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Integration of GIS-Based Model with Epidemiological data as a Tool for Dengue Surveillance

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Abstract

This study aims to fully integrated and validated spatial temporal statistical model using epidemiological data as a predictive model for surveillance and control of DF cases. Kernel-density estimation (KDE) method was carried out by using spatial union analysis in order to predict and visualize the DF hotspot area by monthly basis in the Subang Jaya area. The generated maps were then verified using Receiver operating characteristics (ROC) was performed to validate the DF hotspot simulation model. Spatial analysis showed that the dengue epidemics in Subang Jaya were spatially dependent. This analysis demonstrated spatial clustering of dengue activity which can facilitate prediction of the magnitude, timing and location of future dengue epidemic. The model developed highlights the adaptation capabilities of the approach where the accuracy assessment result showed accuracy about 60% agreements between the hotspot map and the actual DF location data. It can thus be suggested that any future population increase will be associated with increased DF risk in areas which already accommodate this disease environmentally, climatically and socioeconomically. Future risk could be modelled using the same methods. This would help decision maker in choosing which areas should be under intensive treatment to counter mosquito breeding and reduce prevalence of DF.

Keywords: dengue; epidemiological data; surveillance; GIS; Malaysia

1. Introduction

Dengue Fever (DF) typically has a strong spatial and temporal pattern because mosquito density and longevity depend on a number of environmental and ecological factors such as temperature, precipitation and mosquito breeding habitat. There is a wealth of publications expanding on the Geographic Information System (GIS) analysis in DF research because of its capabilities to display and model the spatial relationship between cause and disease (Cressie, 1991; Clarke *et al*., 1996; Khan, 1999; Kistemann *et al*., 2002; Lozano-Fuentes *et al*., 2008; Eisen and Lozano-Fuentes, 2009; Azil *et al*., 2010; Dom *et al*., 2013).

Epidemic surveillance is defined as the "ongoing systematic collection, collation, analysis and interpretation of data; and the dissemination of information to those who need to know in order that action may be taken" (Fischer and Nijkamp, 1993; Chan and King, 2011). Surveillance provides data and information for action for monitoring disease trends, monitoring progress toward control objectives, estimating the size of a health problem, detecting outbreaks of an infectious disease, evaluating interventions and preventive programs, and identifying research needs (Matthews, 1990; Ai-leen and Song, 2000; Gong *et al*., 2006; Eisen and Lozano-Fuentes, 2009; Shirayama *et al*., 2009; Thai *et al*., 2010; Eisen and Eisen, 2011; Duncombe *et al*., 2012; Nazri *et al*., 2012; Nguyen *et al*., 2016). DF control in Malaysia is primarily based on case surveillance by notification of suspected DF cases by medical practitioners, and vector control by space spraying of insecticides. This reactive mode of surveillance is very insensitive where the health authorities are waiting until the medical community recognizes the DF cases before reacting to implement control measures (Kumarasamy, 2006).

Therefore, a good system in managing disease outbreak is crucial especially in collecting information for surveillance action. The present system of prediction of DF outbreak is based on the use of various entomological indices such as the House (Premises) Index, the Breteau Index, etc. However, it has been observed that these indices may not be suitable for outbreak prediction because no epidemiological components are incorporated in the process. The year to year variations in the threshold of transmission of a particular locality may reflect the actual efficiency of the vector control operation. Despite that, most of surveillance systems in managing DF outbreak are not able to simultaneously investigate, simulate and predict the outbreak in spatial environment. These attributes were essential in providing a better understanding of the outbreak for effective prevention and sustainable DF control strategies.

The effective pairing of information systems and epidemic surveillance is important for disease control and decision-making in public health. Technology has increasingly played an important role in the delivery of health data for computation and analysis (Moore and Carpenter, 1999; Bhandari *et al*., 2008; Porcasi *et al*., 2012). Database and information systems are necessary to input, store, retrieve and analyses health data and are utilized at all levels of public health decision making. Designing and implementing effective information systems are the keys to developing tools to better predict major changes in endemic diseases and the occurrence of epidemics. Geographic Information Systems (GIS) technology currently enables the integration of various data layers, representing physical and social data, on a spatial analysis platform. Recently emerging modelling approaches have enabled the development of sophisticated data analytical approaches for forecasting transmission biology and for predicting public health outcomes (Allen and Shellito, 2008; Burattini *et al*., 2008; Estallo *et al*., 2008; Honorio *et al*., 2003; Azil *et al*., 2010; Astutik *et al*., 2011).

Most of the previous studies concerned with factors that influence the transmission of DF have not taken into account the spatial temporal features of this disease in the modelling process. Thus this study aims to fully integrated and validated spatial temporal statistical model using epidemiological data as a predictive model for surveillance and control of DF cases or others vector-borne disease.

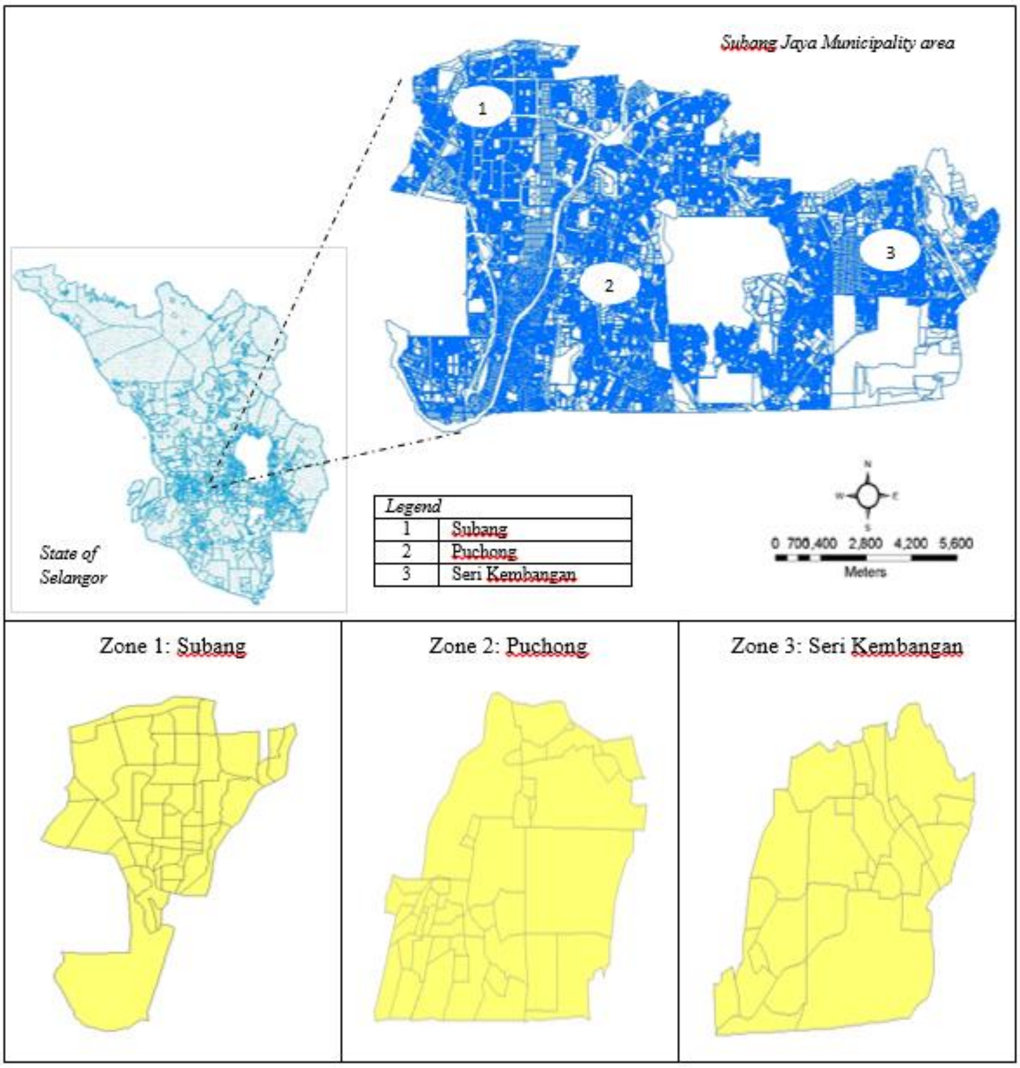


Figure 1. A geographical map of Selangor showing the location of Subang Jaya used in the study and its administrative boundaries namely; Zone 1: Subang; Zone 2: Puchong and Zone 3: Seri Kembangan.

2. Materials and Methods

2.1 Study site and study population

In this study, Subang Jaya area was selected as the main research site to study the spatial temporal relationship between socio-ecological variables (climate variability, vegetation, mosquito density and socio-economic status) and the transmission of DF infection. The selection of this area was justified by several factors. First is it has a high population density in the state of Selangor and has significant public health implications in relation to the control and prevention of DF. Besides that Subang Jaya had the highest number of DF cases reported yearly in the state of Selangor, in year 2006 to 2010. Subang Jaya is divided into three administrative boundaries of Subang, Puchong and Seri Kembangan (Fig. 1).

The incidence of DF cases has been high in Selangor during the past decades. Subang Jaya is a city of metropolitan area of Kuala Lumpur. It has a geographic area of 181 km^2 at latitude 3°05'48.74" North and longitude 101°33'02.39 which is surrounded by rapid development and has a high population density. Based on the temperature reading acquired from the Malaysia Meteorological Service Department, the overall temperature of the Subang Jaya is typically warm (sometimes hot) with bright sunny days and relatively cools in the evening. Temperature typically ranges from 23°C to 33°C. Humidity level is generally in the range of 80% or higher and the annual rainfall recorded often exceeds 2600mm. Although some rainfall can be expected throughout the year, period from December to February is considered as the rainy or wet season. When the rainy season ends, day time will be much warmer and hot but not particularly dry as the humidity level remains high. This period will begin from late January and last up to April. From March to October, both rainfall and humidity are at their lowest levels and the temperature is pleasantly comfortable.

2.2 Study design

This study was design in order to develop epidemics forecasting model for disease control and risk management planning. The variation on the transmission of DF was assessed by firstly, examining the spatial temporal distribution of DF cases and the expansion of the epidemic foci were examined at Subang Jaya area with the GIS, over the period 2006-2010. Then a preliminary epidemic forecasting model of DF and supportive tool were developed for improving surveillance system in Subang Jaya, Selangor, Malaysia (Fig. 2).

Osei and Duker (2008) defined hotspot "as a condition indicating some form of clustering in a spatial distribution". This study used the terms of DF hotspot by Ministry of Health Malaysia in indicating the epidemic area. The ministry considered the DF outbreak when the condition have two or more DF cases which have onset within 14 days and are located within 200m radius of each other (based on residential and workplace addresses as well as movement history).

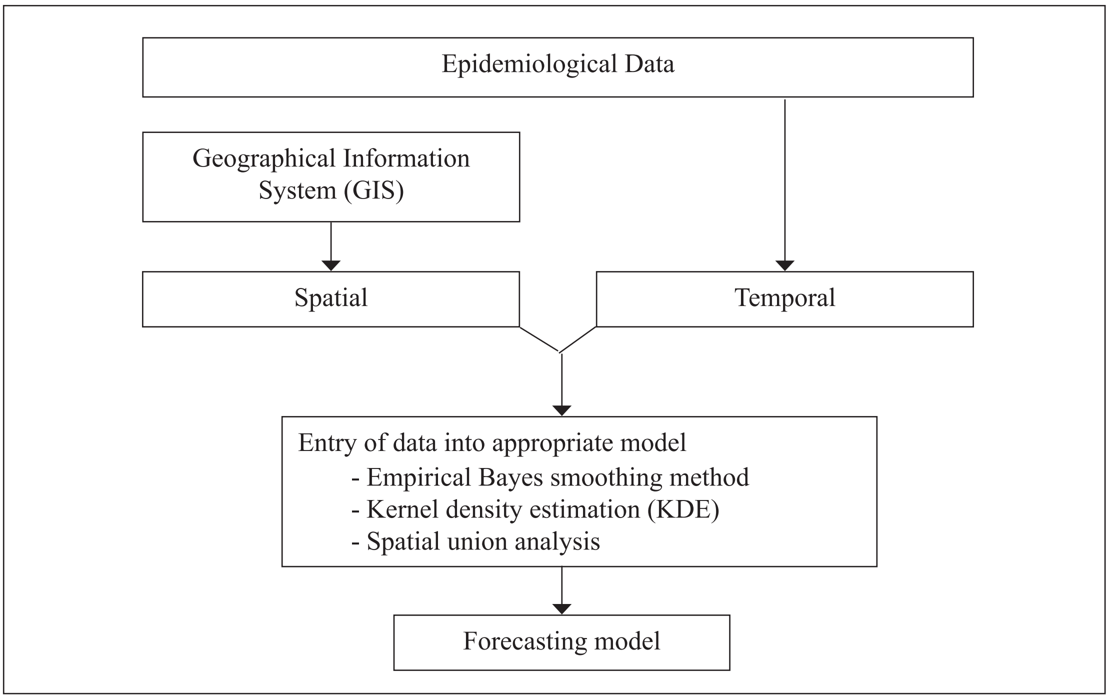


Figure 2. Study design process for data incorporation in dengue fever outbreak modelling in Subang Jaya Selangor

2.3 Data collection and management

Epidemiological data on daily DF cases between 2006-2010 which included the onset date, place of the notified DF cases, age and sex of patients and laboratory test date was obtained from the Vector Control Unit, MPSJ (DF is a notifiable disease, positive test results have to be reported by laboratories to the Vector Control Unit, MPSJ). Daily average of maximum temperature, minimum temperature, rainfall and relative humidity for Subang Jaya from 2006-2010 were provided by the Malaysia Meteorological Service Department. Annual population data in each locality in Subang Jaya for the period 2006-2010 were obtained from the Department of Statistics. The data included a variety of population characteristics including educational level. The epidemiological data initially collected from the Vector Control Unit, MPSJ was used to study the DF distribution and transmission (Table 1).

Data were analyzed using the Geographic Information System software package, ArcGIS version 9.3 (ESRI, 2009) to construct Subang Jaya hotspot maps. All digital geographic dataset were represented as thematic layer and converted to a common geographic coordinate system, WGS 1984 to support uniform analysis of the data.

2.4 Data analysis

The epidemiological data of DF cases was used to estimate underlying risk by using the empirical Bayes smoothing method in order to generate dynamic time-series map. A total of 4710 patients household addresses during the study period (2006-2010) in Subang Jaya were geo-referenced on a GIS map and saved in dBASE format. Kernel-density estimation (KDE) method was carried out for findings DF incidence hotspot zonation map. This density was estimated by counting the number of DF incidence cases in Subang Jaya area, centering the location where the estimate was to be made. DF incidence zonation maps were created using KDE methods. The mean centre of spatial mean gave the central location of disease points. In this study, the WGS 84 coordinate system was adopted. With that reference, the mean centre can be made by calculating the mean of x-coordinates (or Easting) and the mean of the y-coordinates (or Northing). These two means of the coordinates defined the location of the mean centre of DF incidence location as:

$$(\bar{x}_{mc}, \bar{y}_{mc}) = \left(\frac{\sum_{i=1}^{n} x_i}{n}, \frac{\sum_{i=1}^{n} y_i}{n} \right),$$

Where x_{mc} and y_{mc} are the coordinates of DF incidence mean centre, x_i and y_i are the coordinates in each points. Thus, the incidence dynamic time-series map was generated based on KDE methods by using spatial union analysis for monthly basis. Each level of risk was assigned by a different classes ranging from 1 to 10 (low to high). Average risk level was calculated for each area by adding the risk level for each month. Each risk category was given the same weight in order to assign the risk level for each area.

Table 1. Disease, GIS and Environmental Data Matrix of Subang Jaya, Selangor

Data	Parameter	Geographic	Resolution	Time Period	Sources
Population	Sex and age groups	Township	Annually	2006-2010	Town Planning Department, MPSJ
Demographic and Housing Census	Sex, age distribution, elders, landuse	Township	Annually	2006 - 2010	MPSJ, Town Planning Department
GIS Database	Zoning, Hectare, Activity, Section		1:89741 Decimal Degree Latitude Longitude	2010	MPSJ, Town Planning Department
Disease Notification	Dengue	Township	Daily, weekly	2006 - 2010	MPSJ, Vector Control Unit
Hospital Admission	Dengue	Township	Daily	2006 - 2010	MPSJ, Vector Control Unit
Death Registration	Dengue	Township	Daily	2006 - 2010	MPSJ, Vector Control Unit

3. Results

A total of 4710 cases were reported during the study period (2006-2010) in Subang Jaya. According to the data obtained, Table 2. Summarizes the numbers of DF cases which were successfully geo-referenced over a five year period (2006-2010). An average of 90% of cases were geo-referenced, the remaining cases (< 10%) had insufficient information of the DF case record such as missing address or unspecified location. Thus the actual spreading pattern of DF cases is clearly reflected since the database coverage was more than 90%.

The hotspot model based on annual data of DF, was then developed by extrapolating the pattern of the DF activity in the previous inter epidemic period in order to predict and visualize the DF hotspot area in the Subang Jaya area. The analysis of DF hotspot was performed by interpolating the values over the space using Kernel Density Estimation as interpolation method. Fig. 3 illustrates the spatial simulation of DF risk mapping and its stratification on a monthly basis by using colour contour. DF hotspot risk indices from 1-10 was used to represent the magnitude of predictive DF outbreak (DF hotspot risk index: 1-4 (Low), 5-6 (Alert) and 7-10 (High) risk of the epidemic).

These maps showed clear spatial patterns of DF hotspot on a monthly basis. By plotting the hotspots of DF outbreak in year 2006 to 2009, it was found that the DF epidemic in Subang Jaya was spread throughout study area during the early years between December to June, and the wide spatial distribution was conserved during the peak of the epidemic in February. Further spatial analysis showed that the highest density of DF hotspot was occurred within the residential area where the development level and socio-economic status of people were very low. What is interesting in this data is that DF epidemic in Subang Jaya were spatially dependent. Besides that the timing of the DF epidemic cycles was less spatially dependent. Overall, this analysis demonstrated spatial clustering of DF activity which can facilitate prediction of the magnitude, timing and location of future DF epidemic.

Furthermore, the simulation model of DF hotspot was then validated with the timing (monthly) and location of DF incidence in 2010. The hotspot categories are expressed as probabilities in qualitative form (e.g. none, low, moderate, high). Fig. 4 shows the selected simulation model of hotspot map for March (qualitative) of the study area for 2010. Then the hotspot simulation map was verified using the actual cases to measure its performance in the study area. Receiver operating characteristics (ROC) was performed in order to validate the DF hotspot simulation model. This study used “true alarm” to evaluate the success rate of the model performance. True alarm is defined as a measure of how many actual DF cases were successfully predicted, which allowed us to estimate the goodness of the fit of the predictive model. There were two assumptions to support the verification of this simulation model. One is that, there is a general agreement about DF can attack anyone in area which historically had experienced with DF virus outbreak. Secondly, DF typically had strong spatial and temporal pattern because mosquito density and durability depended on a number of environmental and ecological factors.

Fig. 5 tabulated all values observed which were sorted on a monthly basis. Subsequently, all values were then accumulated according to the values obtained. To compare the result quantitatively, the ROC were calculated as the total area = 1 which means perfect prediction accuracy. Therefore the ROC curve can be used to assess the prediction accuracy quantitatively. The line graph explained the verification result of simulation model whereby the model developed was able to forecast DF outbreak 60% accurately in predicting its timing and their location of the epidemics. In terms of sensitivity and specificity the values obtained from the verification result were 82.1% and 30.2% respectively.

Table 2. Summary of address geo-referenced of DF cases over the study period (2006-2010) in Subang Jaya area

Year	Total of confirmed dengue fever (DF) cases	Geo-referenced confirmed dengue fever (DF) cases	
		(n)	(%)
2006	965	900	93.26
2007	904	781	86.39
2008	1191	1079	90.60
2009	1033	972	94.09
2010	617	600	97.15
total	4710	4333	91.99

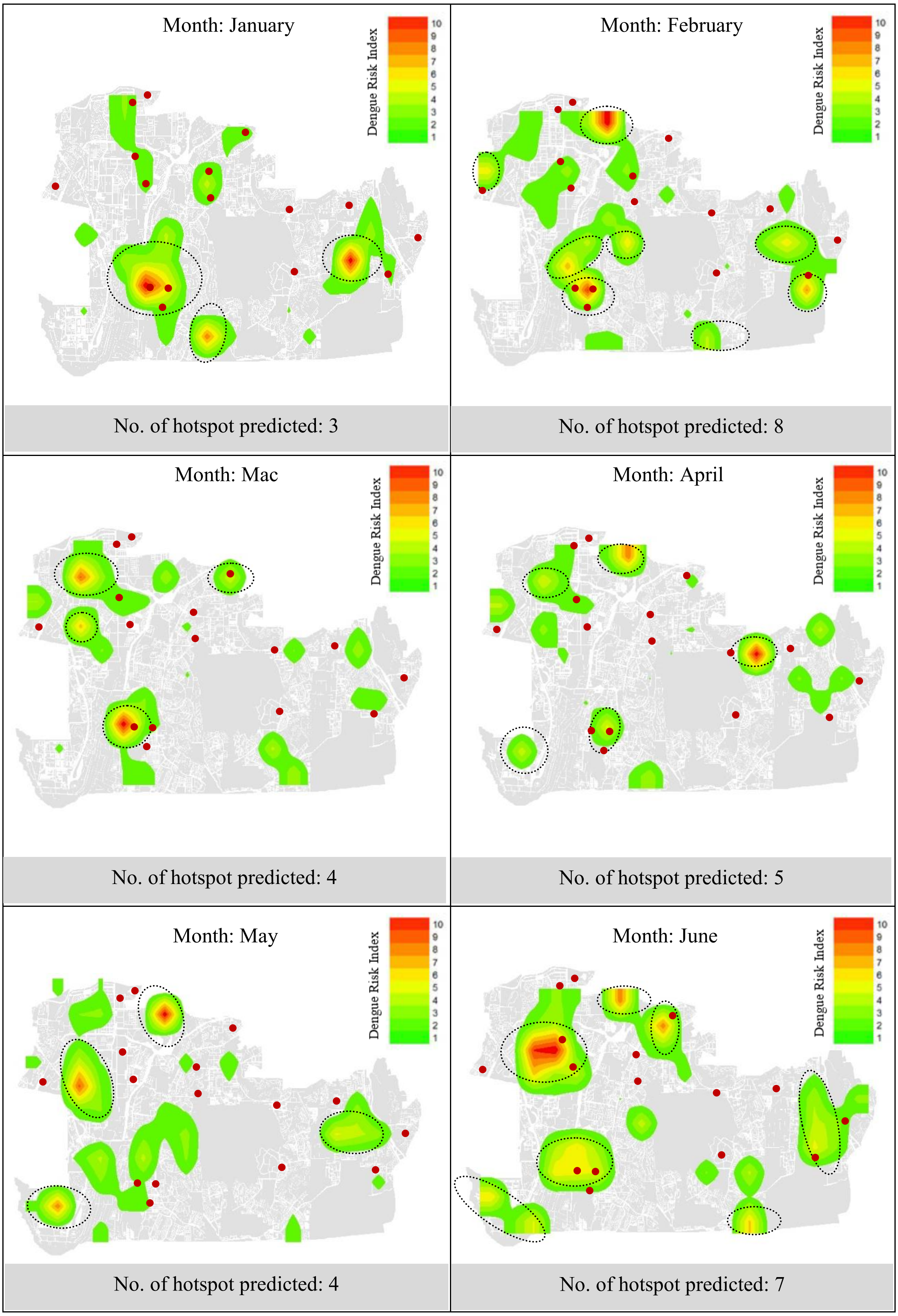
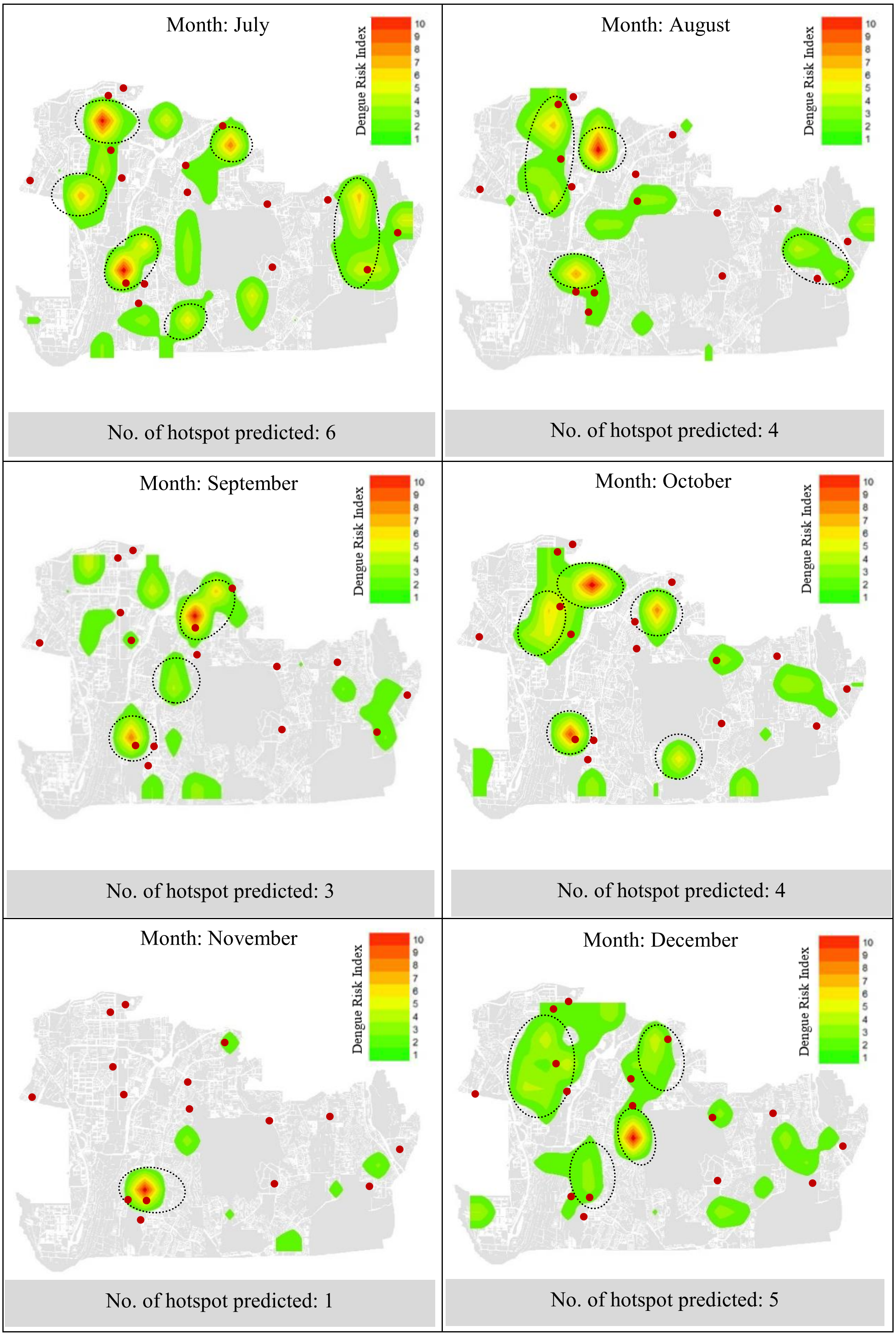


Figure 3. Monthly dengue risk indices generated from DF hotspot model (2). Dengue risk indices from 1-10 was used to represent the ascending threat of outbreak. Note: Index 1-4 (Low risk), 5-6 (Alert) and 7-10 (High risk). Red point represent the distribution of actual dengue hotspot.



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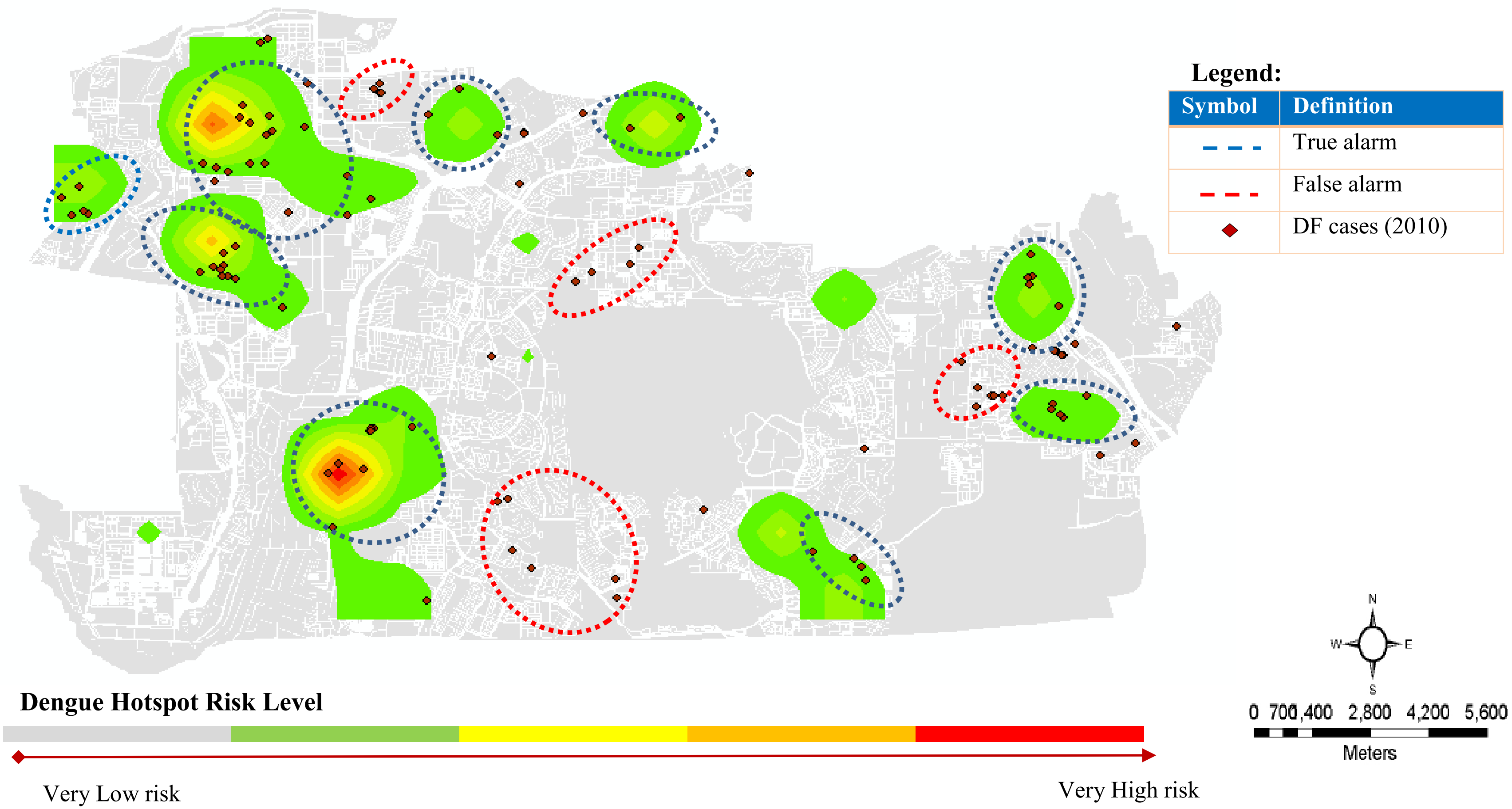

Figure 4. Sample of simulation model of DF hotspot for March 2010. Note: Circular (Blue) dotted line indicate true alarm; Circular (Red) dotted line indicate false alarm and Red (diamond) represent actual incidence of DF cases

4. Discussion

This study subsequently developed the simulation of DF hotspot model by extrapolating the pattern of the DF activity in the previous inter epidemic period. From the result obtained, it is possible that the level of risk can be describe based on the analysis of historical data. In order to provide reference, the prediction of DF outbreak was translated into a color code to indicate the risk level. This study used a color contour to show the monthly risk of DF outbreak in the locality. It can thus be suggested that this representation approach of DF risk indices can be used to establish rapid interpretation and alert to indicate DF

A. Measurement of actual DF cases for 2010 with simulation model

Months	No of DF cases*	Observed frequencies		Cumulative rate	
		True alarm	False alarm	True alarm	False alarm
January	118	68	50	0.18	0.21
February	148	102	46	0.45	0.41
Mac	117	83	34	0.68	0.55
April	69	29	40	0.75	0.72
Mei	37	24	13	0.82	0.77
Jun	25	15	10	0.86	0.81
July	38	26	12	0.93	0.86
August	19	9	10	0.95	0.91
September	14	6	8	0.97	0.94
October	14	4	10	0.98	0.98
November	6	5	1	0.99	0.99
December	6	3	3	1.00	1.00
Overall	611	374	237		

B. ROC curve showing the accuracy of simulation model in the study area (Subang Jaya)

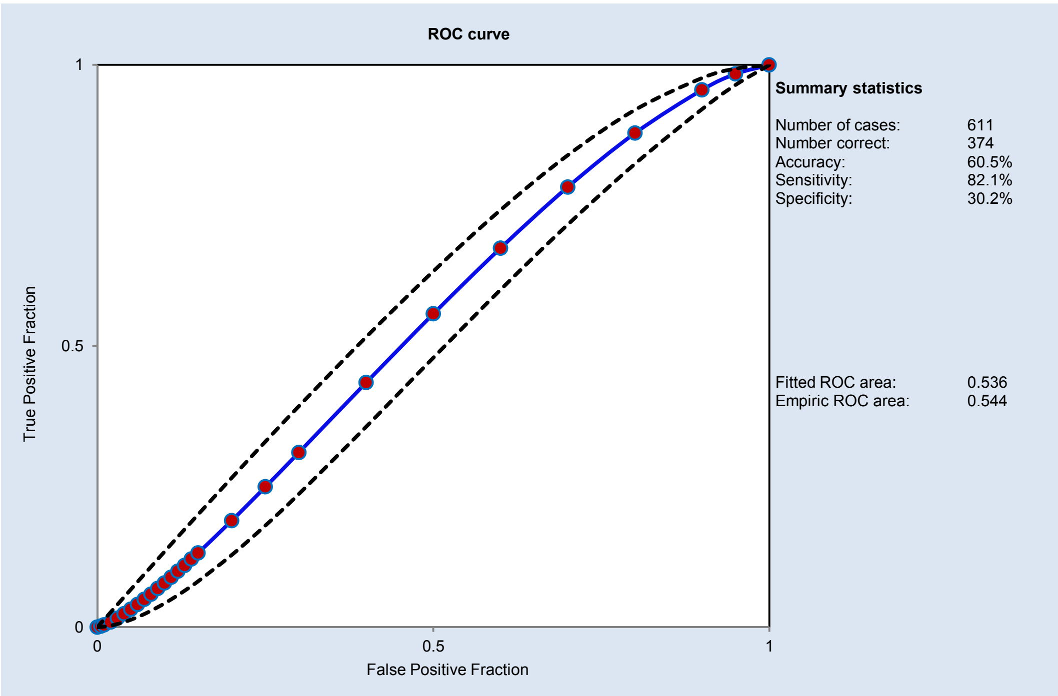

Figure 5. Verification process of simulation model in Subang Jaya A: Measurement of actual DF cases for 2010 with simulation model; B: ROC curve showing the accuracy of simulation model in the study area

epidemic in the locality. The model developed highlights the adaptation capabilities of the approach where the accuracy assessment result showed accuracy about 60% agreements between the hotspot map and the actual DF location data. It can thus be suggested that any future population increase will be associated with increased DF risk in areas which already accommodate this disease environmentally, climatically and socioeconomically. Future risk could be modelled using the same methods. This would help decision maker in choosing which areas should be under intensive treatment to counter mosquito breeding and reduce prevalence of DF.

However the research findings of this study may be influenced by several other alternative scenarios. Firstly, the quality of the notification data varies with time and space. It is well recognised that the increase incidence of DF is partly due to the increased awareness of this disease among medical practitioners and the general public. Nevertheless, the impact of such a factor on the notified incidence of DF is unlikely to differ substantially with spatial and temporal scales used in this study. Secondly, the ecology of DF is complex and many factors (including virus, vector, host and environmental condition) are involved in its transmission cycles. Some social factors also influenced the transmission of DF virus. Changes in land-use have created ideal larval habitats. Clearing land for urban development could increase the potential of DF transmission (Mackenzie *et al*., 2000; Tong *et al*., 2002.). The increased in human population living in intimate contact with increasingly high densities of mosquito populations created ideal conditions for increased DF. Despite many socio-ecological factors that may affect the pattern of DF outbreak, the findings of this study suggested that changes in environmental conditions are also the key determinant of re-emergence of DF incidence.

The findings from this study have the potential to affect the planning of public health interventions. GIS and spatial analytical approach developed through this study may be used in the surveillance of DF and other infectious diseases to identify and monitor high risk areas over different periods of time. The results suggested that the major determinant of the DF disease may differ at the local level. Therefore, different public health strategies may need to be developed in the disease control and risk management program. Apart from that, human population density was also found to be a significant determinant of DF incidence in high risk areas. Thus, health education and vector control programs should focus on communities with a high population density in order to control seasonal disease outbreak.

5. Conclusions

In addition, systematic and integrated training may be necessary for medical practitioners and public health professionals to achieve adequate and current knowledge of DF disease outbreak. Computer model needs to be developed on the basis of these findings to predict epidemic activity under different socio-environmental change. The development of epidemic forecasting system is important for the control and prevention of infectious disease outbreak in the future. Early warning system based on forecast from the model can assist in improving vector control and personal protection. For example, increasing insecticide spraying during high risk period and decreasing it during low risk period will improve cost effectiveness of operations. The disease surveillance data obtained can be integrated with social, biological and environmental database. These data may provide additional input into the development of epidemic forecasting models. These attempts, if successful, may have significant implications in environmental health decision making and practices by helping health authorities in identifying public health priorities and use resources sustainably.

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