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Spatial and Temporal Analysis of Dengue Cases in Peninsular Malaysia; A Five-Year Analysis from 2016 to 2020

Khushairi Muhd Nor¹, Nazri Che Dom^{1,2}, Samsuri Abdullah³, Nopadol Precha⁴

¹ Faculty of Health Sciences, Universiti Teknologi MARA, 42300, UITM Puncak Alam, Selangor, Malaysia

² Institute for Biodiversity and Sustainable Development (IBSD), Universiti Teknologi MARA, 40450 Shah Alam, Selangor, Malaysia

³ Faculty of Ocean Engineering Technology and Informatics, Universiti Malaysia Terengganu, 21030 Kuala Nerus, Terengganu, Malaysia

⁴ Department of Environmental Health and Technology, School of Public Health, Walailak University, Nakhon Si Thammarat, Thailand

Email of All Authors: 20211466572@student.uitm.edu.my, nazricd@uitm.edu.my, samsuri@umt.edu.my, nopadol.pr@wu.ac.th
Tel: 03-32584300

Abstract

Dengue fever is one of the most common vector-borne diseases spread by *Aedes albopictus* and *Aedes aegypti* mosquitos. The regional and temporal trends of dengue cases in East Malaysia are investigated in this study. The study aims to assess the prevalence of dengue cases across 91 districts in Peninsular Malaysia from 2016 to 2020 and, hence, to identify dengue disease's hotspot and cold spot regions. By using ArcGIS, summarised yearly data of dengue cases were analysed. The study results showed that dengue cases mainly occurred in the central part of Peninsular Malaysia.

Keywords: GIS; Vector-borne diseases; Aedes; Spatial epidemiology

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1.0 Introduction

Aedes albopictus and *Aedes aegypti* are responsible for the increment of dengue cases. The number of infected people by the virus increases gradually every year (Majid et al., 2019). In 2019, the cases recorded the highest number of dengue cases which was 5.2 million (WHO, 2022). According to WHO, the world statistic of dengue cases has increased dramatically from 505,430 cases in 2000 to 4.2 million in 2019. In Malaysia, the trend of dengue cases is unpredictable when cases abruptly fluctuated in 2019, which recorded 130,000 dengue cases and indicated the highest number of cases since 2015. It is found that the rate of dengue transmission depends on environmental factors such as the average temperature of not more than 28°C and suitable places to breed, such as clean stagnant water (Anis Hasnan et al., 2017). Malaysia is experiencing a humid and hot climate with an average temperature of 27°C. Under this favourable condition, the spread of the dengue virus occurs rapidly along with the high adaptive tendency of climate change. Understanding the patterns and dynamics of dengue cases is crucial for effective surveillance control. Identification of hotspot regions using autocorrelation of spatial analysis (GIS) may provide invaluable information to better understand dengue distribution patterns. Hence, the authorities can improve intervention programs, emphasising epidemiological surveillance of Aedes mosquitoes and providing more resources. Therefore, this study aims to examine the distribution patterns of dengue cases across Peninsular Malaysia between 2016 to 2020 by using the ArcGIS application. The study used data from dengue cases across 91 districts in Peninsular Malaysia for a comprehensive understanding of dengue distribution patterns.

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2.0 Literature Review

Dengue disease has emerged as a global public health problem in the 21st century when the illness threatens approximately half of the world's population infection (Deng et al., 2020). Since dengue does not have any specific treatment, vector control is the only control measure available (Arboleda et al., 2009). Prediction of transmission risk of the dengue virus can be developed as a model in environmental dimensions which used environment behaviours approaches. By understanding environmental behaviours, dengue cases can be forecasted through effective risk mapping. Tran et al., (2013) found that rainfall and temperature parameters significantly predict mosquito abundance. Then, Alto & Bettinardi (2013) improved the model by incorporating the relevance of immature stages' ambient temperature in generating adult phenotypes.

The study showed the relationship between the environmental temperature of immature stages and selectively modified traits of adult mosquitoes related to virus transmission and lead to the dengue cases. Similar findings were also found in the study in Singapore by Hii (2013), which found that temperature and rainfall have significantly impacted the dengue cases, and the developed forecasting model can predict the prognosis of dengue up to 16 weeks in advance with enough accuracy. In their model, Messina et al., (2019) indicated that the dengue infection will speed up to 2.25 billion worldwide by 2080.

Climate plays a vital role in spreading the dengue virus by interfering with the mosquito life cycle (Faruk et al., 2022). This was supported by Wagner et al., (2020), which found that precipitation assists the larvae development stage and hatches mosquito eggs. The dengue virus transmission constitutes a complex interrelation with environmental factors. Many previous studies show the association of rainfall, temperature, relative humidity, and population density with dengue cases in high-risk areas (Sharmin et al., 2018; Zhu et al., 2016). In Malaysia, investigations revealed that dengue fever incidence was related to rainfall, temperature, relative humidity, and land use (Khushairi et al., 2021; Nazri et al., 2011; Syaza et al., 2017). Due to the climate-sensitive nature of dengue, the preventive program should denote the hotspot locations with a combination of environmental data.

3.0 Methodology

3.1 Study Area

In 2019, Malaysia recorded the highest number of dengue cases since 2015 which was over 130,000 dengue cases. Its increment of 61% from 2018 and this historic had beaten the high record of 120,836 in the whole year of 2015. The trend of dengue cases in Malaysia is still unpredictable. Peninsular Malaysia is selected as study area as it contains 13 states which can be generalized to a population of Malaysia. Malaysia, located in Southeast Asia, consists of two central regions (Peninsular Malaysia & Malaysian Borneo). The South China Sea separates them. Peninsular Malaysia, also known as West Malaysia, accounts for most of Malaysia's population and economy. Peninsular Malaysia's land area is 131, 598 km². States and territories involved in Peninsular Malaysia are divided into four regions: Northern region (Perlis, Kedah, Penang & Perak), Central region (Selangor, federal territories of Putrajaya & Kuala Lumpur), Southern part (Negeri Sembilan, Malacca & Johor) and East coast region (Kelantan, Terengganu & Pahang) as illustrated in Figure 1. This study focuses on 91 district health offices available in Peninsular Malaysia. Peninsular Malaysia overcomes its climate, which is humid, hot and rainy throughout the year. The average temperature in Peninsular Malaysia is 27 °C, and its range is between 23 °C to 34 °C. An annual average of rainfall is approximately 2,540 mm per year, and its range varies from 1,400 to 4,400 mm. Southwest monsoon (SWM) and northeast monsoon (NEM) bring rainfall variation in Peninsular Malaysia. During the monsoon seasons, the precipitations become more abundant.

3.2 Data on Dengue Cases in Peninsular Malaysia

Confirmation of dengue cases will be notified in the e-notifikasi system, and the Ministry of Health Malaysia will perform a compilation of reports. This study used confirmed dengue case data from 2016 to 2020 from MOH. The dataset contained information on several dengue cases according to states, districts, week, and year. The dengue cases' demographic characteristics were conducted using descriptive epidemiological analysis. Registration with National Medical Research Register has been performed (NMRR ID-21-02105-IQX) and obtained ethical approval from the Malaysia Research Ethical Committee (MREC). Data collection of dengue cases was obtained every week according to epidemiological week one until 53 for five years from 2016 to 2020. Redundant and missing datasets are managed as a part of data pre-processing. Measures of dispersion were performed to show the variation in a data set. Assuming the MOH checked the data, no additional quality checks are required.

3.3 Spatial Analysis of Dengue Cases in Peninsular Malaysia

Spatial analysis of dengue cases refers to the statistical research of the dengue phenomena by using spatial statistics techniques to investigate varied geographic data, spatial dispersion, distributions, trends, processes, and relationships. During the research process, this study did spatial analysis for 91 districts in East Malaysia and the normality of the data was observed. Using both Global and Local Moran's I statistics, dengue hotspot locations and spatial autocorrelation were identified. A continuous index value is utilised as an indication of clustered distribution (value near to zero to +1.0), random distribution (value of zero or near to zero) or dispersed by organised distribution (value near to -1.0) when the global Moran's I test is employed to detect the spatial autocorrelation of dengue cases (value close to -1.0). The equation for Global Moran's I is as follows:

$$I = \frac{n}{w} \frac{\sum_{i=1}^n \sum_{j=1}^n W_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2}$$



Figure 1 Map of Peninsular Malaysia with states (split into admirative levels) and federal territories

Where \bar{x} represents the mean of the variable, n represents the total number of observations, x_i represents variable's value at one place, x_j represents the variable's value at another position, and W_{ij} represents the value indexing position of i relative to j . The development of Local Indicators of Spatial Association (LISA) statistics is to find statistically significant spatial clusters of disease (Hotspots and Cold spots) and identify outliers in the Local Moran's test. The equation for local Moran I statistics is as follows:

$$I_i = z_i \sum_j w_{ij} z_j$$

With z_i and z_j are deviations from the mean.

According to (Anselin, 1995), LISA values indicate four types of clusters: high-high, low-low, high-low, and low-high. High-high clusters are associated with many dengue cases (hotspots), whereas low-low clusters are associated with a low number of cases (cold spots). Low-high and high-low are categorised as outliers. The statistics inference of both tests was performed by Monte Carlo simulation with 99,999 permutations to generate the p-value. False Discovery Rate (FDR) correction was applied to reduce alpha risk (Type 1 error) and resulted in a p-value = 0.008 being identified as the significant cut-off. Global and Local Moran's I tests were performed by using GeoDa 1.20. Data visualisation was performed with ArcGIS 10.8 (UiTM License) to demonstrate the spatial analysis of dengue cases in Peninsular Malaysia from 2016 to 2020. Hotspot districts of dengue cases were identified using summarised yearly cases throughout the study period. ArcGIS method has been widely used to understand the patterns and dynamics of dengue cases and the procedures are in line with previous studies (Dom et al., 2016; Galli & Neto, 2008; Kan et al., 2008; Morrison et al., 1998).

4.0 Findings

4.1 State-Level Trend of Dengue Cases in Peninsular Malaysia from 2016 to 2020

In Peninsular Malaysia, 457,968 dengue incidents were registered between 2016 and 2020. Among these instances, 259,450 (56.5%) were from Selangor, while 47,407 (10.35%) and 46,953 (10.25%) were from Kuala Lumpur and Johor, respectively (Table 1). The reported cases show a trend of a transient drop from 94,849 in 2016 to 76,268 in 2018. However, dengue cases fluctuated in 2019 and recorded the highest during the study period, 121,397. In 2020, the number of cases dropped to 37,271 (18.03%). No state was reported with no case. The trend of dengue cases is unpredictable, and a comprehensive analysis of secondary data might provide valuable information to the epidemiological study.

4.2 Spatial Analysis of Dengue Cases by District-Level in Peninsular Malaysia from 2016 to 2020

Data on dengue cases were summarised yearly by states from 2016 to 2020. ArcGIS software was performed throughout the study period to explore the dengue case distribution pattern in Peninsular Malaysia. Figure 2 shows the spatial-temporal annual dengue case distribution at study location during the study period. Overall, based on Figure 2, dengue case transmission was observed to be more concentrated in Peninsular Malaysia's central region, with the number of dengue cases being more than 900 every year for five years of study duration. Districts in Selangor and Kuala Lumpur consistently recorded higher cases and infection rates every year during the study period.

Table 1 Number of dengue cases in Peninsular Malaysia and by states from 2016 to 2020

States	Annual Number of Dengue Cases					Total	%
	2016	2017	2018	2019	2020		
Total	94,849	80,247	76,269	121,937	84,666	457,968	100
Perlis	183	175	369	288	80	1,095	0.24
Kedah	994	1,430	2,190	1,587	780	6,981	1.52
Pulau Pinang	2,576	2,681	6,071	4,119	1,043	16,490	3.60
Perak	3,777	5,411	2,736	3,226	2,665	17,815	3.89
Wilayah Putrajaya	520	553	453	1,068	652	3,246	0.71
Kuala Lumpur	8,140	7,797	7,136	14,355	9,979	47,407	10.35
Selangor	51,652	45,290	45,355	72,543	44,610	259,450	56.65
Negeri Sembilan	2,852	3,055	1,863	2,304	2,891	12,965	2.83
Melaka	2,326	1,425	722	2,156	2,843	9,472	2.07
Johor	10,641	7,932	5,885	10,873	11,622	46,953	10.25
Kelantan	6,124	2,515	1,950	6,003	3,889	20,481	4.47
Terengganu	2,008	292	550	542	404	3,796	0.83
Pahang	3,056	1,691	989	2,873	3,208	11,817	2.58

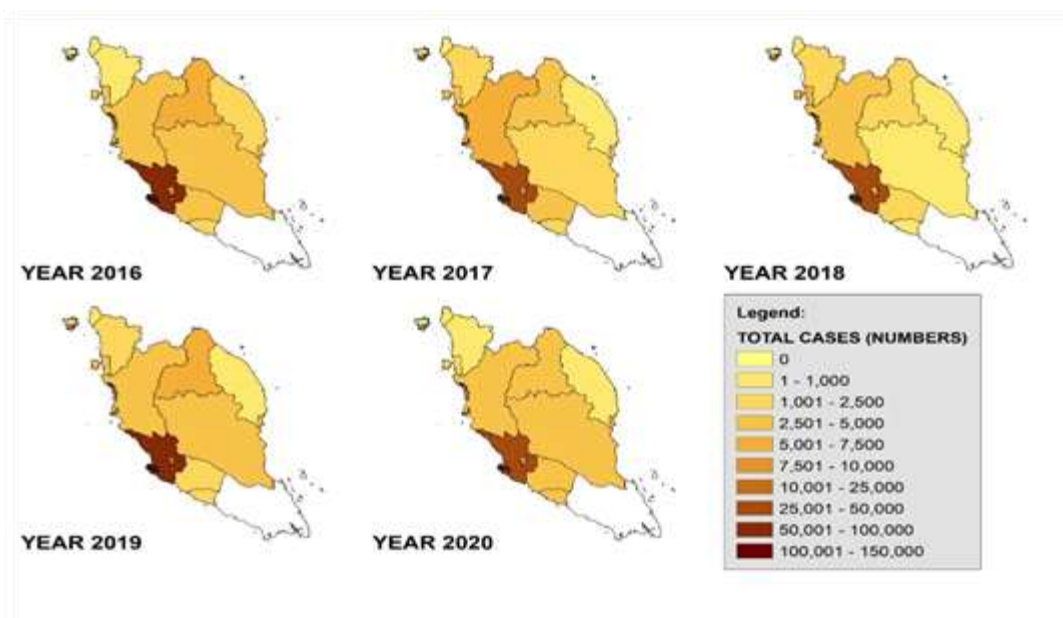
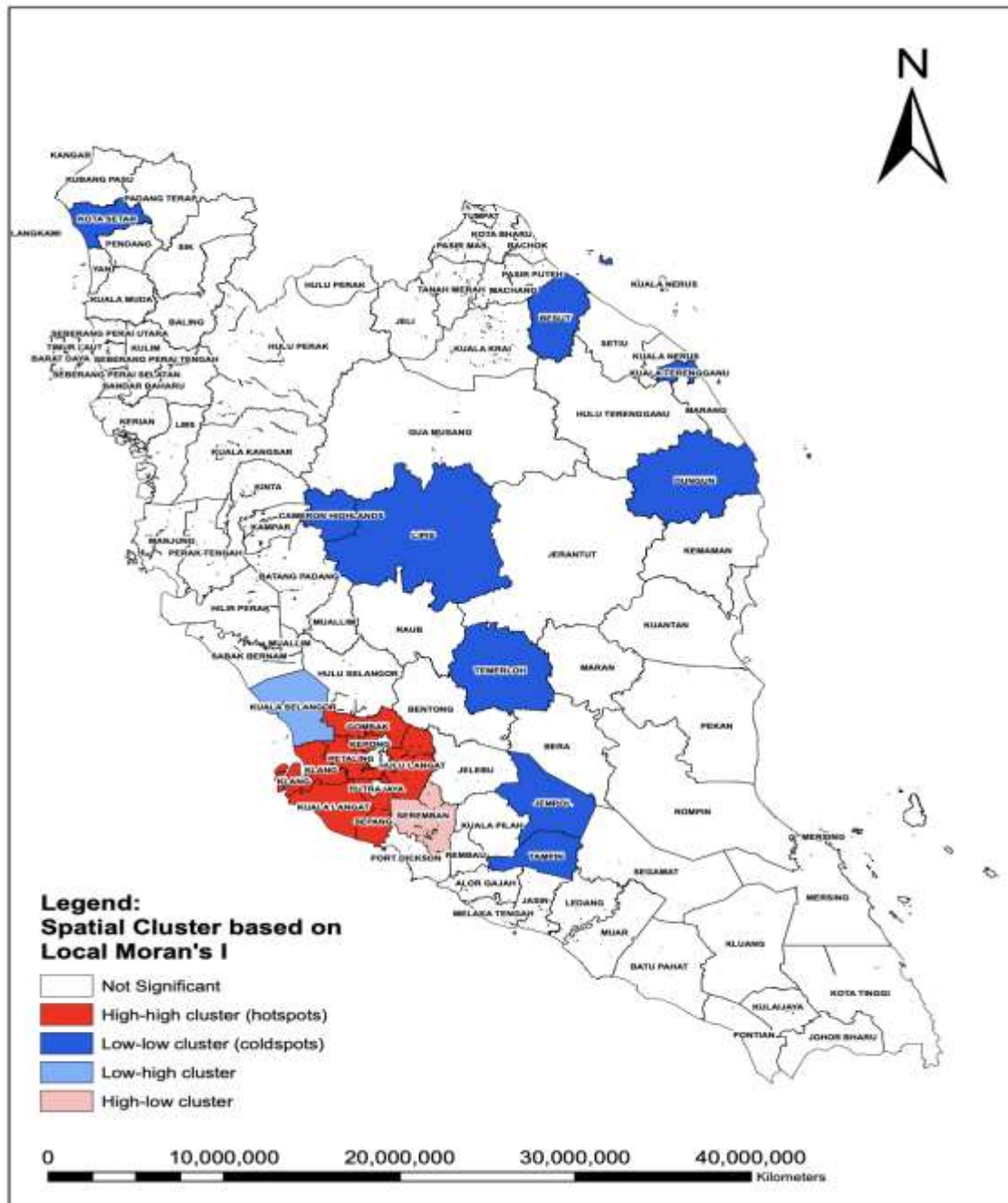


Figure 2 Spatial-temporal distribution of dengue cases by using summarized yearly data in Peninsular Malaysia during study period (2016-2020)

In investigating the hotspot and cold spot, this study compiled the dengue data every year and is district-based. The monthly dataset is used in evaluating spatial autocorrelation. Results revealed that there exists significant positive spatial autocorrelation via Global Moran's I (Global Moran's I = 0.486, $p < 0.000$, $Z = 10.616$). It indicates that the spatial dependence and clustering of dengue cases in Peninsular Malaysia occurred. Local Moran's I test identified major hotspots (high-high spatial clusters) involving eight districts (Table 3 and Figure 3). Cold spots (low-low spatial clusters) comprising nine districts were identified near major cities. All hot spots were in regions with high population density (average of 6,890 per square km), whereas cold spots comprised locations with low population density (average of 1,305 people per square km). Low-high and high-low spatial clusters were identified in 2 districts (Kuala Selangor and Seremban).

A



B

Cluster Type	District	Number of Cases	Number of populations	IR	LISA Index	p-value
High-high	Gombak	34,037	668,694	50.90	5.70	0.001
	Kepong	11,581	71,000	163.10	1.24	0.008
	Petaling	92,303	1,765,495	52.28	9.53	0.001
	Hulu Langat	58,114	1,138,198	51.06	12.06	0.001
	Putrajaya	3,246	68,361	47.48	0.00	0.000
	Kuala Langat	6,186	220,214	28.09	0.27	0.001
	Selangor	10,362	207,354	49.97	1.39	0.002
	Klang	47,376	842,146	56.26	6.91	0.009
Low-low	Kota setar	1,164	357,176	3.26	0.10	0.005
	Besut	347	136,563	2.54	0.13	0.005
	Cameron Highlands	19	36,978	0.51	0.14	0.043
	Lipis	190	86,484	2.20	0.13	0.020
	Temerloh	1,379	158,724	8.69	0.09	0.016
	Kuala Terengganu	2,141	337,553	6.34	0.08	0.001
	Dungun	311	149,851	2.07	0.13	0.005
	Jempol	386	112,740	3.42	0.12	0.028
	Tampin	578	82,165	7.03	0.12	0.018
Low-high	Kuala Selangor	4,118	205,257	20.06	-0.17	0.001
High-low	Seremban	10,644	536,147	19.85	-0.14	0.011

Figure 3 (A) District-level hotspot and cold spot spatial clusters of dengue cases (2016-2020); (B) Statistically significant district-level of spatial clusters of dengue cases

5.0 Discussion

This study demonstrated the basic epidemiology of dengue case infections across all districts in Peninsular Malaysia, with a higher prevalence of dengue cases in central regional, specifically Selangor, Kuala Lumpur and Putrajaya. These locations were identified as having an increased number of incidences of dengue cases due to many reasons such as climatic factors, air pollutants related to environmental factors, high density of population, travelling and high rise of buildings. The result of an increased number of dengue cases in this central region is similar to many studies (Jamil et al., 2021; Salim et al., 2021; Tay et al., 2022).

In this study, Selangor, Kuala Lumpur and Putrajaya had consistently recorded many dengue cases. These states have a high-density population and a rapid urbanisation process. Association with the rainy season shows a higher dengue virus transmission, closely related to two monsoon wind seasons known as southeast monsoon (May to September) and northeast monsoon (October to March). Based on the result of the study, dengue cases spiked in May, July and November; meanwhile, dengue infection peaked in January. Climate changes, such as heavy rainfall, have induced the abundance and distribution vectors and intermediate hosts (Lai, 2018). The basic fundamental of dengue transmission begins with aquatic larval and pupal, which requires water for breeding to become mosquitoes (Kakarla et al., 2019). Determination of presence and absence of breeding sites based on precipitation in that area. When there is a downpour of rainfall or floods, this will enable the outbreak of dengue cases by increasing the breeding process of vector mosquitoes.

The central region denoted a high infection rate of dengue cases based on the spatial analysis. Compared to other districts, Selangor, Kuala Lumpur and Putrajaya recorded the highest infection rate. They are neighbouring districts, and most infected patients live in high-density places and are associated with the exact climate change and urbanised areas. Urbanisation and industrialisation have a positive correlation; in other words, the higher the urbanisation, the higher the industrialisation (Nsemo & David Nsemo, 2019). The impact of automation on the environment, especially air pollution and water pollution, is occurring primarily in urban areas. Air pollutants can trigger climate change and increase the temperature, which eventually can increase the transmission rate of dengue cases. When temperature increases, it shortens the periods of development of mosquitoes' life cycle, which can increase population growth. Eventually, contact with humans increases and a surge of infected people is reported.

Climate change has a complex relationship with air pollutants. Both of them are closely related. Air pollutants harm human health and the environment. Carbon monoxide (CO) can increase the temperature by trapping light, and an increase in temperature can result in the melting of ice, glaciers and icebergs. Climate change can affect the incidence and prevalence of dengue cases by interfering with the duration, timing, and intensity of the outbreaks. Dengue infection by vector mosquitoes is extremely climate-sensitive when firstly, warming can shorten the viral incubation period and secondly, it can shift the geographic map of the vector (Rocklöv & Tozan, 2019). Nowadays, the spread of epidemics is associated with natural climate disasters and floods. Further analysis will be conducted to establish the relationship between climatic factors and air pollutants towards dengue infection.

This study evaluates dengue fever case distribution in Peninsular Malaysia by spatial and temporal ArcGIS software. Moreover, it lays the groundwork for future research into social and environmental factors that influence shifting illness patterns, and the findings of the study might help provide baseline data in the identification of spatial and temporal dengue cases, which health authorities can use for diseases surveillance and public health interventions in the future. This study is subject to a few limitations. For instance, reported dengue cases were aggregated by districts, preventing analysis at a higher spatial resolution and perhaps resulting in the absence of critical clusters. Nevertheless, this is the maximum level at which data are currently accessible. Secondly, underreporting of dengue cases is likely to occur when the public does not seek medical attention when they have dengue infection symptoms. Finally, this study merely focuses on dengue cases rather than other diseases transmitted by the same type of mosquitos, such as Zika and Chikunga.

6.0 Conclusion & Recommendations

As a conclusion, this study emphasised the temporal and spatial pattern of dengue cases for 5 years timespan. Spatial pattern constructed using ArcGIS could be beneficial for dengue surveillance programs in focussing dengue hotspots location in Peninsular Malaysia for intervention through programming. This study has embarked a few limitations such as this study only covers Peninsular Malaysia as higher number of dengue cases at Peninsular Malaysia compared to Sabah and Sarawak. Limitation of the study period remains for 5 years between 2016 to 2020. This study is limited to dengue cases only and other mosquito borne diseases such as Zika, Chikungunya, Malaria, Lymphatic filariasis and Japanese Encephalitis (JE) were excluded. The future recommendation of the study is to establish the relationship of environmental factors, air pollutants towards dengue cases in the region of hot and cold spots for further analysis. Environmental factors such as temperature, relative humidity, amount of rainfall and wind speed might influence the trend of dengue cases by increasing the rate of dengue viral transmission. Air pollutants such as Carbon monoxide, Nitrogen dioxide, Sulphur dioxide, Ozone and Coarse particulate matter (PM₁₀) could be co-factors towards environmental factors which might interfere the rate of dengue cases to increase.

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Paper Contribution to Related Field of Study

This study provides baseline data to advance the knowledge of dengue pattern distribution and its interaction with environment behaviors in the prediction model of dengue outbreak.

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