Spatial-Temporal Analysis for Identification of Vulnerability to Dengue in Seremban District, Malaysia

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Abstract
Dengue is a major public health threat in Malaysia, which is known for the hyperendemicity with all the four serotypes of the dengue virus circulating concurrently. Annual dengue cases reported were 43,000 cases for 2013, and this imposed a heavy toll on the resources for dengue prevention and control program. The objective of mapping in our study is to determine the spatial clustering of the dengue cases and to identify the areas that are vulnerable to dengue outbreaks. A Geographical Information System (GIS) was used to assess the vulnerability of Seremban district. Dengue data were obtained from the Ministry of Health. We determined the spatial distribution, the average distance of dengue cases and identified hotspots areas using the Moran's I, Average Nearest Neighbourhood (ANN), Kernel density estimation. Vulnerability to dengue was assessed with the spatial temporal analyses and Local Indicator for Spatial Autocorrelation (LISA). From 2003-2009 Seremban recorded 6076 dengue cases. Moran's I showed the cases occurred in clusters with a Z-score of 16.384 (p<0.001). ANN 0.264 (p<0.001) indicated the mean distance between every dengue case was 55 meters. Kernel density estimation showed hotspots of dengue were concentrated in two subdistricts. This paper discusses how spatial-temporal approach can be used to assess the vulnerability of Seremban to dengue where control activities can be more focused to these high risk areas. Mapping the dengue distribution using spatial-temporal approach is useful and guides the public health management of dengue.

1. Introduction

Dengue fever/dengue haemorrhagic fever (DF/DHF) is one of the major threats to public health in Malaysia, with an increasing incidence as well as expanding geographical distribution of both the mosquito vectors and the dengue virus (Seng et al., 2005). Throughout 2009, a total of 38,749(DF) and 2737(DHF) cases were recorded respectively (Ministry of Health Malaysia, 2010a). The clinical manifestations of DF include sudden onset of high fever which usually begins 4 to 6 days after the infection, lasting up to 10 days. Other symptoms can also include severe headache, pain behind the eyes, severe joint and muscle pain, nausea and vomiting, skin rashes and mild bleeding. A more serious form of the disease would be characterized by bleeding (from nose, gums), liver enlargement and failure of the circulatory system. A life threatening form is the Dengue Shock Syndrome (King et al., 2008). Mapping the spatial distribution of dengue cases against time can be a useful method of assessing a society's vulnerability towards dengue. With this mapping tool, the public and health authorities will be able to identify and locate the source of epidemic outbreaks as well as spatially identify the high risk areas. Thus, public health interventions can be targeted towards these areas (Wen et al., 2006). The geographical information system (GIS) can provide paths or patterns, relationships and trends that are not shown in tabular data (Shaharuddin et al., 2002). The use of GIS technology in modeling and prevention of diseases will not only encourage the development of the epidemiology and geographic information sciences, but will also encourage the formation and the development of spatial epidemiology, which has

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theoretical and practical values that will further increase significant global awareness of the infectious disease (Yang et al., 2007). The usage of GIS to control and prevent dengue outbreak should be explored extensively and put under serious consideration (Houghton et al., 1996, Yang et al., 2007, Aziz, 2011 and Er et al., 2010). Map showing the mosquito vector data (presence or abundance patterns, epidemiological data (location of dengue or dengue cases pattern scene), or vector control coverage performed a useful tool in vector and dengue control programs. Map can be used to guide and assess the progress of operations and activities to disseminate information to outside parties. For example, the map can help to alert people to the area in a city with a particularly high risk exposure to dengue virus (Eisen and Lozano-Fuentes, 2009). Dissemination of spatial and temporal characteristics of the spread of the disease can be monitored and used by the party responsible for carrying out control measures. Identifying key nodes in the spread of infection, defined by time spent at unique locations, can help us understand past infectious episodes, and predict future developments (Meliker and Sloan, 2011). With the spread of disease models available, this diffusion process is dynamically simulated and visualized in two or three dimensions spatial scale (Yang et al., 2007). High-risk populations can be identified and the location of the spatial distribution pattern is described and transmission behaviors of the disease may be found. Prevention through more effective decisions can be made by government and public health institutions through the provision of better medical resources using GIS network analysis model (Yang et al., 2007). The objective of this study was to identify the vulnerable areas to dengue using spatial temporal analysis. Vulnerable areas in this study area will be explained using spatial-temporal indexes (the frequency index, the duration index and intensity index) of dengue cases and Local Indicator of Spatial Autocorrelation (LISA).

2. Materials and Methods

2.1 Study Area and Data

The Seremban district is one of the 7 districts in Negeri Sembilan, which is located on the west coast of Peninsular Malaysia. The administration of Seremban district is divided between the Seremban Municipal Council (inner Seremban) and the Nilai Municipal Council (outer Seremban). Seremban is the capital of Negeri Sembilan and consists of mostly urbanized area.

Seremban was selected as our study area because it has the highest recorded of dengue cases for Negeri Sembilan. We focused on surveillance data, based on reported dengue cases from the year 2003 to 2009. The data was obtained from Seremban district health office. Dengue cases were based on clinically confirmed cases. The MOH Clinical Practice Guidelines (Ministry of Health Malaysia, 2010b) were used to diagnose and classify DF and DHF. The software used for mapping was ArcGIS 10. The dengue data was used to map the location of each dengue case using the Global Positioning System (GPS). The data obtained from the field observations were then utilized to construct a database as incidence points. The statistical analysis used in our research was the spatial-temporal analyses such as the Moran's Index, ANN, Kernel density and the spatial-temporal indexes. We also used the Local Indicator of Spatial Autocorrelation (LISA). LISA is a spatial risk index to identify spatial patterns including clustering and outliers (Anselin, 1995, Odland, 1998 and Wen et al., 2010). This research focused on the clustering of the dengue cases which can be identified using the features of frequency-time-incident cases and the number of cases occurring in a certain period of time or in an epidemic. These factors give a true and more realistic picture of the epidemic events.

2.2 Moran's Index

Spatial autocorrelation of Moran's index was used to analyse whether the dengue cases within the study district is spatially correlated. It is determined by calculating a mean for observation and then comparing the value of each incident with the value at all other locations (Wen et al., 2010). Moran's I values range from -1 which is negative spatial autocorrelation (approaching scattering incident) to +1 of positive spatial autocorrelation (approaching grouping incidents). Value approaching 0 refers to the random distribution pattern.

2.3 Average Nearest Neighbourhood (ANN)

Average nearest neighborhood (ANN) was used to assess the pattern of clustering of the incidence of dengue. ANN calculates the distance between each feature centroid to its nearest centroid. It then calculates the average nearest neighbor distance. The average ratio was calculated as the average of the observed distance divided by the expected average distance (Wen et al., 2010).

2.4 Kernel Density Estimation

Hot spots analysis using Kernel density estimation interpolation techniques was carried out. Kernel density estimation is a technique used to identify high-risk areas based on the pattern of disease incidence or the hotspot. It calculates the density of point features around each output raster cell (Bithell, 1990). This hotspot identification is an important tool to focus on the control activities to prevent further transmissions of the mosquitoes-borne disease.

2.5. Spatial-Temporal Indexes and LISA

Vulnerability of the population towards the dengue cases in this study was assessed by conducting a spatial autocorrelation in which all three of the spatial-temporal indexes (frequency index, duration index and intensity index) were calculated and LISA. The frequency of a disease during an epidemic can be described by a probability that one or more laboratory confirmed cases occurred in certain week(s) out of the total epidemic period (Wen et al., 2006).

Occurrence index (α) can be defined as:

α = number of weeks of the epidemic / number of weeks in the year

An epidemic period usually involves several epidemic waves. Duration index (β) of an epidemic can be described as the average number of weeks in which occurrence of cases persists during the whole epidemic period (Wen et al., 2006).

Duration index (β) can be defined as:

β = number of epidemic weeks / total epidemic wave

The duration index (β) is very important for practitioners and administrators of public health and environment agencies because it reflects the effectiveness of the prevention or control strategies used during the epidemic. Intensity refers to the likely magnitude within an epidemic wave when more than one case occurs (Wen et al., 2006). Incidence rate is taken as an index to measure the magnitude of new cases appearing during a specified period.

Intensity index (γ) is measured as:

γ = incidence rate/ total epidemic wave

The vulnerability assessment is presented with a map of the local indicators of spatial autocorrelation (LISA). LISA considers the possible combinations of the three indices, namely O, D and I, and to distinguish these risk characteristics. Then, the high-risk areas were identified and mapped out and compared (Wen et al., 2010). LISA provides eight possible types of indexes summarized as O for occurrence index, D for duration index and I for intensity index.

3. Results

A total of 6076 dengue cases were recorded in Seremban district from 2003 to 2009. The highest incidence of dengue, during that period was in 2003, followed by 2004 and 2008 with respective incidence rates of 37.4, 23.5 and 20.5 per 10,000 populations. The spatial distribution of dengue cases in the study area was identified using spatial autocorrelation i.e Moran's index. This index measures the autocorrelation based on the location and distribution of the dengue cases. The Moran's Index of dengue incidence was 0.16 at $p < 0.001$ with a Z score of 16.38. This finding showed that the incidence of dengue cases in this study area showed a positive autocorrelation. Average nearest neighborhood (ANN) results showed the average distance of dengue cases to the nearest neighbors is less than 1 which is 0.26. The Z score for the incidence of dengue cases in study area was -109.73 with $p < 0.001$ and the ANN of 55 meters. These Moran I and ANN results indicate the pattern of clustering patterns of the dengue cases. Our findings on Kernel density estimation is shown in Figure 1 where the dark red areas presents the maximum density of dengue cases which were concentrated in two sub- districts A and B. Assessment of vulnerability using LISA analysis shows that in 2003, there were 8 units as high ODI areas (Figure 2). This means that eight types of vulnerable areas were defined from all the possible combinations of high values of the three temporal indices in the year 2003. These areas were located at 2 sub-districts. LISA analysis for the year 2004 showed that there were no areas with a high ODI (Figure 3). However, there were two areas with the high index of OD and DI. These areas were the second most vulnerable area after the high ODI areas. In 2005, there were four groups identified areas of high ODI which consist of 15 unit area (Figure 4). These vulnerable areas for dengue were located in three sub-districts.

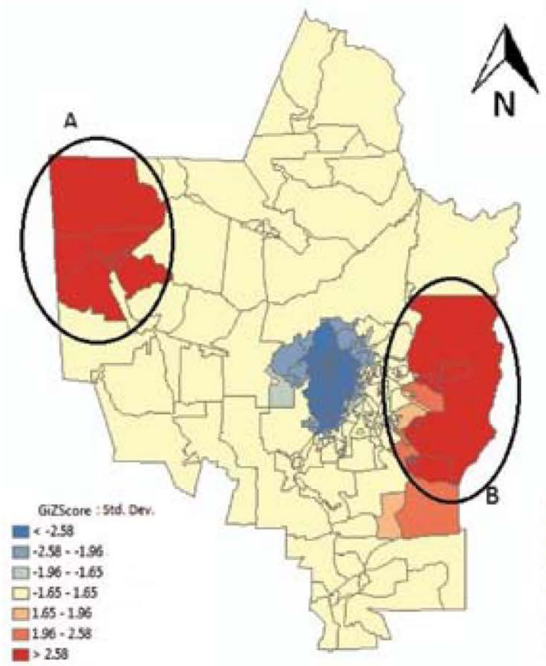

Figure 1: Hotspot areas consist of two sub districts

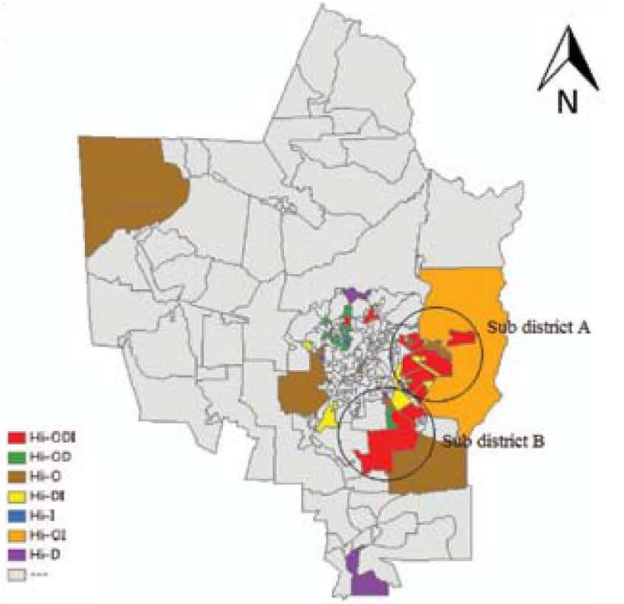

Figure 2: Vulnerability areas in 2003. Eight types of vulnerable area were defined from all the possible combinations of high values of the three temporal indices in year 2003. Red area is the most vulnerable

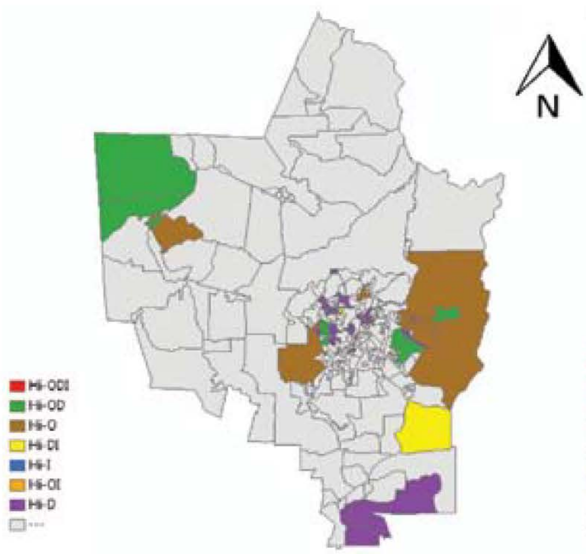

Figure 3: Vulnerability areas in 2004. Eight types of vulnerable area were defined from all the possible combinations of high values of the three temporal indices in year 2004

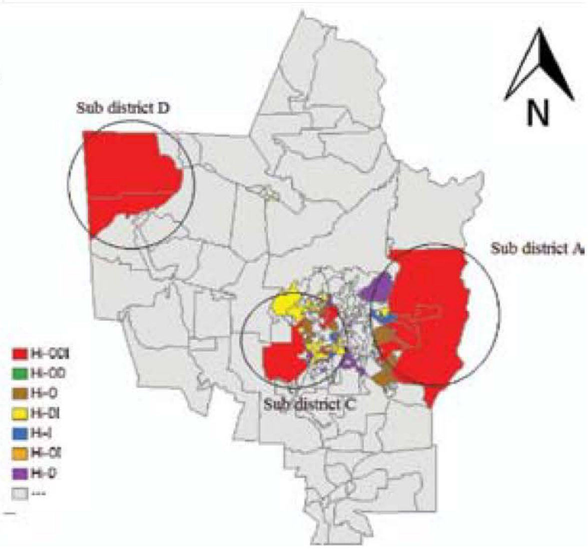

Figure 4: Vulnerability areas in 2005. Eight types of vulnerable area were defined from all the possible combinations of high values of the three temporal indices in year 2005. Most of red areas are in 3 subdistricts in Seremban

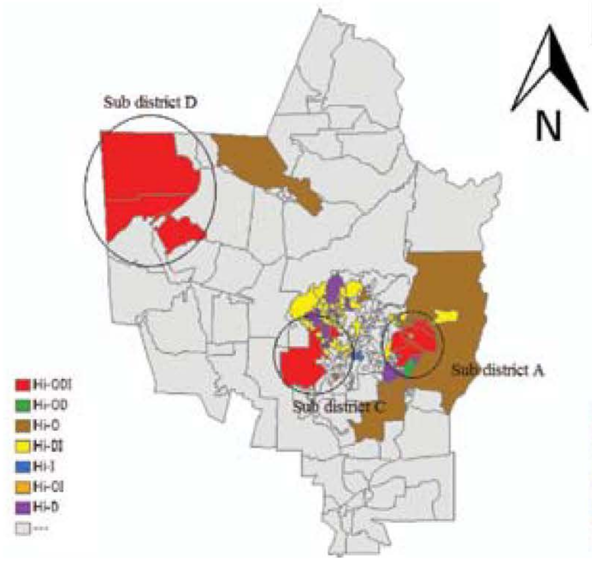

Figure 5: Vulnerability areas in 2006. Eight types of vulnerable area were defined from all the possible combinations of high values of the three temporal indices in year 2006

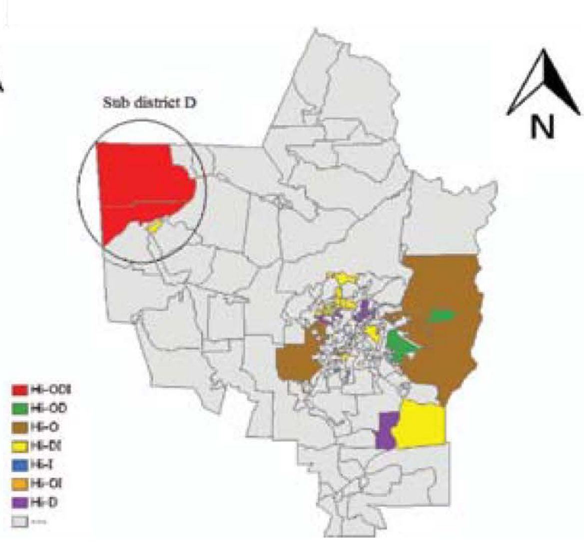

Figure 6: Vulnerability areas in 2007. Eight types of vulnerable area were defined from all the possible combinations of high values of the three temporal indices in year 2007. Highest vulnerable areas is only in a subdistrict in Seremban

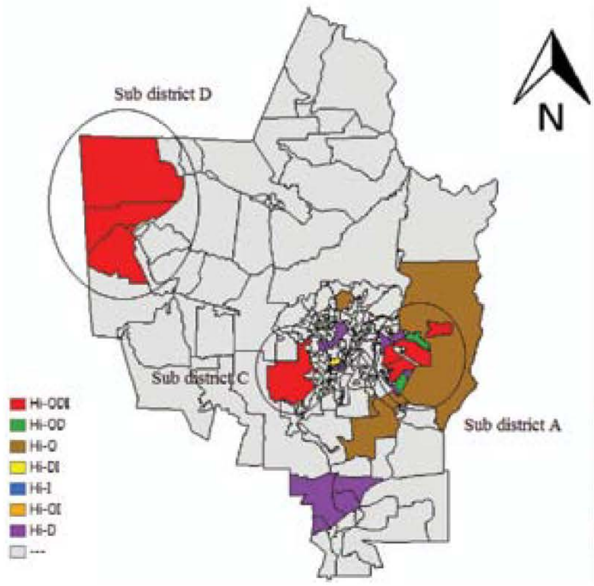

Figure 7: Vulnerability areas in 2008. Eight types of vulnerable area were defined from all the possible combinations of high values of the three temporal indices in year 2008

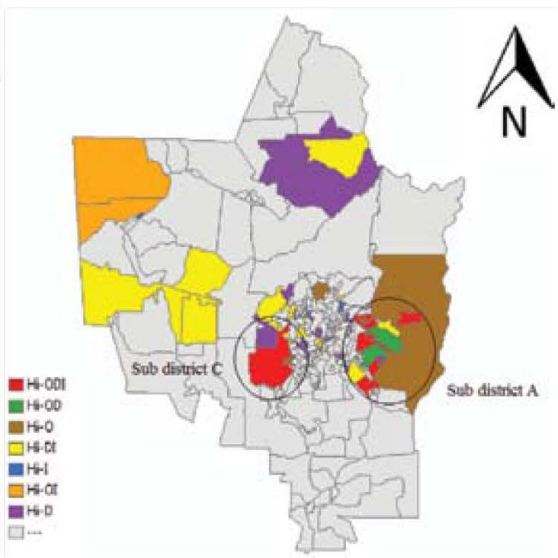

Figure 8: Vulnerability areas in 2009. Eight types of vulnerable area were defined from all the possible combinations of high values of the three temporal indices in year 2009

In 2006, there were also three sub districts with high ODI. There were 12 units with high ODI (Figure 5). In 2007, LISA analysis showed there was only one high ODI area consisting of two units (Figure 6). In 2008, LISA analysis showed clearly the 3 high ODI areas were located at 3 different sub districts (Figure 7). This area consisted of 8 units of the High ODI. In 2009, there were 10 units with high ODI located in two of sub-districts (Figure 8).

4. Discussion

This study evaluated the spatial-temporal distribution of dengue cases in Seremban, an urban district in Malaysia. Data manipulation and GIS presentation and spatial statistics were used to map the distribution of the dengue incidence in the study area. The study found a significant clustering pattern of the dengue cases in the study area with Moran's Index of 0.16. The Average Nearest Neighborhood (ANN) found was a distance of 55 meters between dengue cases and other cases (with z score of -109.73 and p value less than 0.05). This differs with Er et al., (2010) that found a Moran's Index of 0.75 with an average nearest neighborhood (ANN) analysis of 380 m. The difference could be attributed to the density of population and the pattern of housing in both areas. The district in this study is more developed compared to the areas of study in Er et al., (2010).The significance of the 55 meters ANN in this study means that the control and prevention activities such as destruction of breeding sites, fogging and health promotion activities could be focused on a smaller area, hence the control of transmission should be easier to achieve. Moran's Index reported in by Nakhapakorn and Jirakajohnkool (2006), and in Rio de Janeiro, Brazil by Almeida et al., (2009) showed similar findings of significant clustering patterns of dengue cases. This study showed the potential of an area at risk even in the absence of data on the mosquito density or other environmental factors. However, Aziz (2011) reported a spatial relationship between the incidences of dengue with the environmental factors that were associated with the breeding of mosquitoes. For dengue risk, areas marked with dark color signified the locations with the maximum number of dengue incidence. Dengue density map using LISA analysis showed that most cases were concentrated in two sub-districts as discussed below. In 2003, LISA analysis showed that the high-ODI mostly occurred in the two sub districts. The year 2004 recorded the absence of high-ODI. There was a decline in dengue cases as compared with those recorded in 2003. However, in 2005, the high ODI areas of dengue cases were seen to be increasing. This showed that in some areas, the dengue control program was still not adequate. For 2005, the areas that have high ODI was mainly in the three sub-districts. In 2006, the High ODI is still located at the same sub-district but with few changes. In 2007, there was only one area with high ODI. However, 2008 showed that the same area had a high ODI and with addition of two areas located in two different sub districts. In 2009, there were only two sub-districts that have high ODI. The same areas located at same sub-districts were found as high ODI throughout the study period. Similar findings were found by Wen et al., (2010) in southern Taiwan where in 2002 during a dengue outbreak, there were 20 high ODI areas which were concentrated in two areas in the city of Kaohsiung and Fengshan. In the high ODI area, 13 out of 52 epidemiological weeks have confirmed cases of dengue. During this dengue outbreak, the average duration is longer than a month with an average intensity of 3.2 cases per 10 000 people per epidemic wave. Similar findings were reported in a previous study of Wen et al., (2006). Galli and Netto (2008) also used LISA to identify the area at risk in the city of São José do Rio Preto, Brazil. Their research reported that in the year 2001/2002, there were 6 units of ODI area where the most vulnerable area was in the city. Their findings showed that the most vulnerable area for dengue was in the northern region of the city. This study showed the advantage of using spatial temporal analysis which enables us to identify the specific areas that are vulnerable to dengue outbreaks. This finding could guide the planning and implementation of dengue control and prevention programs and prioritizing the resources in risk management. It will enable the health authorities as well as other stakeholders such as the municipal agencies, solid waste management, urban development agencies to plan and implement the dengue prevention and control programs more comprehensively and effectively (Wen et al., 2010). The limitation of our study is due to our dependence on the surveillance data which is based on the dengue incidence. We could not include data on the mosquito density due to the unavailability of this data. In understanding the dynamics of dengue outbreaks, the inclusion of the mosquito density data is important because the disease transmission depends on the contacts between human and the mosquito which carries the dengue virus. Data on the number of breeding sites and mosquito density would be extremely useful in measuring the risk.

The application of this analysis could be used in the future by incorporating other variables that may contribute to the dengue outbreaks, such as information on the human population density, human movement and habits, availability of breeding sites and the entomological data. This analysis could also be applied to other localities to help identify the high risk area more effectively.

5. Conclusion

Dengue cases showed a clustering pattern in the study area. The Average Nearest neighborhood analysis (ANN) showed that the average distance of those dengue cases was within 55 m ($p<0.001$) and the clustering was concentrated in two areas, which are explained by the fact that these two areas coincide with being highly populated areas in Seremban district, due to the rapid urbanization process. Spatial-temporal analysis with LISA showed that the vulnerable dengue areas were in three sub districts. Dengue control and prevention programs should therefore be focused on these high-risk areas.

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