spatial connections within a dataset. This matrix operates as a tool for quantifying the geographical relationships among different geographical regions present in the data. These values within the matrix are assigned in accordance with predetermined criteria that delineate the spatial associations among these locations, ultimately influencing the calculation of spatial autocorrelation statistics (Xu & Lee, 2019). The foundation for these spatial relationships is rooted in concepts like Queen, Rook, and Bishop contiguities, each of which prescribes specific rules to determine how neighboring areas are connected. Specifically, areas in close proximity are assigned a value of 1, while those farther apart receive a value of 0 (Anselin, 1995; Rey & Anselin, 2010).

2.3. Moran's index

Moran's index (Moran's I) is an indicator of spatial autocorrelation and is commonly used to determine spatial autocorrelation coefficients. Moran's index can be used to determine local spatial patterns (LISA). Moran's index is used to determine the correlation of a variable in all observed data sets (Lee & Wong, 2001; Vogl & Mikula, 2021). Moran's index can be calculated by the following equation:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(X_i - \bar{X})(X_j - \bar{X})}{W \sum_{i=1}^{n} (X_i - \bar{X})^2} \quad (1)$$

where n is the number of observations, W is the number of weights, X_i is the observed variable at the i-th location, $i = 1, 2, \ldots, n$, X_j is the variable observed at the j-th location, $j = 1, 2, \ldots, n$, w_{ij} is the ij element of the spatial weights matrix W (which has been standardized), and $\bar{X}$ is the average of X on n locations (Chen, 2009; Bivand, 2009).

The Moran's Index value falls within the range of -1 to 1, and both negative and positive values indicate a spatial association with the surrounding area (Ren et al, 2016; Yu & Chang, 2021). The expected value of the Moran Index is shown in the following equation:

$$E(I) = \frac{-1}{n-1} \quad (2)$$

Moran scatterplot can be constructed by plotting the variable of interest on both the x-axis and y-axis. Each point on the scatterplot represents a specific location on the map. The position of the point is determined by the value of the variable at that location. Different symbols or colors can also be used to indicate the direction of spatial autocorrelation (Negreiros et al., 2010).

On the other hand, the Local Indicators of Spatial Association (LISA) is a valuable tool for examining spatial associations within a research area. The LISA method serves as an effective means to identify areas of contraction or outliers in spatial phenomena within a given region. LISA is defined by the equation:

$$I_i = \frac{(x_i - \bar{x})}{\left[\sum_{i=1}^{n} (x_i - \bar{x})\right]} \sum_j w_{ij} \left(x_j - \bar{x}\right) \quad (3)$$

where x_i is the observed value at location i, x_j is the observed value at location j, $\bar{x}$ is the average value of the observed variables, and w_{ij} is the weighted measure between region i and region j (Anselin, 1995).

To test the parameter I_i, we can use statistic Z in which the null hypothesis (H_0): $I_i = 0$ (indicating no spatial autocorrelation) versus the alternative (H_1): $I_i \neq 0$ (indicating the presence of spatial autocorrelation).

The calculation of statistic Z is as follows:

$$Z_{calc} = \frac{I_i - E(I_i)}{\sqrt{var\ (I_i)}}$$

Here, Z_{calc} stands for the LISA Index test statistic, I_i represents the LISA Index, $E(I_i)$ represents the expected value of the LISA Index, and var (I_i) represents the variance of the LISA Index. The null hypothesis H_0 will be rejected if the absolute value of $Z(I) > Z(\alpha/2)$, indicating the presence of spatial autocorrelation.

LISA Index measures the degree of a particular location to its adjacent counterparts by contrasting the value of a chosen variable at a given site with those of neighboring locations. LISA analysis assigns local indicators to each dataset location, categorizing them into one of four distinct groups (Negreiros et al., 2010):

1. High-High (HH): Indicates locations with high values enclosed by other high-value locations, signifying the presence of clusters with elevated values.
2. Low-Low (LL): Identifies sites with low values encompassed by neighboring low-value locations, suggesting the existence of clusters with diminished values.
3. High-Low (HL): Recognizes locations with high values bordered by low-value sites, implying spatial outliers.
4. Low-High (LH): Pinpoints sites with low values surrounded by high-value areas, also indicating spatial outliers.

The application of LISA analysis is advantageous across various domains such as geography, urban planning, economics, and more. By delineating local spatial associations, it facilitates the comprehension of the presence and extent of spatial clustering or spatial outliers within datasets, thereby unveiling the underlying spatial structure (Anselin, 1995).

2.4. Thematic map

A thematic map serves as a geographic representation that conveys specific information related to a designated theme, encompassing both surface and subsurface data pertaining to that theme. These maps are alternatively known as statistical maps or special purpose maps, and they offer a concise depiction of spatial patterns or characteristics within a particular area, as per the chosen thematic focus (Kettani & Moulin, 1999).

Thematic maps fulfill the role of conveying information of a specific theme, accommodating both qualitative and quantitative data. They share a profound connection with GIS, as thematic maps frequently constitute the output of GIS projects. Such maps are available in both digital formats and traditional paper map forms, serving as valuable tools for visualizing and communicating thematic data in geographical contexts (Slocum et al., 2005).

3. Research Methods

The data used are the reported number of DHF cases in Baubau City in 2018 – 2020 obtained from the City Health Office of Baubau. The research procedures for this study are outlined as follows.

Preparation of geographical description. This step involves describing the location, area, population, climate, and other relevant features of Baubau City, which is the study area for this research. The geographical description helps to provide the background and context for the analysis of DHF cases in the city. We used secondary data sources, such as census reports, maps, and official websites, to prepare the geographical description of Baubau City.

Descriptive statistics of DHF cases. This step involves summarizing the number, frequency, and distribution of DHF cases in Baubau City from 2018 to 2020. The descriptive statistics help to provide an overview of the magnitude and trend of DHF cases in the city. We used primary data sources, such as health records, surveillance reports, and laboratory tests, to obtain the data on DHF cases in Baubau City.

Spatial distribution of DHF cases. This step involves analyzing the spatial pattern of DHF cases in Baubau City across its sub-districts. The spatial distribution helps to identify the areas that have higher or lower incidence of DHF cases than expected by chance. We used the following analytical steps to investigate the spatial distribution of DHF cases in Baubau City: (a) compute the spatial weights matrix, which measures the spatial proximity and connectivity of the sub-districts, (b) determine the statistics related to Moran's Index, which measures the global spatial autocorrelation of DHF cases, generate and identify Moran's scatterplot, which visualizes the local spatial autocorrelation of DHF cases.

Hotspots and coldspots of DHF cases. This step involves identifying the areas that have significantly high or low incidence of DHF cases compared to the average of Baubau

City. The hotspots and coldspots help to detect the spatial clusters or outliers of DHF cases in the city. We used the LISA index, which stands for Local Indicators of Spatial Association, to test the hypothesis of spatial dependence of DHF cases in Baubau City.

Thematic map of DHF cases. This step involves creating a thematic map that depicts the vulnerability of enclave areas to DHF cases in Baubau City. The thematic map helps to communicate the results and implications of the spatial analysis of DHF cases in the city. We used ArcView GIS 3.3, which is a geographic information system software, to produce the thematic map of DHF cases in Baubau City.

4. Results and Discussion

4.1. Description of DHF cases in Baubau City

Baubau City, situated within Southeast Sulawesi Province, is comprised of eight sub-districts: Betoambari, Wolio, Murhum, Batupuaro, Sorawolio, Kokalukona, Lea-lea, and Bungi, covering a total area of 294.99 square kilometers. In the year 2018, the city reported 98 cases of DHF, with the highest incidence recorded in Wolio (31 cases), followed by Murhum (29 cases) and Batupuaro (26 cases), while the remaining sub-districts reported an average of 5 to 6 cases each. Notably, there was a significant surge in DHF cases in the subsequent year, 2019, with a total of 160 cases, of which 80 cases were concentrated in the Wolio sub-district and 29 in the Murhum sub-district. However, in 2020, efforts to combat the disease proved effective, resulting in a reduction of DHF cases to 74.

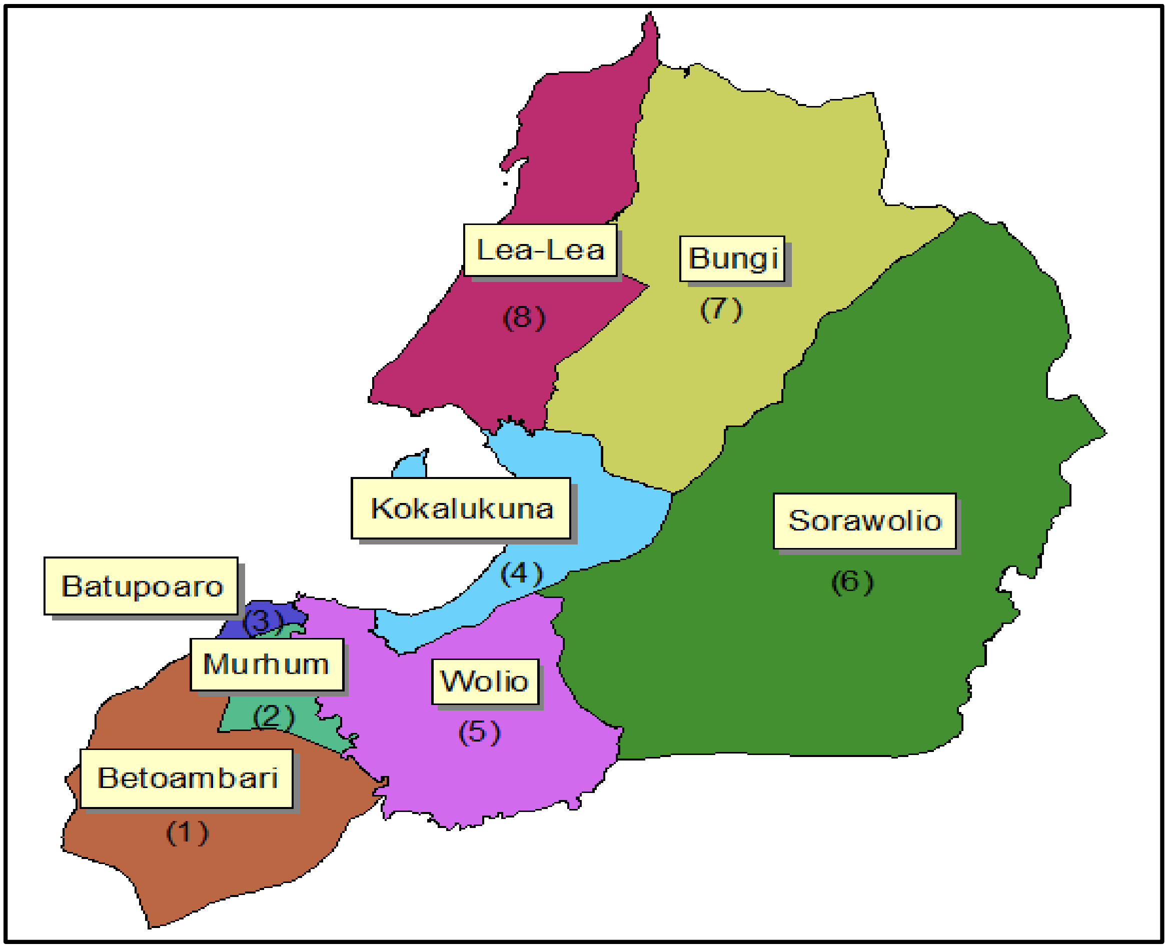
4.2 Spatial Pattern of DHF Cases in Baubau City

The contiguity matrix is formed based on the location of each sub-district as depicted on the administrative map of Baubau City shown in figure 1.

The legends for each district and its adjacent districts is generated based on the Queen's Move principle. To illustrate, consider the Betoambari sub-district, which shares its borders with three nearby neighbors: Murhum, Batupoaro, and Wolio sub-districts. Similarly, the Murhum sub-district is in proximity to Betoambari, Batupoaro, and Wolio sub-districts. This same rationale holds for determining the number of neighbors for the remaining districts.

Figure 1

Baubau City map with its sub-districts



The outcomes of the Moran's *I* analysis conducted for annual DHF cases in Baubau City via Rstudio are presented in table 1.

Table 1

Moran index values for Baubau City in 2018-2020

Year	Moran's Index (*I*)	Moran's Expectations Index (E(*I*))	Spatial Pattern
2018	0.26569479		Clustered
2019	-0.03491325	-0.14285714	Dispersed
2020	-0.06539569		Dispersed

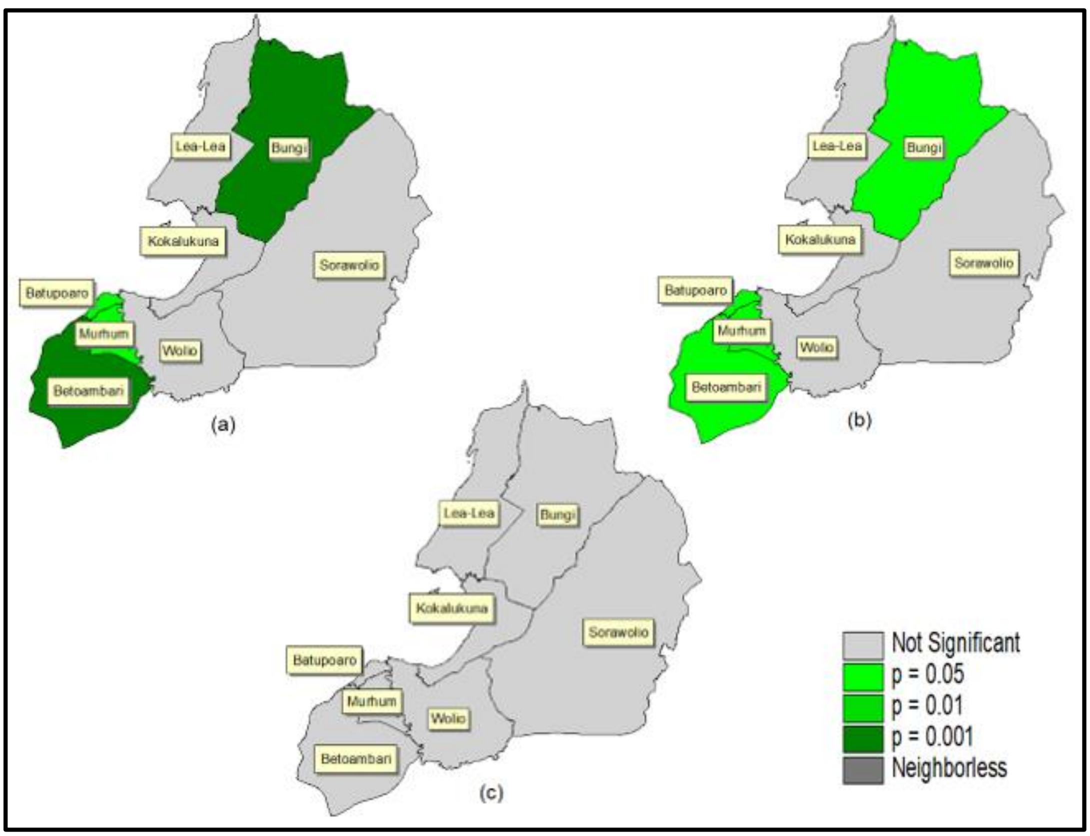
By referring to table 1, we can imply that the Moran Index value for 2018 manifests as positive, denoted by $I > E(I)$, showing the significance of a clustered spatial pattern. This suggests that in neighboring areas or sub-districts, occurrences of DHF cases tend to exhibit a similar or identical count. Conversely, there is a negative Moran Index value for 2019 and 2020, as indicated by $I < E(I)$, which means dispersed spatial patterns, where neighboring areas or sub-districts tend to display varying and dissimilar numbers of DHF incidents.

4.3. LISA index of DHF cases in Baubau City

The outcomes of the LISA index test for the year 2018 reveal that there were two sub-districts with statistically significant results at a significance level of α=5%, namely Murhum and Batupoaro. Additionally, two other sub-districts, Bungi and Betoambari, exhibited statistical significance at a more stringent α=0.1%. These findings indicate a spatial relationship among these sub-districts, particularly with their immediate neighbors. Conversely, there were four districts that did not yield statistically significant results, namely Wolio, Sorawolio, Lea-Lea, and Kokalukuna. The results of the 2018 DHF LISA analysis are shown in figure 2.

Figure 2

DHF cases in Baubau City using LISA Index



Legend: (a) 2018; (b) 2019; (c) 2020

In 2019, there were four sub-districts to have significant results at α= 5%, namely Betoambari, Batupoaro, Bungi and Murhum. These indicate that the sub-districts have spatial relationship with their neighboring sub-districts or their direct adjacent. There are four sub-districts to have no significant results, namely Wolio, Sorawolio, Lea-Lea and Kokalukuna. The map shows the results of the 2019 DHF data using LISA index.

In 2020, there were eight sub-districts to have no significant results, namely Murhum, Betoambari, Wolio, Sorawolio, Lea-Lea, Kokalukuna, Batupoaro and Bungi. The map provides the results of the 2020 DHF case using LISA index.

4.4. Map of the spread of dengue fever in Baubau City

Summary of the results of Moran's scatterplot is presented in table 2 and the thematic map of the results of Moran's scatterplot is presented in figure 3.

Table 2

Position of each sub-district in Moran's scatterplot for 2018-2020

Year	HH	LH	HL	LL
2018	Murhum Batupoaro	Betoambari Sorawolio	Wolio	Lea-lea Bungi Kokalukuna
2019	Murhum	Betoambari Batupoaro Kokalukuna Sorawolio	Wolio	Bungi Lea-lea
2020	Murhum Kokalukana	Betoambari Sorawolio Batupoaro	Wolio	Bungi Lea-Lea

In 2018 as shown in table 2, there were two sub-districts located in quadrant I (High-High), namely Murhum and Batupoaro. This indicates that these two sub-districts have high number of DHF cases and the surrounding sub-districts also have high DHF cases. There are two sub-districts in quadrant II (Low-High), namely Betoambari and Sorawolio. These two sub-districts have low number of DHF incidents while the surrounding districts have high DHF cases. Quadrant III (Low-Low) indicates an area that is safe from DHF cases, namely

Kokalukuna, Lea-Lea and Bungi sub-districts. Wolio is the one and only sub-district in Quadrant IV (High-Low) with high incidence while the surrounding districts are low.

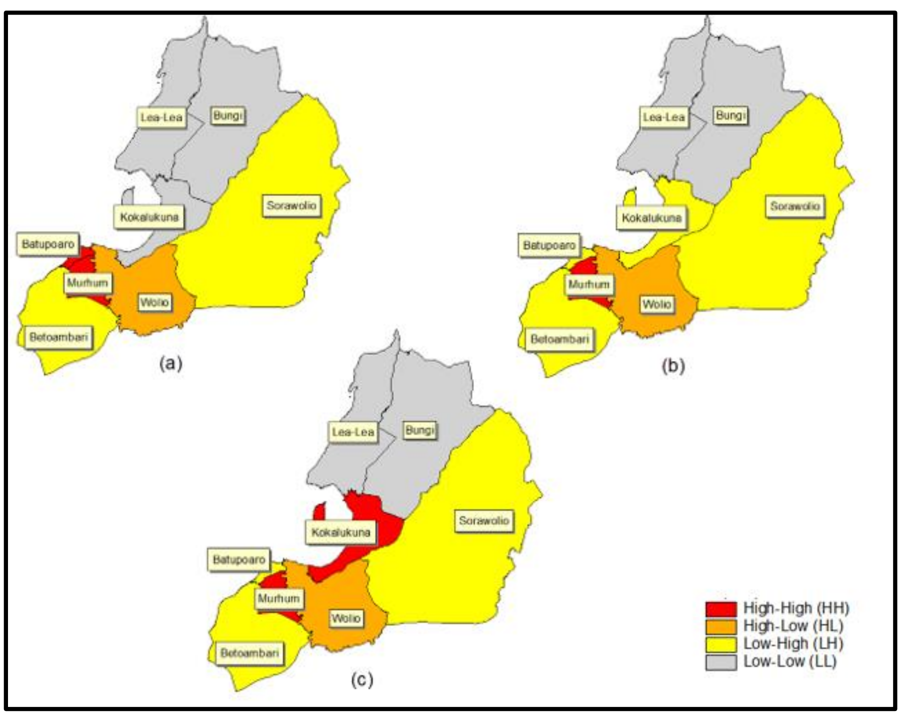
The composition of quadrant changed in 2019. In Quadrant I, there is only one district, Murhum, where there is a high number of DHF cases in the sub-district and in the surroundings. In Quadrant II, where the incidences are low while the surroundings are high, there are four districts, namely Sorawolio, Kokalukuna, Batupoaro and Betoambari. In Quadrant III, there are two districts, namely Lea-lea and Bungi, which are considered safe areas from dengue. In Quadrant IV, there is also only one district, Wolio, where the sub-district itself has high number of incidences while the surroundings are low.

In 2020, the constellation of sub-districts in the quadrants changed again. In Quadrant I, where the area and the surroundings have high number of incidences, there are two districts, namely Kokalukuna and Murhum. Betoambari, Sorawolio and Batupoaro sub-districts are in Quadrant II. In this quadrant, the number of DHF incidents is low while the surroundings are high. In quadrant III, there are two districts, namely Bungi and Lea-Lea. This quadrant is a safe area from dengue. Quadrant IV, where the number of DHF incidences is high while the surroundings are low, consists only of one sub-district, Wolio.

4.5. DHF thematic map of Baubau City

Figure 3

Thematic map of Moran's scatterplot



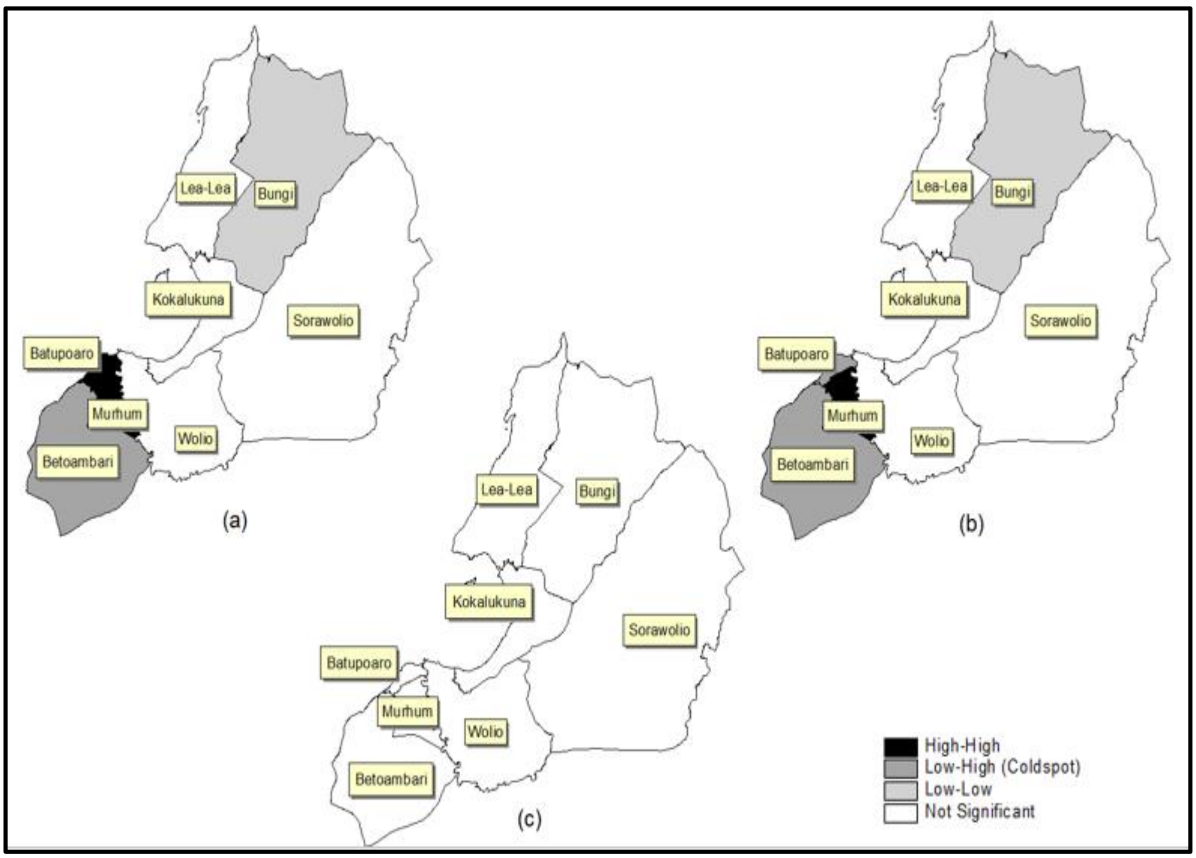
Legend: (a) 2018; (b) 2019; (c) 2020

In figure 3, it can be seen that Murhum and Wolio sub-districts are both with high DHF IR during three years of observation (2018-2020), while for Lea-lea, Betoambari, Sorawolio and Bungi sub-districts have low DHF IR. It also can be seen that the DHF incidences in Kokalukuna sub-district increased annually. Being in Low-Low quadrant in 2018 and Low-High in 2019, it became High-High in 2020. This is due to the lack of local people in carrying out mosquito-nest eradication activities. There are still many local people who collect rainwater which can result in providing breeding sites for Aedes aegypti and Aedes albopictus mosquitoes.

4.6. Map of dengue fever cases in Baubau City

Figure 4

Dengue disease vulnerability map in Baubau City



Legend: (a) 2018; (b) 2019; (c) 2020

The results of the LISA Index test during the three-year period of observation showed four significant sub-districts, namely Murhum, Betoambari, Bungi and Batupoaro. Batupoaro, categorized as cold-spot area in 2019. Meanwhile, in 2018 and 2019, Betoambari is considered as cold-spot area. The cold-spot area has negative autocorrelation or outlier pattern with low number of DHF incidences while the surroundings are high. However, this area has the potential to be prone to the spread of dengue fever, which is probably transmitted by the high number of surrounding areas. Meanwhile, the LISA test for 2018 and 2019 showed that the Murhum sub-district is classified as an area with high DHF incidence rate and the surrounding areas are also high. These areas should be monitored by all stakeholders to prevent the spread of dengue to the neighboring sub-districts. LISA test for Bungi shows that the sub-district is categorized as low incidence of DHF while the surrounding areas are also low. This area is safe from DHF incidences.

5. Conclusions and Recommendations

Our analysis reveals significant fluctuations in the number of DHF cases in Baubau City between 2018 and 2020. Notably, there was a substantial spike in DHF cases in 2019. Throughout this period, Wolio consistently reported the highest number of DHF cases among the sub-districts. Moreover, our examination employing the Moran Index demonstrates varying spatial patterns. In 2018, the Moran Index registered a positive value of 0.2, indicating a clustered spatial pattern in DHF distribution across Baubau City. In contrast, 2019 exhibited a negative Moran Index of -0.03, signifying a dispersed spatial pattern. A similar dispersed pattern was observed in 2020, with a Moran Index of -0.06. Positive Moran's Index values indicate a uniform DHF distribution across sub-districts, while negative values suggest variation in DHF distribution among sub-districts.

A closer look through LISA analysis highlights that in 2018, both Murhum and Batupoaro sub-districts experienced high DHF incidence. However, in 2019, only Murhum exhibited a notable increase in DHF cases. Consequently, targeting interventions for DHF reduction and prevention should prioritize the Murhum sub-district. Additionally, the data from 2019 indicates that Betoambari and Batupoaro sub-districts are potential areas at risk for DHF transmission from their neighboring sub-districts while the Bungi sub-district appears to be a safer zone with a lower risk of DHF transmission.

It is essential to note that this research exclusively focuses on spatial patterns and does not account for other contributing factors. Hence, future research endeavors should aim to incorporate other factors to comprehensively model the influences on the number of DHF cases in Baubau City.

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