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Spatial Distribution of Dengue and Forecasting in South Denpasar, Bali Province, Indonesia

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ABSTRACT

Background and purpose: The incidence of dengue hemorrhagic fever (DHF) in Bali continues to increase. A new strategy is required to control dengue in Bali. The purpose of the study is to conduct spatial mapping with a geographic information system to help determine the distribution pattern and areas at risk of DHF and to predict increasing vector density and dengue cases.

Methods: A cross-sectional study was conducted in the South Denpasar Public Health Center service area from January to June 2020. It was conducted in 3 villages, including Kelurahan Sesetan (3,446 households), Sidakarya Village (2,859 households), and Kelurahan Panjer (2,907 households). A total of 191 cases of DHF were recorded during the study period.

Results: Calculation of the spatial analysis of the Average Nearest Neighbor (AAN) with the value of Z score=-8.03 show a spatial pattern of the distribution of DHF cases. AAN value of 0.69 (<1) means that the pattern of spread of DHF incidence is clustered. Time series forecasting by modeling using the Autoregressive Moving Average (ARIMA) and Double Exponential Smoothing Method Routine shows that larva control efforts are predicted to affect the number of dengue cases. The pattern of the spatial distribution of cases occurs in clusters.

Conclusion: There is a spatial relationship with population density. It is predicted that routine larvae control will reduce dengue cases.

Keywords: dengue, population, density, spatial analysis

INTRODUCTION

Dengue hemorrhagic fever (DHF) is a major public health problem in the tropical and subtropical countries. This mosquito-borne disease has spread rapidly in the last 50 years. WHO estimates that by 2020, the annual cases of dengue infection will reach 50-100 million people,[1] which was tripled to 390 million, placing 70% of the world's population at risk.[2]

Indonesia has a huge burden of DHF. The first DHF case was reported in 1968 in Surabaya. Since then, the incidence rate (IR) has increased from 0.05 to 35-40 per 100,000 population and peaked in 2010 (IR 85).[3] In 2019, there were 137,000 dengue cases reported and 917 deaths. In 2020, the total cases reached 108,303 and 727 deaths. In 2021, there were 68,614 cases and 664 deaths.[4]

Bali Province is one of the dengue-endemic areas in Indonesia which is also one of the most popular tourist destinations worldwide. Cases of DHF among Bali residents are high, which is also potential to Dengue infection in tourists when they are visiting Bali.[5] All districts in Bali are DHF endemic areas with Denv-3 sero-variance was dominant, followed by Denv-1, Denv-2, and Denv-4.[6] A report from the Bali Provincial Health Office in 2016 showed the incidence rate was 544 per 100,000 population, and in 2017 was 105.9 per 100,000 population.[7]

To better understand distribution of a health problem and its potential risk factors, geographic information system (GIS) technology is applicable to provide map according to geographic distribution.[8,9] This technology has been applied in several regional-based disease control decisions.[10] The spatial mapping of certain diseases has been applied to improve public health surveillance in many different settings.[11-13]

The pattern of distribution of dengue cases with larvae density and population density can be made using GIS.[14-16] This information will be able to provide insights for policymakers regarding vulnerable areas; it will also enable the health offices to prepare resources, carry out early prevention strategies, and develop surveillance systems and vector intervention actions. This study aims to determine the distribution pattern of dengue cases based on population density and the buffer zone of dengue incidence based on population density mapping of water containers inside and outside the house. Then, this is used to predict the density of larvae and cases of dengue infection.

METHODS

Study Design and Setting

The design of the study was a cross-sectional survey conducted in 3 villages of South Denpasar Sub-District, Denpasar City, Bali Province. This area has a high population density and a large urban population. This study was conducted in Denpasar City which was selected in the South Denpasar Sub-District. Geographical location of South Denpasar Sub-District is between 08 040'00" - 08 044'49" south latitude and 115 011'23"-115 015'54" east longitude. The area of the South Denpasar Sub-District is 4999 hectares or 39.12 percent of the total area of Denpasar City.[17] The South Denpasar Sub-District is mostly a coastal area, where 8 villages and their wards are in coastal areas and 2 villages are non-coastal areas. The status of village areas in South Denpasar is urban, while the elevation of all villages in this sub-district is at an altitude of fewer than 100 meters above sea level. South Denpasar Sub-District is one of the endemic areas for dengue hemorrhagic fever which has high cases in Denpasar.

Data collection

The data of DHF cases was obtained from hospital reports to the Denpasar City Health Office. There were 191 cases of DHF recorded. This study used a global positioning system (GPS) to determine the coordinates of cases of dengue infection. The report was obtained from hospital data that was reported to the Denpasar City Health Office. Local Public Health Center (PHC) surveillance officers conducted an epidemiological investigation. Data contained age, gender, address, telephone number, platelet status, and hospital admission date.

The primary data collection was conducted from January to June 2020. It was conducted in 3 villages with a population of Sesetan (3,446 households), Sidakarya (2,859 households), and Panjer (2,907 households). The larva density data were obtained from entomological surveillance of the density of mosquito larvae in each village conducted by *jumantik* volunteers. *Jumantik* is a community volunteer who monitors mosquito larvae. All data on DHF cases were then taken in coordinates. The data is sent to the city health office for mapping.

Analysis

The dengue case data and larva density were then mapped using the ArcGis Pro 2.0 application to perform the spatial mapping. The analysis uses univariate analysis and spatial analysis using the average nearest neighbor (ANN), namely ANN = 1 means random pattern, ANN <1 means clustered, and ANN >1 means dispersed. Average nearest neighbor can show the average distance between cases of DHF and spatial patterns of dengue. Buffers are used to determine the spread of dengue cases based on the flying distance of mosquitoes. Through buffer analysis, it is known that the areas at risk of outbreaks are identified. Vulnerability map was produced accounting for both larva and dengue case density.

The technique used to predict larva density for the following 6 months is the Autoregressive Moving Average (ARIMA) and Double Exponential Smoothing Method.[18-21] Data processing using MINITAB 18 software with the initial steps of identification of tentative models (p,d,q), estimation of model parameters, diagnostic tests, and finally the model used for forecasting. Time series data of cases compared to larval density were projected using Poison regression analysis to find out the relationship. Forecasting the trend of dengue infection cases and larval density were analyzed using double exponential smoothing.

Exponential Smoothing Forecasting is a category of time series method that uses exponential weighting of past data. In this category, several methods are commonly used, including the Single Exponential Smoothing, Double Exponential Smoothing, and Triple Exponential Smoothing methods. In this study, double exponential smoothing is used to forecast the potential for DHF cases and larva density. In this study, the prediction of the potential increase in dengue infection cases and the potential for larval density using the Autoregressive Moving Average (ARIMA) method is a forecasting algorithm based on information in the past values of the time series that can be used to predict future values.[22]

Ethical Approval

This study's ethical clearance was obtained from the Faculty of Medicine, Udayana University (No: 1169/UN14.2.2. VII. 14/LT/2020). This study was carried out in accordance with the declaration of Helsinki and the recommendation of those committees with written informed consent from all participants.

RESULT

Table one shows the distribution of cases' sociodemographic characteristics. Almost a third (26.2%) were aged 21-30 years, followed by 31-40 years (17.3%) and 11-15 years (15.2); whilst the majority (60.2%) were males. The distribution by village shows that 44.5% cases resided at Sesetan Village, while the majority shows 1 to 4 larva positive buildings.

Table 1. Demographic characteristics of Dengue cases

Variables	Frequency	Percentage (%)
Age (years)		
1-5	18	9.4
6-10	12	6.3
11-15	29	15.2
16-20	21	11.0
21-30	50	26.2
31-40	33	17.3
41-60	24	12.6
>60	4	2.1
Gender		
Male	115	60.2
Female	76	39.8
Residence		
Sidakarya	64	33.5
Sesetan	85	44.5
Panjer	42	22
Larva positive building		
1-4	172	90
≥5	19	10

Percentage of container types

Table 2 shows the results of data collection on larvae density with the number of home visits in Sesetan Village (3,446 households), Sidakarya Village (2,859 households), and Panjer Village (2,907 households). Data on the percentage of types of water reservoirs outside the house were positive for 121 containers and inside the house for 713 containers. The types of water reservoirs that are positive for larvae are buckets (19%), traditional baths (18%), drains (16%), and flower vases (12%).

Table 2. Number of water reservoirs inside and outside the house

Village	Water Containers				Total Number of water containers	
	Inside		Outside			
	(+) f (%)	(-) f (%)	(+) f (%)	(-) f (%)	(+) f (%)	(-) f (%)
Sesetan	279 (39.1)	3179 (31.4)	68 (56.2)	6426 (38.2)	347 (42.1)	9605 (35.8)
Sidakarya	233 (32.7)	4789 (47.4)	18 (14.9)	4980 (29.6)	248 (30.1)	9647 (36.0)
Panjer	201 (28.2)	2143 (21.2)	35 (28.9)	5427 (32.2)	229 (27.8)	7570 (28.2)
Total	713 (100.0)	10111 (100.0)	121 (100.0)	16833 (100.0)	824 (100.0)	26822 (100.0)

*f=frequency

Mapping of dengue risk areas

Figure 1 shows map of dengue risk areas based on larva density. This map shows the Sesetan Village is a high-risk area with larva density above 1,250 positive larvae containers. Then followed by the Sidakarya area which has a larva density of 850-1,250 larvae positive containers.

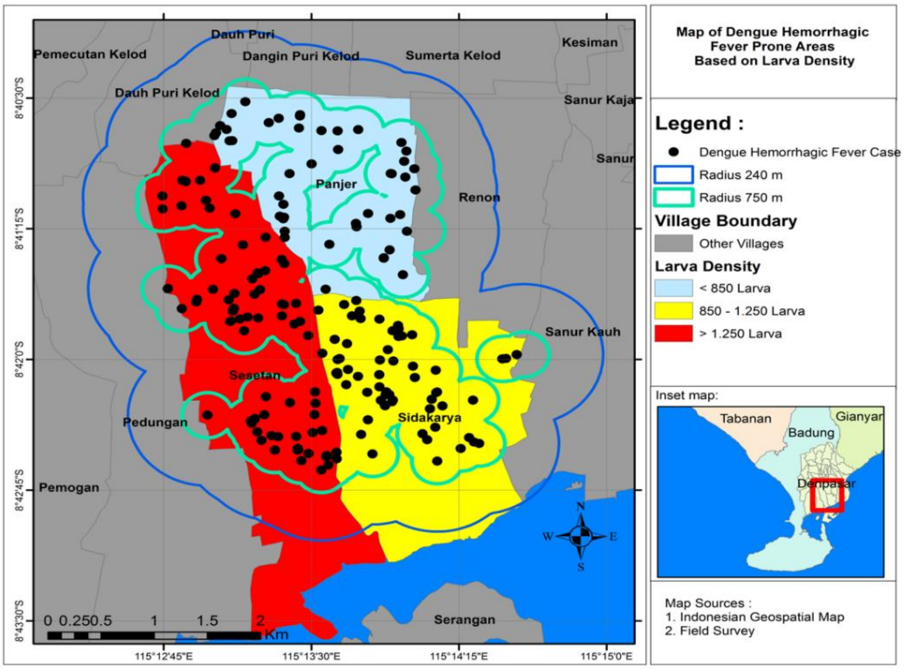


Figure 1. Mapping of dengue risk areas based on larva density

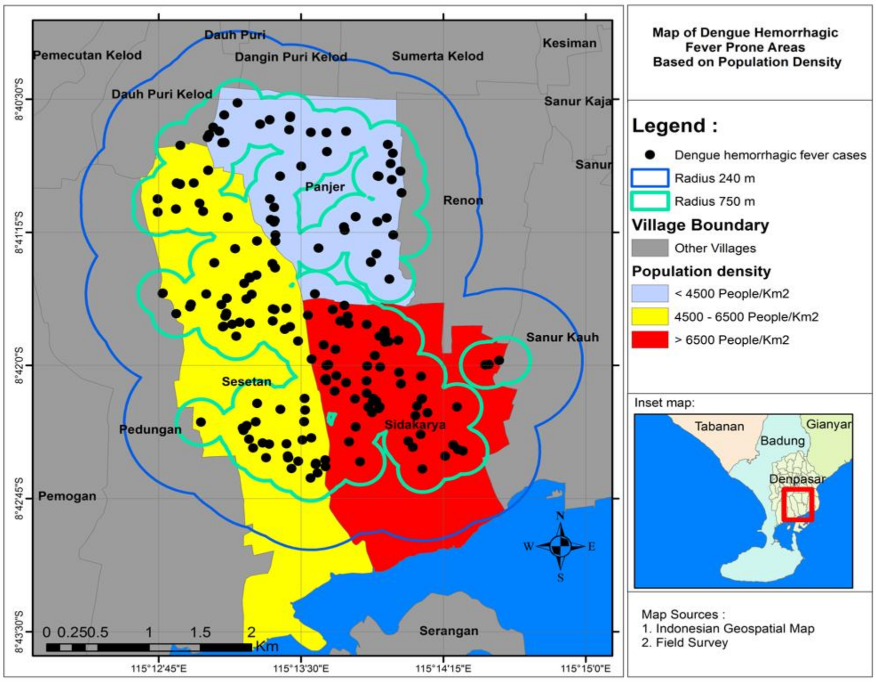


Figure 2. Distribution of DHF cases by population density

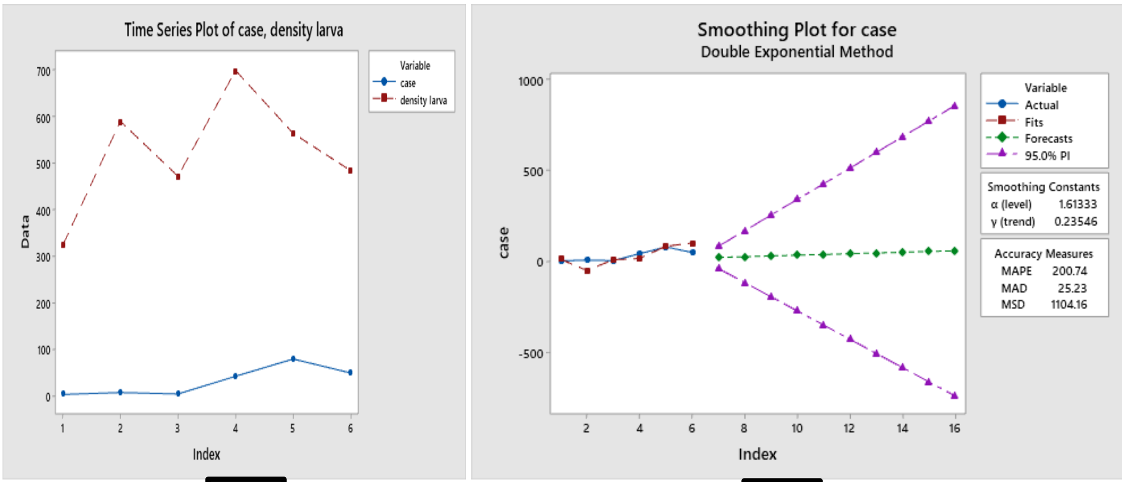
Figure 2 shows the mapping of areas at risk of dengue infection based on DHF cases and population density. This map shows the Sidakarya Village has a high population density above 6,500 people/km^2. Followed by the Sesetan Village which has a density of 4500-6500 people/km^2, while Panjer Village with <4500 people/km^2. High population density is one of the risk factors for the spread of dengue cases. The denser the population in the area, the more susceptible it is to the transmission of mosquito bites.

Based on the statistical analysis of the average nearest neighbor (ANN), the Z-score value is (-8.038822). This means that there is a spatial pattern of dengue cases in this area. The result of the calculation of the nearest neighbor ratio also show a value of 0.695950 (<1), which signifies clustered dengue cases. The average distance between cases is 88.2 meters, and the p-value shows the significance of the cluster formed from the point (case).

The spread of clustered cases is also influenced by the population density in each region. The highest population density is in the Sesetan Village followed by Sidakarya Village.[2] The character of the *Aedes aegypti* mosquito that bites repeatedly on several people can transmit quickly in dense settlements.

Time series of larval density and dengue cases

Based on the time series analysis of larval density and the number of cases, we found the Poisson regression value is significant, with p-value <0.001. This value indicates a relationship between the density of larvae and the incidence of DHF in these areas. The increase in DHF cases was also followed by the discovery of larvae in the field.



A B

(A=Time Series Plot of density larva and dengue cases, B=Double Exponential Smoothing for DHF)

Figure 3. Time series and double exponential DHF

In the forecasting of DHF cases, it is known that DHF cases in the following month will decrease if continuous intervention is carried out on larval density. Efforts to control mosquito larvae density must be carried out continuously and simultaneously.

Forecasting larval density

This study shows that with the double exponential method at = 0.52 and = 1.01 and MAPE (32.8), it is possible to predict a decrease in larval density (Figure 4). The role of the *jumantik* volunteer program to monitor the density of larvae in residents' homes needs to be carried out regularly. Community participation to carry out independent larval inspection greatly affects the number of household larvae density.

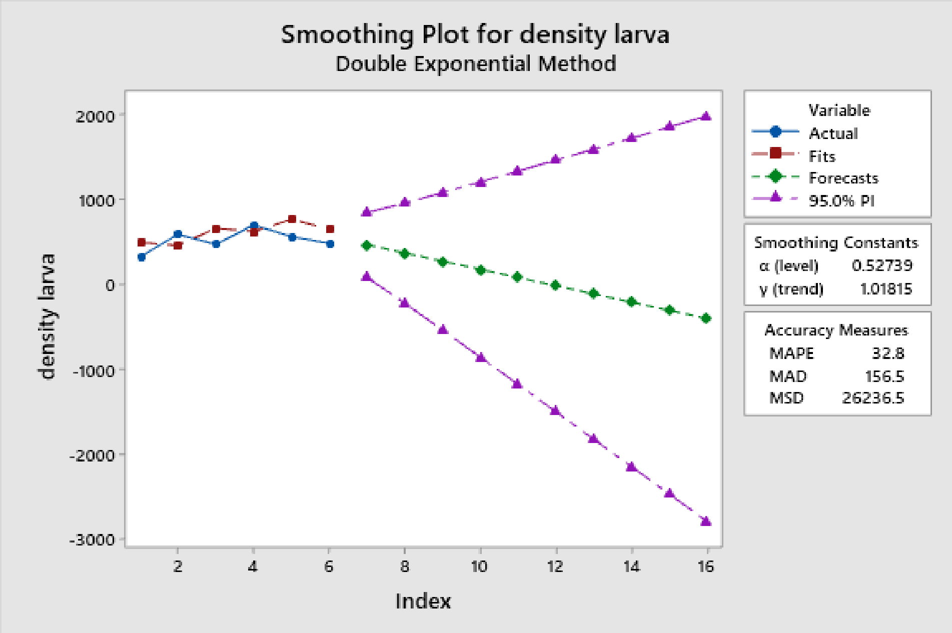


Figure 4. Forecasting larva density

DISCUSSION

Dengue Hemorrhagic Fever in Denpasar spatially forms clusters. Areas that have dengue infection are areas prone to dengue transmission. The presence of people infected with dengue, and the presence of Aedes aegypti mosquito larvae in the area cause the area to be at high risk. Dengue transmission can occur quickly because it is supported by mobility and population density.

Previous studies found that there are four types of dengue virus serotypes circulating in Denpasar City. The most dominant is serotype 3 then serotype 1, 2 and 4.[6,17] Denpasar is a dengue endemic area with the presence of various dengue serotypes and the dense population of Aedes aegypti mosquitoes that affect the area's susceptibility to dengue infection.

Spatial mapping of dengue infection helps to prioritize intervention for dengue-prone areas. Globally, there are 128 countries with confirmed cases of DHF.[18] Studies related to spatial and temporal mapping of dengue were also carried out in Brazil supported by data on the incidence and mortality index.[19] Spatial and temporal studies in Thailand also found clusters of transmission.[20] Several studies in Indonesia on spatial dengue have also been carried out, such as in Lumajang,[21] Kendari,[22] Samarinda,[23] Pekanbaru,[24] and Klaten.[25] During the COVID-19 Pandemic, there was also an increase in dengue cases in Bali Province. There was a co-epidemic of dengue and COVID-19.[26]

The most common types of water containers that contain larvae were traditional bathroom tubs and buckets. For outdoors, water containers that often contain larvae from drains, used tires and bottles. The number of water containers owned by the family has the potential to become a breeding ground for the Aedes aegypti mosquito. Various types of water containers, container colors, and closed places become potential breeding places for mosquitoes.[23,24] Container capacity, location, and time of mosquito laying can affect dengue vector pattern.[25]

This study found high population density followed by the number of containers and the mobility of the population could affect the increase in dengue cases. Densely populated areas tend to have an increase in dengue cases. Dengue cases tend to form clusters within 80 meters. Research in Brazil found that the density of *Aedes aegyp*ti and *Aedes Albopictus* is influenced by population density and meteorological variables.[26] High population density affects dengue infection.[27-30]

This study also found that high larval density has the potential to be a predictor of the spread of dengue infection. In an area with a high larval density, DHF cases are also high. There is a tendency for dengue-endemic areas to have a high larval density. Research in Vietnam also found that water scarcity causes people to collect water so that it becomes a breeding ground for Aedes mosquitoes.[31] Other studies have also found that temperature and population density affect the density of Aedes.[32]

Forecasting results show that there is a relationship between the density of larvae with an increase in cases of dengue infection. Efforts to control the population of Aedes larvae continuously can reduce cases of dengue infection. However, it is also influenced by meteorological factors such as high rainfall. There are lots of water reservoirs during the rainy season and the density of household containers. The use of the ARIMA method in forecasting the potential incidence of dengue outbreaks can be done by calculating time series.[33-35]

CONCLUSION

Spatial analysis of dengue infection in South Denpasar has a clustered pattern, especially in densely populated areas. The distribution of dengue infection based on population density with buffer analysis shows that all areas have the potential for dengue transmission. The modeling uses the Autoregressive Moving Average (ARIMA) and Double Exponential Smoothing methods, which routinely predict larvae control efforts to affect the number of dengue cases. Program to reduce larvae density should be conducted regularly and continuously, while community participation should be also improved.

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AUTHOR CONTRIBUTION

SGP: formulated the research questions and participated in questionnaire construction and data collection. SU: carried out data entry and statistical analysis. PK: participated in questionnaire construction and aided in drafting the manuscript. MS: aided in selecting the design of the study and drafting of the manuscript. All authors read and approved the final manuscript.

COMPETING INTEREST

The authors declare that they have no competing interests

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