ORIGINAL ARTICLE

Spatial and Temporal Distributions Pattern of Dengue Fever Cases: A Ten Years Trends in Kuantan, Pahang

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ABSTRACT

Introduction: Dengue fever (DF) is a prominent vector-borne disease spread by mosquitos of the Aedes genus (mainly *Aedes aegypti*, and even *Aedes albopictus*), a tropical regions vector. The purpose of this research was to establish the spatial and temporal distribution patterns of DF cases in the study area between 2010 and 2020. **Methods:** The correlation between the Kuantan sub-district and dengue haemorrhagic fever (DHF) incidence is examined in this study using spatial analysis. The correlation was calculated using spatial autocorrelation, Moran's Index (Moran's I) and Spatial Autocorrelation of Local Indicators (LISA). Moran's index is a worldwide indicator used to determine whether or not disease transmission has geographical autocorrelation in disease transmission. **Results:** The results indicated that between 2011 and 2020, the monthly Moran's I of dengue transmission in Kuantan was estimated to range between -0.685 and 0.338. The lowest reading of Moran's index was -0.685 in May 2015, whereas the highest reading was 0.338 in May 2019. This reflects the strong spatial autocorrelation of dengue transmission in Kuantan over the last decade. The LISA analysis revealed significant spatial autocorrelations on DF cases in Kuantan for three (3) out of six (6) sub-districts (50%) with a significance level of 2%. This suggests that there are spatial autocorrelations in Kuala Kuantan, Beserah and Penor sub-district that influence the distribution of DHF transmission. **Conclusion:** The results reveal that the spatial autocorrelation analysis method can be a tool for relevant researchers to understand the pattern of DF transmission study and establish the direction for further study.

Keywords: Dengue, Spatial analysis, Moran's I, LISA, GIS, Temporal

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INTRODUCTION

Dengue fever (DF) is a prominent vector-borne disease spreads by mosquitos of the Aedes genus (mainly *Aedes aegypti*, and even *Aedes albopictus*), a tropical regions vector. The infection is currently prevalent in over 100 countries, especially in Southeast Asia, the Western Pacific, and the Americas (1,2). DENV-1-4 are the four antigenically distinct dengue virus serotypes that cause DF. All four of them have the potential to cause significant illnesses. Yellow fever virus, West Nile virus, Japanese encephalitis virus, and St Louis encephalitis viruses are all RNA viruses in the Flavivirus genus/Flaviviridae family (3). However, throughout the previous 50 years, neither vaccinations nor special therapies have effectively widened its geographical spread or shortened its epidemic cycle in many regions. (4,5). Dengue fever (DF) is currently estimated to be endemic in 124 countries globally, with 50 million clinical DF cases recorded each year, 2.1 million dengue haemorrhagic fever (DHF) cases, and roughly 21,000 deaths each year.

DF is the most common in South-East Asia and the Western Pacific. The tropical regions of Asia are highly sensitive and exposed to the disease (6). Dengue fever (DF) is currently a highly endemic diseases in Malaysia, which has a population density of 86 people per square kilometre and a population of 28.33 million people (7). The infection has been classified as a national public health risk in Malaysia (8). Dengue fever (DF) is widespread in the country, with the highest prevalence seen in the most developed and heavily populated areas. Dengue cases in Malaysia have increased year on year, from 19,884 cases reported in 2011 to 90,304 cases in 2020, an increase of nearly five times. All age groups are impacted, with school-aged children and young people are bearing the greatest risk. Infection threatens people of all races. (9). This rise of DF transmissions occurred despite the Ministry of Health's active outdoor insecticide fogging and search and destroy campaigns to control the Aedes mosquito in semi-urban and rural areas.

Disease mapping may be used to identify outbreak hotspots and effectively target high-risk regions for early prevention and control (10). A Geographic Information System (GIS) is a novel method of transmitting and integrating data connected to location and time. By employing GIS software, it offers a more substantial result, providing in-depth analysis across field data. GIS and statistical analysis of a disease's spatial characteristics have enabled identification of clustering of cases and the linkage of clustering dynamics with geographical places that include certain risk factors favourable for infection origins and transmission.

The distribution of DF is geologically distributed in rural and suburban areas. The geographic term indicates that the areas of data information can be evaluated in the points-of-interest (POI) geographic arrangement known as longitude and latitude. The spatial and temporal analysis is one of the most effective methods for developing an exact model or imagining a health-related event from different perspectives. Health events and spatial-temporal relationships interact with one another, becoming an important component of public health research and disease transmission analysis (11).

Furthermore, explanatory spatial approaches can determine the region or zone for cases and, more importantly, contribute to a useful and substantial execution to determine the health effects. As a result, the current study intends to use spatial analytical tools to investigate the geographical pattern of DF incidence in Kuantan and identify high-risk sub-districts. This study's findings are believed to be related to the occurrence of DF transmission from one sub-district to the next. The research can also help local health authorities predict dengue epidemics and plan and conduct timely targeted intervention programs.

MATERIALS AND METHODS

Study Area

Kuantan (3.816667N, 103.333333E) is a growing city on Peninsular Malaysia's east coast, situated 250 kilometres from the federal capital of Kuala Lumpur. Kuantan is divided into seven sub-districts, having a population of about 608,000 people, making it Malaysia's ninth-largest city. In the last ten years, significant industry and urbanisation have led to tremendous economic growth in Kuantan as well as a massive increase in population and road traffic. Currently, Kuantan has diverse land uses, including traffic, industry, enterprise, residence, garden, and tourism, suggesting various activity patterns, enhancing people's mobility and mosquito breeding sites. The reason for selecting Kuantan as the research location is because there has been limited research undertaken in the area recently. Because Kuantan has the highest amount of dengue fever incidents in Pahang, it is believed that this study would establish the spatial and temporal pattern of DF transmission in the area.

Data Collection and Management Retrieval

Our research will look at all confirmed dengue infections [including DF, DHF, and DSS] reported between January 2011 and December 2020. All dengue cases detected in hospitals and health clinics must be notified to the Kuantan District Health Office within 24 hours of diagnosis, using a standardized reporting form. An Assistance Environmental Health Officer (AEHO) then investigates the reported cases, verifying them by an epidemiologist before entering into the e-dengue system. All dengue infections were diagnosed using the Malaysian Ministry of Health's nationally standardised diagnostic criteria. For example, a patient with DF would typically have a fever as well as two or more of the following symptoms: headache, retro-orbital discomfort, myalgia, arthralgia, rash, and haemorrhagic signs. To confirm dengue infection, a positive anti-dengue virus IgM or Non-Structural Protein-1 (NS1 Antigen) antibody titre in acute or convalescent serum samples and/or a 4-fold increase in specific IgG antibody titres between acute and convalescent samples or virus by isolation or detection of dengue antigen or RNA in serum were used (12). The Department of Statistics Malaysia provided population statistics for Kuantan and each sub-district.

Data Analysis

Spatial data analysis is statistical research of specific phenomena represented in space (13). Special methodologies and methods have been created to classify objects with topological, geometric, and geographic features. These procedures are commonly known as spatial analysis or spatial statistics techniques, and they are largely used to investigate varied geographic data and its spatial dispersion. A set of approaches for characterising and modelling spatial data is known as spatial statistics. They broaden what the mind and senses do spontaneously to examine spatial patterns, distributions, trends, processes, and relationships in a variety of ways.

Spatial autocorrelation analysis by Global Moran's statistic

The application of spatial statistical methods in GIS to leverage spatial autocorrelation has its own set of restrictions and structure. To accomplish validation of the outcome when employing global methods of spatial autocorrelation, the null hypothesis notion must be investigated. Moran's index is a method for estimating spatial autocorrelation, or similarity between various features, based on the position of a feature and the values for that feature at the same time and in many directions. It analyses surrounding areal units across the entire research region and informs if the neighbouring units have similar values, indicating positive spatial autocorrelation (clustering).

Negative spatial autocorrelation (dispersal) is shown when the values of contiguous units differ. Geospatial dispersion is less common than clustering, although it can be seen in competitive or territorial spatial activity when similar characteristics want to be as far apart as possible. The Global Moran's I statistic was used to analyze the geographical autocorrelation of dengue numbers, which quantifies the correlation between spatial observations and enables for the identification of a global pattern (clustered, dispersed, random) among locations. According to Getis and Ord (14), the formula can be defined as;

$$I = \frac{n}{S_o} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} Z_i Z_j}{\sum_{i=1}^{n} Z_i^2} \qquad (1)$$

Where n is the total number of spatial units indexed by i and j; i and j are the spatial units. Z_i is denoted as the attribute for feature i derived from its mean (x_i - $\overline{X}$). x_i is the variable of interest and $\overline{X}$ is the mean of x_i. $w_{i,j}$ denotes the spatial weight between feature i and j and S_o is the sum of all the spatial weight. The method above produces a dispersion index ranging from -1 to +1, corresponding to the maximal negative and positive autocorrelation, respectively. A value of 0 indicates that no spatial autocorrelation exists. Fig.1 depicts the Moran scatter diagram, split into four quadrants.

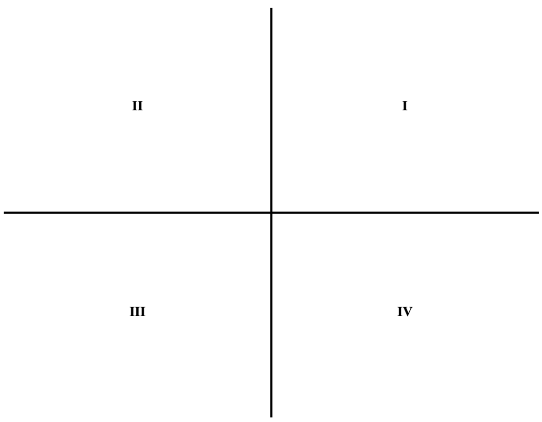

Fig 1: Quadrants of Moran's index scatter diagram

Quadrant I (upper right), also known as high-high (HH), describes a zone with a high observation value for the variables under consideration. Quadrant II (upper left), often known as low-high (LH), shows a low-observation-value zone surrounded by high-observation-value regions. Low-low (LL) quadrant III (bottom left) displays a low-observation-value area surrounded by low-observation-value sectors. Quadrant IV (lower right), often known as high-low (HL), represents a high observation value region surrounded by low observation value regions. Moran's index scatter diagrams with the majority of the area/object in quadrants HH and LL have positive spatial autocorrelation, whereas those with the majority of the area/object in quadrants HL and LH have negative spatial autocorrelation.

Local Moran's Index of Spatial Correlation (LISA)

The Anselin Local Moran's Index (LMI) detects clustering on a local scale, with more exact calculation capabilities and results globally than Moran's index, which evaluates spatial autocorrelation of the area under consideration on a global scale. LMI identifies spatial clusters with high (HH) or low (LL) values, as well as spatial outliers (HL) (LH). To construct this LMI, the local Moran's Index value, z-score, p-value, and a code representing one of the four code classes must be calculated (HH, LL, HL, and LH). According to Anselin (15), the Local Moran's Index is as follows:

$$\boldsymbol{I_i} = \frac{x_i - \bar{X}}{S_i^2} \sum_{j=1, i \neq i}^{n} w_{i,j}(x_i - \bar{X}) \qquad (2)$$

Where unknown are x_i which is the attribute for feature i. $\overline{X}$ denotes the mean of the corresponding attribute and $w_{i,j}$ represents the spatial weight between feature i and j. The presence of a positive LMI value shows that a feature has nearby featured with equally high or low values of the phenomena being studied and that these features are also components of a specific sort of cluster, implying that they are clustering. If the LMI values are negative, it means that a feature has nearby featured with differing values, indicating that the feature is an outlier. It also means that the feature does not correlate with other neighbouring features, implying that they are not clustering. The p-value must be significant enough ($p < 0.05$) in both circumstances for the cluster or outlier to be judged statistically significant. Not significant features are those that have no statistical significance. If the p-value, which reflects the likelihood, is more than ($p > 0.05$), they occur because LMI is a relative measure, and z-score and p-value must be computed to comprehend it. If all three values are appropriately assessed, LMI can be understood as one of the inferential statistics processes within the null hypothesis. There are four (4) possible solutions for the result fields, each labelled in Table I with a different cluster or outlier type (CO type).

The spatial unit of analysis in this study was all sub-districts (n = 6). All dengue cases were connected with sub-district IDs and polygons in ArcGIS v.10.6. Dengue cases were computed and mapped at the sub-district level using sub-district population data as the denominator. the based on queens, a spatial contiguity weight matrix was developed (where the sub-district polygon shares a common edge or vertex). The spatial autocorrelation of DF across Kuantan was then determined using Moran's I analysis between 2011 and 2020 Moran's I values vary

Table I: The outcome of different cluster or outlier interpretation

CO type	Interpretation
High-High (HH)	Statistically significant, p-values are lower than 0.05 representing cluster of high values
Low-Low (LL)	Statistically significant, p-values are lower than 0.05 representing cluster of low values
High-Low (HL)	Statistically significant, p-values are higher than 0.05 representing outlier in which high value is surrounded by low values
Low-High (LH)	Statistically significant, p-values are higher than 0.05 representing outlier in which low value is surrounded by high values.

from -1 to 1, with positive values indicating positive spatial autocorrelation, negative values indicating negative spatial autocorrelation, and values close to zero indicating that the data is randomly distributed. All maps were created using ArcGIS v.10.6. Furthermore, a local indicator spatial association (LISA) analysis was utilized to categorize sub-districts as HH or LL (15). HH's geographic attributes point to high-rate sub-districts that are also adjacent to other high-rate sub-districts. Low-low (LL) sub-districts, on the other hand, have low rates and are in close to other low-rate sub-districts.

RESULTS

Global Moran's Index of dengue in Kuantan

Results from ArcGIS, such as the Global Moran's Index, will be interpreted within the context of the null hypothesis, indicating the presence of the dispersing pattern as a global occurrence in the Kuantan district. The values represented by the statistical data are the same. The visual outcomes are presented in a variety of formats. All Moran's Index results show the Kuantan sub-district (Beserah, Kuala Kuantan, Penor, Sungai Karang, Ulu Kuantan, and Ulu Lepar) a dispersing pattern, which is visible in the spatial autocorrelation reports shown in Fig. 2.

The Moran's index for DF transmissions in the Kuantan area was tabulated monthly from 2011 to 2020,

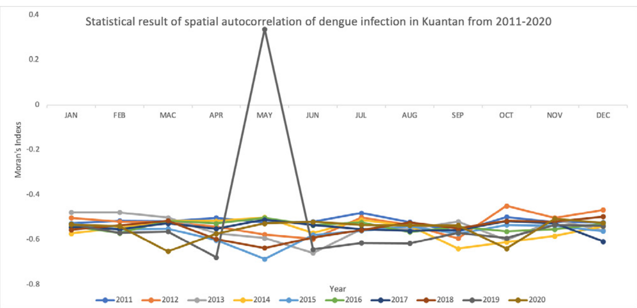

Fig 2: Statistical result of spatial autocorrelation of dengue infection in Kuantan from 2011-2020. Note that the Moran's I will range from -1 to 1. Positive spatial autocorrelation will reveal clustered values

according to Fig. 2. The monthly Moran I of dengue transmission in Kuantan was estimated to range between -0.685 and 0.338. The lowest reading of Moran's index was -0.685 in May 2015, while the highest reading was 0.338 in May 2019. This reflects the strong spatial autocorrelation of dengue transmission in Kuantan over the last decade. The values of Moran's Index also reflect negative spatial autocorrelation, and their distribution provides the best fit for a dispersal pattern. The null hypothesis can be used to reject the concept of complete spatial randomness. Although the dispersal pattern in the Kuantan district region can be accepted, the LISA approach must be used to explore the locations and development of distinct spatial clusters.

Local method of spatial autocorrelation

We are certain that the Local Moran's index results and p-values will be statistically significant, thus the clusters or outliers established by LMI in ArcGIS will be studied based on the Global Moran's index results, which revealed the presence of a dispersion pattern in the Kuantan district. Fig. 3 depicts the LISA value produced from the LISA cluster map in ArcGIS software, which is divided into two groups: LH (L-H) and HL (H-L). At the start of the study period in 2011, the L-H (marked with a dark blue colour) category was found in the Beserah and Penor sub-districts, which are close to Kuala Kuantan and have a higher number of DHF cases than surrounding areas with a lower number of DHF cases. The H-L (marked with bright red) category began to be revealed in the Kuala Kuantan sub-district after 2011, which occurs practically every year except in 2018 and 2019, signifying the area with a high number of DHF patients and surrounded by areas with a low number of DHF cases.

Fig. 3 also reveals significant spatial autocorrelations on DF cases in Kuantan for three (3) out of six (6) sub-districts (50%) with a significance level of 2%. This suggests that there are spatial autocorrelations in the three locations that influence the distribution of DHF transmission. Fig. 4 reveals that the Moran Scatter plot showed a negative spatial autocorrelation with spatial dispersal patterns. As a result, a significant number of DHF cases are scattered among a big number of DHF patients and vice versa. As a result of these studies, it has been shown that DHF cases in Kuantan are influenced not only by time but also by place and that DHF cases can be mapped in spatiotemporal patterns.

DISCUSSION

The study's findings revealed significant variation in the spatial distribution of DF incidence in Kuantan, as well as the fact that the geographic range of confirmed cases has expanded over time in the Kuala Kuantan, Beserah, and Penor sub-districts. Even though the study was unable to identify a HH or LL cluster, we were able to identify HL and LH outliers, which were predominantly

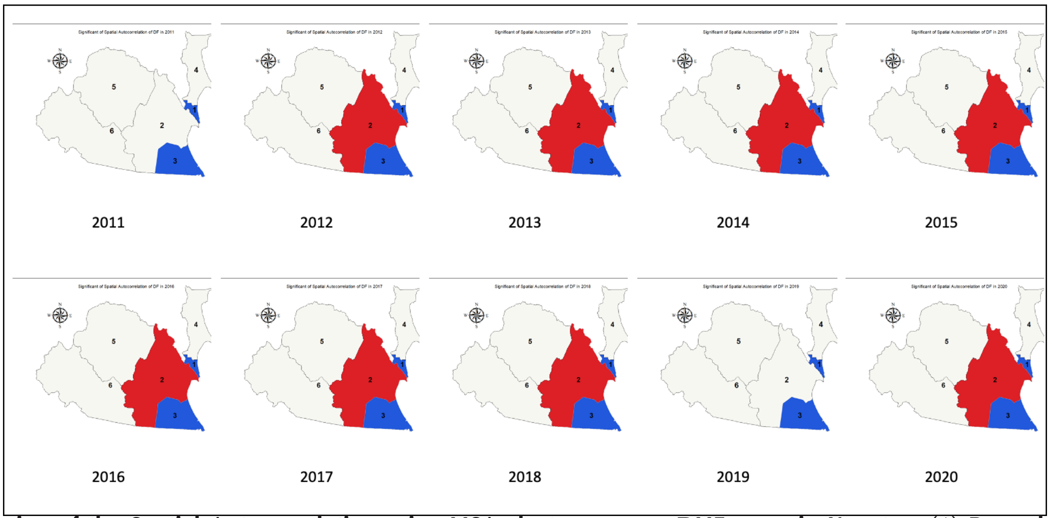

Fig 3: The mapping of the Spatial Autocorrelation using LISA cluster map on DHF cases in Kuantan. (1) Beserah, (2) Kuala Kuantan, (3) Penor, (4) Sungai Karang, (5) Ulu Lepar and (6) Ulu Kuantan. Note: Blue colour indicate Low-High outlier and red indicate High-Low outlier

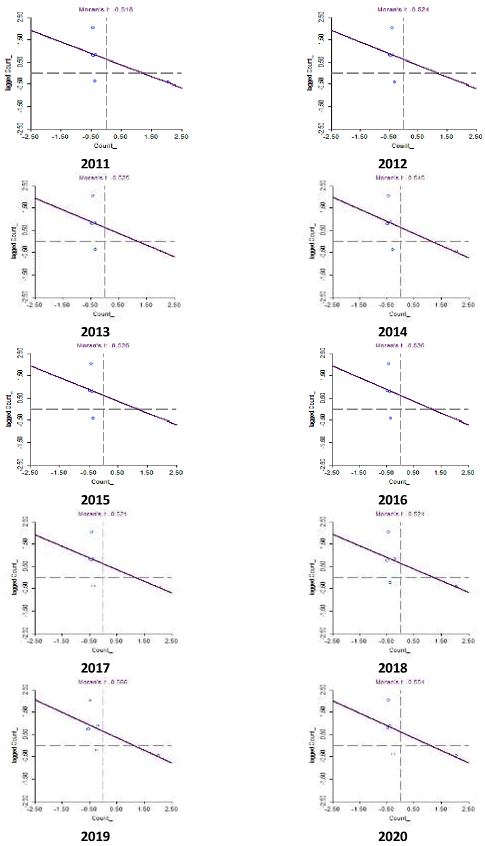

Fig 4: Moran Scatter plot in LISA analysis from 2011 to 2020

concentrated in the Kuala Kuantan sub-district. Dengue fever (DF) transmission appears to have occurred in the Kuala Kuantan sub-district between 2011 and 2020. In May 2019, the results demonstrate a substantial spatial autocorrelation of dengue transmission in Kuantan during the last decade. This could be related to the fact that diseases clustering is essentially unavoidable because human populations tend to dwell in spatial clusters rather than in random distributions in space. Kuantan is located in a tropical country with hot weather, high humidity, and a lot of rain. The average annual temperature is around 27 degrees Celsius, while the average annual rainfall is around 2500 mm. All year, warm, humid weather promotes the development of Aedes mosquitos, viral replication, and dengue transmission (16,17). Dengue fever (DF) outbreaks have increased in frequency and intensity in the Kuala Kuantan district in recent years. Dengue fever (DF) is now prevalent in Malaysia, with local transmission primarily initiated by local movements and infected visitors who spread the disease indirectly (18).

Social and economic factors may also influence dengue fever (DF) transmission (19). Tourism and travel have also played a significant influence in the spread of dengue fever and its vectors (20,21). Dengue transmission is further facilitated by unplanned urbanisation and dwindling/inadequate vector control resources (22). LISA analysis and spatial autocorrelation are effective approaches for investigating how spatial patterns evolve. According to this analysis, from 2011 to 2020, DF has a high-to-low spatial autocorrelation in Kuantan, demonstrating clustering patterns inside Kuantan. Dengue clustering was discovered in the Kuala Kuantan sub-district, exhibiting a negative spatial autocorrelation between these sub-districts in this area, according to LISA. There was an LH outlier of sub-districts in Penor and Beserah from 2011 to 2020, indicating a mild negative spatial autocorrelation on average in the region (Figure 3). The discovery of HL and LH clustering across the study periods shows that socio-ecological factors may continue to play a role in DF transmission, land-use changes have a significant impact on the trend of dengue case distribution. It has been discovered that the main exposure location for disseminating the dengue virus is a residential region, followed by an open space, an industrial area, and a commercial sector. Land-use patterns and dengue case distribution suggest a larger distribution in residential areas due to higher population density as well as suitable breeding locations generated by humans in residential areas, particularly one-story houses (19). A research also discovered that land cover and spatial organization of communities, as well as the surrounding landscape, play a role in dengue infection. They also underlined the importance of land cover as a breeding habitat supply (23).

As a result, the spatial method used in this work could be used to identify and monitor high-risk sites in DF and other infectious disease surveillance across time. This is the first study to evaluate the regional variation of dengue transmission in Kuantan using GIS and spatial analysis. Furthermore, it lays the groundwork for future research into the social and environmental factors that influence shifting illness patterns. The findings can also be used to identify high-risk areas where surveillance and public health interventions are most needed.

There are three limitations to this study. First, in our study, reported DF events were aggregated by sub-district, preventing analysis at a higher spatial resolution and perhaps resulting in the absence of key clusters. However, this is the maximum level at which the data are currently accessible. Second, the quality of the data from the National Infectious Disease Information System was anticipated to vary. For example, medical practitioners and the general public's knowledge of DF may vary over time and place, affecting estimates of the disease's global distribution. Underreporting is likely when people infected with dengue have subclinical infections and/or do not seek medical attention. Finally, this study only looked at the geographic variation in dengue transmission rather than the disease's aetiology.

CONCLUSION

In conclusion, our research discovered that the transmission cycles of DF in Kuantan appear to be nearly the same, with the disease concentrating in spatiotemporal settings and the disease's geographic distribution not extending in recent years. Dengue fever (DF) transmission in Kuantan appears similar, with the disease concentrating in only three sub-districts. Future research should focus on identifying the key socio-ecological factors that determine DF transmission patterns (e.g., social, demographic, climate, vegetation, and mosquito density). Because there is no vaccine against specific strains of the dengue virus, early warning systems should be developed to improve the effectiveness and efficiency of dengue control and prevention efforts. To attain these objectives, a well-coordinated, interdisciplinary strategy is necessary and crucial.

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