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Spatial dispersal of *Aedes albopictus* mosquitoes captured by the modified sticky ovitrap in Selangor, Malaysia

Muhammad Aidil Roslan,[1-3] Romano Ngui,[1] Muhammad Fathi Marzuki,[4] Indra Vythilingam,[1] Aziz Shafie,[4] Sabri Musa,[2,3] Wan Yusoff Wan Sulaiman[1]

[1]Department of Parasitology, Faculty of Medicine; [2]Department of Paediatric Dentistry and Orthodontics, Faculty of Dentistry; [3]Office of Deputy Vice-Chancellor (Student Affairs); [4]Department of Geography, Faculty of Art and Social Sciences, University of Malaya, Kuala Lumpur, Malaysia

Abstract

Dengue is a major mosquito-borne disease in many tropical and sub-tropical countries worldwide, with entomological surveillance and control activities as the key management approaches. This study aimed to explore the spatial dispersal of the vector *Aedes albopictus*, captured by the modified sticky ovitrap (MSO) in residential areas with low-rise buildings in Selangor, Malaysia. Distribution maps were created and shown as temporally distinguished classes based on hotspot analysis by Getis-Ord; spatial autocorrelation assessed by semivariograms using the exponential Kernel function; and universal Kriging showing areas with estimated high and low vector densities. Distribution, hotspot and interpolated maps were analysed based on the total number of mosquitoes by month and week. All maps in the present study were generated and visualised in ArcMap. Spatial autocorrelation of *Ae. albopictus* based on the monthly occurrence of *Ae. albopictus* was found in March, April, October, November and December 2018, and when based on the weekly numbers, in weeks 1, 2, 3, 5, 7, 12, 14, 25, 26, 27, 31, 33, 42, 49 and 52. Semivariograms, based on the monthly and weekly numbers of *Ae. albopictus,* indicated spatial autocorrelation of the species extending between 50 and 70 m. The mosquito density maps reported in this study may provide beneficial information to facilitate implementation of more efficient entomological control activities.

Correspondence: Romano Ngui and Wan Yusoff Wan Sulaiman, Department of Parasitology, Faculty of Medicine, University of Malaya 50603 Kuala Lumpur.
Tel.: +603.79674978 / +603.79675732 - Fax: +603.79674754.
E-mail: romano@um.edu.my ; wanyus@um.edu.my

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Introduction

Dengue remains endemic in Malaysia. Entomological surveillance and control activities play vital roles in the management of dengue disease in the country. *Aedes aegypti* has been acknowledged as the primary vector for dengue worldwide, including in Malaysia, due to its anthropophilic and endophagic behaviour (Johari *et al*., 2019). However, the role of *Ae. albopictus* as a secondary vector should not be dismissed as the species has started to adapt and adjust to urban environments where there are low populations of *Ae. aegypti* (Bagny Beilhe *et al*., 2012). However, *Ae. albopictus* can replace *Ae. aegypti* and could serve as a competent transmitter of the dengue virus (Rozilawati *et al*., 2015).

Without vaccines or specific treatments to cure dengue (Flipse and Smit, 2015), knowledge of the spatial dispersal and abundance of its vectors is essential (Kamal *et al*., 2018). In the latest decade, the spatial dispersal of the dengue vectors has become more accessible by integrated surveillance and control actions based on geographical information systems (GIS) and geostatistical approaches that can capture and analyse spatial and geographic data (Duncombe *et al*., 2013). The GIS user can create interactive queries, store and edit spatial and non-spatial data, analyse spatial outputs as well as present the results as maps (Wieczorek and Delmerico, 2009). GIS has been used as an epidemiological tool to determine the distribution patterns of *Aedes* mosquitoes and targeted areas for control purposes via the visualisation of the spread and abundance of vector breeding sites as practiced in dengue-endemic developing countries, including Thailand (Sithiprasasna *et al*., 2004; Tsuda *et al*., 2006), Mexico (Moreno-Sanchez *et al*., 2006; Lozano-Fuentes *et al*., 2008) and the Republic of Nicaragua (Chang *et al*., 2009). In addition, GIS is commonly used to predict high-risk dengue transmission zones by estimating the abundance of infected *Aedes* mosquitoes in high dengue-incidence areas, such as Argentina (Carbajo *et al*., 2001), Bangladesh (Ali *et al*., 2003), Peru (Getis *et al*., 2003) and Thailand (Chansang and Kittayapong, 2007). GIS has also served as a constructive and valuable platform for public health authorities to initiate efficient dengue surveillance and preventative measures by analysing the spatial and temporal patterns of dengue cases, *e.g*., as practiced in Australia (Hu *et al*., 2012) and China (Li *et al*., 2012).

In Malaysia, GIS technology has been applied in local studies to explore the distribution pattern of vector-borne diseases including dengue (Ling *et al*., 2014; Hazrin *et al*., 2016; Majid *et al*., 2019; Murphy *et al*., 2020), chikungunya (Azami *et al*., 2013) and malaria (Ahmad *et al*., 2011; Alias *et al*., 2014; Pahrol *et al*., 2018). Several local studies have visualised the spatial distribution of dengue cases by the use of GIS combined with spatial statistics (Er *et al*., 2010; Aziz *et al*., 2012; Ahmad *et al*., 2015; Masnita *et al*., 2016; Majid *et al*., 2019). Furthermore, the application of GIS allows the development of spatial modelling that can predict the risk of this infection based on environmental, epidemiological and entomological factors (Aziz, 2011; Hassan *et al*., 2012; Nazri *et al*., 2013; Ahmad *et al*., 2018). GIS paired with spatial statistical analysis is also important for monitoring the spatial distribution of dengue vectors and their potential breeding habitats by generating mosquito density maps (Aziz *et al*., 2014; Norzawati *et al*. 2015). Although several studies have done such research, they only focused on cases and larvae index as primary data. To the best of our knowledge, no studies to date have utilised GIS tools to study the distribution of adult *Aedes* mosquitoes in Malaysia. Therefore, this study aimed to explore the spatial dispersal of captured *Ae. albopictus* mosquitoes through the application of a geospatial approach and a modified sticky ovitrap (MSO), a newly developed device designed to capture adult female *Ae. aegypti* and *Ae. albopictus* mosquitoes (described below). Since this approach would be capable of identifying potential high- and low-risk dengue transmission zones, the study was planned for a residential area characterized by low-rise buildings to map and explore the distribution, hotspot occurrence and interpolated density of adult *Ae. albopictus* mosquitoes. In certain circumstances, particularly when the resources are limited, outcomes of the current study could facilitate the design and development of effective, targeted vector control strategies. The gravid oviposition sticky (GOS) trap (Lau *et al.*, 2017; Liew *et al*., 2019), the light trap recommended by the U.S. Centers for Disease Control and Prevention (CDC) (Rohani *et al*., 2016) and landing catches by humans (Vythilingam *et al*., 2014; Rohani *et al*., 2016) are commonly used for the surveillance of adult mosquitoes in this country regardless of mosquito species. However, information regarding their use for the control and prevention programmes is still lacking in Malaysia. This study integrated the use of spatial and geostatistical analysis tools with a recently developed mosquito trapping device, namely the MSO that targets adult *Ae. aegypti* and *Ae. albopictus* mosquitoes. To the best of our knowledge, this is the first study in Malaysia to use GIS to identify hotspots and estimate *Aedes* density (high and low vector density areas) based on the number of adult mosquitoes collected.

Materials and methods

Study area

The surveys took place in Petaling Jaya (101°38'40''E, 3°05'50''N), a township city located in Petaling District, Selangor, Malaysia (Figure 1). Under the jurisdiction of Petaling Jaya City

Figure 1. Location of the modified sticky ovitrap (MSO) at all eleven study locations in the residential areas in Petaling Jaya, Selangor, Malaysia.

Council (MBPJ), the 97.2 km^2 large city has a population of half a million people. Petaling Jaya is one of the wettest cities in the country, as the city receives an average of more than 3300 mm of rainfall annually. There is no dry season, but June and July are considered the driest months (Department of Statistic, 2019).

Mosquito trapping

MSO, a device designed to capture adult female *Ae. aegypti* and *Ae. albopictus* mosquitoes, is practical for either long-term or short-term entomological surveillance. Importantly, it is user-friendly, relatively cost-effective, does not require electricity or any specific instruction and exerts minimal negative environmental impact. Briefly, the trap consists of two plastic containers; the larger sprayed black and the smaller transparent and with a bottom net. The larger one has a height of 9 cm and a diameter of 8 cm, while the corresponding measures of the smaller are 6.5 and 5.5 cm. The latter is lined with sticky paper coated with non-toxic sticky insect glue and placed inside the larger container. Each trap was baited with 100 mL of hay infusion water.

Trap distribution, mosquito collection and surveillance management

From March 2018 to February 2019 (52 weeks), 273 MSOs were distributed over the study area covering 11 collection sites, namely Site A (39 traps), B (30 traps), C (24 traps), D (32 traps), E (24 traps), F (29 traps), G (17 traps), H (26 traps), I (17 traps), J (20 traps) and Site K (15 traps). The general and environmental characteristics of each collection site are illustrated in Table 1. Of the 273 MSOs, 250 were placed outside resident houses (on the porch), 16 at the common playground, 5 at the guard-house and 2 at the community hall. The locations for MSOs instalment were selected using a spatial grid sampling design suitable for geospatial analysis purposes and based on few criteria that included permission by homeowners and the safety of the fieldwork assistants.

A boundary system representing 200-m buffers for each site was created for each trap location according to the average dispersal range of *Ae. albopictus* in human environmental settings as reported in previous studies (Honorio *et al*., 2003; Liew and Curtis, 2004; Maciel-de-Freitas *et al*., 2006). Meanwhile, Thiessen polygons (Brassel and Reif, 1979) were constructed to produce one polygon for each trap location by drawing perpendicular lines through their midpoints. Smaller Thiessen polygons thus appeared in areas where traps and buffer zones were closer together and larger ones in areas where they were farther apart. Collection of adult female *Aedes* mosquitoes was conducted weekly. During this fieldwork, all MSOs were collected and replaced with new units and subsequently transported back to the Vector Ecology Laboratory, Faculty of Medicine, University of Malaya, Kuala Lumpur for further processing and identification. Adult *Aedes* mosquitoes were extracted from the sticky paper that lined the inside of the smaller container. Gender and species identification of each extracted mosquito was done using a stereo microscope (Olympus BX41, Center Valley, PA, USA). The *Ae. aegypti* and *Ae. albopictus* adults were morphologically distinguished based on the white-scale pattern observed at the dorsal part of the thorax (Harwood & James, 1979). Since *Ae. albopictus* was the predominant species captured throughout the sampling period, further analysis focused on this species. *Ae. aegypti* specimens were excluded in the analysis due to the small sample number of adults captured (N=4).

The weekly numbers of captured *Ae. albopictus* were recorded at all trap locations (N=273) and georeferenced using hand-held global positioning system (GPS) devices (GPSMAP®, Garmin Ltd, Schaffhausen, Switzerland) and all data transferred into a Microsoft Excel sheet (Microsoft, Redmond, WA, USA). Using the World Geodetic System (WGS 1984) as its reference coordinate system, with x-longitudes (east-west) and y-latitudes (north-south). the GPS system allows geographic positions to be expressed anywhere on the globe. Prior to construction of distribution, hotspot and interpolated density maps, all databases (*i.e.* data attributes) were established and processed in ArcGIS version 10.4.1 (ESRI, West Redlands, CA, USA). The attributes, including total, monthly and weekly numbers of all *Ae. albopictus* captured by each trap, were recorded in the database for further analysis.

Table 1. General and environmental characteristics of each collection site.

Site	General characteristics	Environmental characteristics
A	Double story terraced houses, bungalows, playground, shops and community hall	Moderate vegetation, trees and shrubs, clean environment but clos to construction sites
B	Double story terraced houses, bungalows, shops and playground	High vegetation, trees and shrubs, clean environment but close to construction sites
C	Double story terraced houses, school and playground	Moderate vegetation, trees and shrubs, clean environment but close to construction sites
D	Double story terraced houses, playground and school	High vegetation, trees and shrubs, clean environment
E	Double story terraced houses, bungalows and playground	Moderate vegetation, trees and shrubs, clean environment
F	Double story terraced houses, playground and shops	Low vegetations area of trees and shrubs, with a clean environment close to construction sites.
G	Double story terraced houses, community hall, playground and shops	Low vegetation, trees and shrubs, clean environment
H	Double story terraced houses, playground and shops	High vegetation, trees and shrubs, unclean environment
I	Double story terraced houses, bungalows, school and playground	Moderate vegetation, trees and shrubs, clean environment but close to construction sites
J	Double story terraced houses, playground and shops to construction sites	High vegetation, trees and shrubs, clean environment but close
K	Double story terraced houses, playground and shops	Moderate vegetation, trees and shrubs, clean environment

Figure 2 summarises the conceptual framework of this study.

Development of distribution maps

Distribution maps were created based on the total, monthly and weekly numbers of *Ae. albopictus* captured. For the total count, five classes with different colours were generated to differentiate between absence (0) of mosquitoes captured and low (1-25), medium (26-50), high (51-75) and very high (76-143) numbers. For the monthly and weekly capture maps, three classes with established, with white colour representing absence (0), blue medium (1-5) and red a high number (>5) of mosquitoes captured.

Hotspot analysis

Hotspot analysis was performed to identify the location of hotspots and cold spots by aggregating points of occurrence into the polygons created. In this study, detection of significant hotspots (traps) was performed using the General G function (Getis-Ord) in the mapping cluster option in ArcMap. The data consisted of the total, monthly, and weekly numbers of *Ae. albopictus* captured. This analysis was done to identify statistically significant spatial clusters of high values (hotspot) and low values (coldspot) within the context of neighbouring features in the dataset. To be termed a significant hotspot, a feature with high value must be surrounded by other features with equally high values (Ord and Getis, 1995).

Inverse Distance, defined as a neighbouring feature with a significant influence on the computations for a particular target compared to faraway features (Ord and Getis, 1995), was selected to conceptualise the spatial relationship. Additionally, *Euclidean distance*, defined as the shortest (*i.e.* straight-line) distance between two points, was selected for the distance method. The Z-score and P-value (probability) for each feature in the dataset determine the statistical significance. A high Z-score with a low P-value for a feature indicates a significant hotspot, while a low, negative Z-score with a low P-value indicates a significant coldspot. A Z-score close to 0 indicates random dispersion, while the higher (or lower) the Z-score is, the more intense the clustering (Ord and Getis, 1995). Only features of the dataset with a 99% confidence level (CL) (P-value <0.01) were selected and labelled according to the number of traps deployed in the respective sampling sites.

Spatial autocorrelation and interpolation

Spatial autocorrelation was assessed by generating semivariograms using the exponential Kernel function with the geostatistical wizard in ArcMap. The semivariograms were created based on the *Ae. albopictus* population obtained at each trap and the total, monthly and weekly mosquito numbers.

Spatial interpolation methods are useful when the variable of interest such as mosquito density is spatially continuous but only can be measured at selected sites, such as a trap (Lam, 2013). Kriging, a robust spatial interpolation technique (Oliver and Webster, 1990) makes predictions derived from values measured (*i.e. Ae. albopictus* density in the MSOs) and distance to the predicted locations, while the spatial autocorrelation can be modelled based on of semivariogram covariance parameters (Pfeiffer *et al.*,

Table 2. Summary of the monthly *Ae. albopictus* capture records.

Month	Comparison of trap contents		
	High (>5)	Low (1-5)	None (0)
1 (March 2018)	19	131	123
2 (April 2018)	26	123	124
3 (May 2018)	45	118	110
4 (June 2018)	33	122	118
5 (July 2018)	21	125	127
6 (August 2018)	13	125	135
7 (September 2018)	9	82	182
8 (October 2018)	19	87	167
9 (November 2018)	20	80	173
10 (December 2018)	21	86	166
11 (January 2019)	8	68	197
12 (February 2019)	4	60	209
Total	238	1207	1831

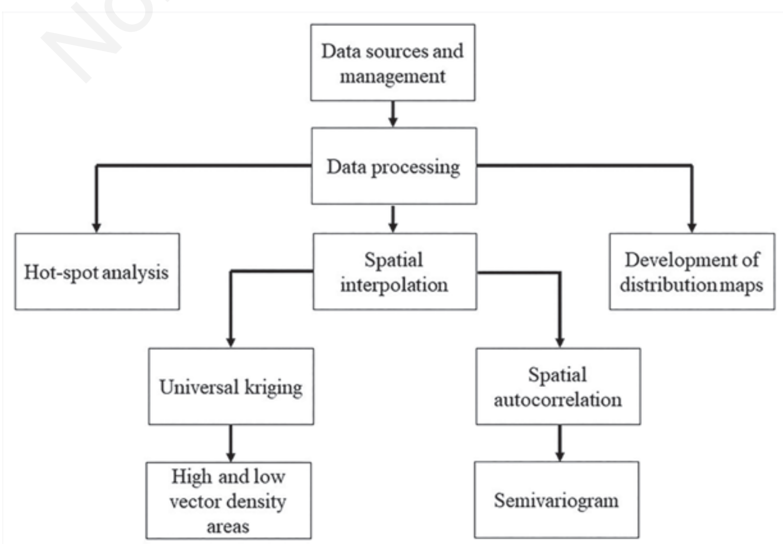


Figure 2. Conceptual framework of the GIS methodology.

2008). Since it accommodates mean trends (*i.e.* large variation in the mean values in different geographical areas), universal kriging (Zimmerman *et al*., 1999) was selected to estimate the number of mosquitoes at unsampled locations throughout the sampling sites considering the number of mosquitoes in nearby trap locations.

The total, monthly and weekly numbers of captured *Ae. albopictus* mosquitoes were counted and interpolated with respect to the 200-m radius buffers at each site. The interpolated areas distinguished between high-vector density areas of *Ae. albopictus* (red areas in the figures) and low-vector density ones (blue areas). All interpolated maps were generated and visualised in ArcMap.

Results

Ae. albopictus distribution maps

Overall, only 4 traps recorded a very high number of captured *Ae. albopictus* mosquitoes followed by 15, 43 and 200 traps with high, medium and low numbers, respectively. Only 11 traps did not record any mosquitoes at all (Figure 3). The monthly results with high numbers of mosquitoes captured were the following: 45 traps in May 2018, 33 in June 2018, 26 in April 2018, 21 in July and December 2018, while the least number of traps (N=4) with high *Ae. albopictus* numbers was recorded in February 2019. These results are summarised in Table 2 with the figures presented in Annex I.

The weekly records showed that week 14 had the highest number of traps capturing high numbers of *Ae. albopictus* (N=16), followed by week 11 (N=6), week 12 and week 38 (each N=5) and week 3, week 10 and week 13 with 4 traps each. For more than a third of the year (19 weeks), only low numbers of *Ae. albopictus* were captured. The tabulated and figurative details of this weekly analysis are presented in Annex II.

Ae. albopictus hotspots

Seven *Ae. albopictus* hotspots, 3 in site H, 2 in site G and 1 each in sites B and D, were identified between March 2018 and February 2019 with none identified in the other sites during this time (Figure 4A). Site H recorded the highest number of hotspots (N=39) followed by 19 in site D and 11 in site G, while both sites E and J recorded the lowest number with 3 each. Overall, however, 110 hotspots were recorded over the year under study as shown in Figure 4B. June 2018 showed the highest number (N=14), followed by 11 in December 2018, 10 in May 2018 and 9 in July 2018, August 2018, September 2018 and January 2019, while

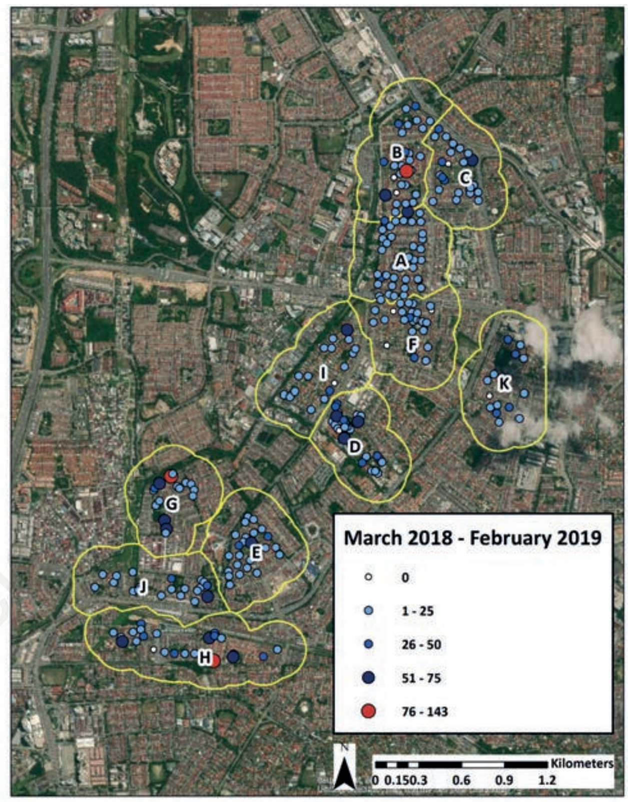
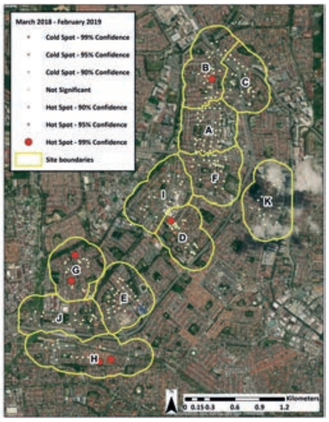


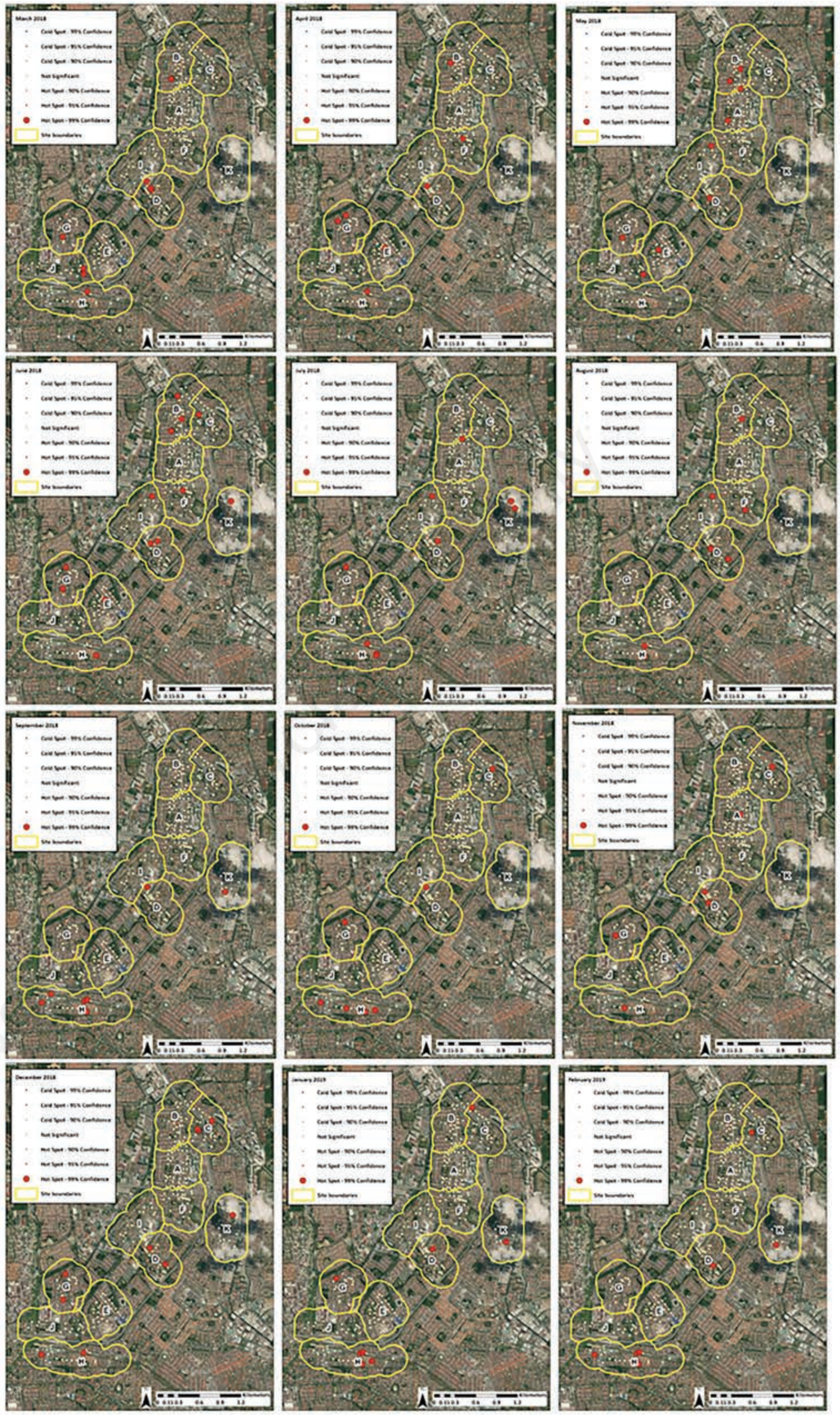
Figure 3. Distribution map *Ae. albopictus* presence in Petaling Jaya, Selangor based on the contents of 273 modified sticky ovitraps (MSOs) distributed over the study area.

Table 3. Summary of the monthly *Ae. albopictus* hotspots among the eleven study sites

Month	Number of *Ae. albopictus* hotspots											Total
	A	B	C	D	E	F	G	H	I	J	K	
1 (Mar-18)	0	1	0	3	0	0	1	1	0	2	0	8
2 (Apr-18)	0	1	0	1	1	1	2	2	0	0	0	8
3 (May-18)	2	2	0	1	1	0	1	1	1	1	0	10
4 (June-18)	0	3	1	2	1	1	2	2	1	0	1	14
5 (July-18)	1	0	0	1	0	0	1	3	1	0	2	9
6 (Aug-18)	0	1	0	3	0	1	0	3	1	0	0	9
7 (Sep-18)	0	0	0	1	0	0	0	7	0	0	1	9
8 (Oct-18)	0	0	1	1	0	0	1	5	0	0	0	8
9 (Nov-18)	1	0	1	2	0	1	0	2	0	0	0	7
10 (Dec-18)	0	0	3	2	0	0	2	3	0	0	1	11
11 (Jan-19)	0	0	1	1	0	0	1	5	0	0	1	9
12 (Feb-18)	0	0	1	1	0	0	0	5	0	0	1	8
Total	4	8	8	19	3	4	11	39	4	3	7	110



A



B

Figure 4. A) *Ae. albopictus* hotspot map based on the contents of 273 modified sticky ovitrap (MSO) sites; B) the monthly *Ae. albopictus* hotspot distribution from March 2018 to February 2019.

November 2018 recorded the lowest number of hotspots (N=7). Table 3 summarizes these results.

Based on the weekly records, 487 *Ae. albopictus* hotspots were recorded over the year investigated. Week 52 recorded the highest number of hotspots with 20, followed by 16 in week 43, 15 in week 41 and 14 in both weeks 5 and 14, with the lowest number (N=4) recorded in weeks 8 and 50. Site H recorded the highest number of hotspots (N=104) followed by 93 in site D, 62 in site G and 51 in site B, while site F recorded the lowest (N=11). The detailed results are presented in Annex III.

Spatial autocorrelation

In general, there seemed to be no spatial autocorrelation based on the total number of *Ae. albopictus* mosquitoes during the study year from March 2018 to February 2019 (Figure 5A). However, when the data were classified into time periods (Figure 5B), the first, second, eighth, ninth and tenth study months stand out. These semivariograms indicated that the number of mosquitoes at any given MSO location was autocorrelated with that of other MSOs within a radius of 50 to 70 m. In relation to the weekly number of *Ae. albopictus* captured, spatial autocorrelation was reported for 15 different weeks. Semivariograms generated for these weeks showed a spatial autocorrelation similar to the 50 to 70 m seen in the monthly data. The details are presented in Annex IV.

Vector density by spatial interpolation

The overall results for the study year showed low *Ae. albopictus* densities (Figure 6). However, the densities were high in site G (northern, north-western and western areas) and site H (northern, central, southern, south-western and south-eastern areas) and at some degree also in site D (in the centre of the study area). With respect to the monthly results, May 2018 recorded the highest number of sites with high vector density areas (N=9) followed by 8 in both August 2018 and February 2019 and 7 in March 2018 and June 2018, while October 2018 recorded the lowest number (N=3). Site H had high vector density areas in all months, while low vector density areas in all sites were found in April 2018, May 2018, June 2018, August 2018, September 2018, November 2018 and January 2019. These results are summarised in Table 4 with the figures presented in Annex V. At the weekly level, week 30 recorded the highest number of sites with high vector density areas (N=10). Site H showed high vector density areas for all weeks except weeks 23 and 52, while low vector densities in all sites were recorded for 34 out of the 52 weeks. The tabulated, weekly analysis details are presented in the Annex VI.

Discussion

The identification of hotspot areas is an important step in optimizing resources for the surveillance of the vector. Intervention activities such as larval/pupal inspection and elimination of potential breeding habitats can be done regularly, which may provide better results in reducing mosquito populations rather than through the traditional approach of control strategies for the whole area (Pessanha *et al*., 2012). For example, identification of the strongest and most consistent *Ae. albopictus* hotspot among many others would facilitate the decision by the health authorities on which site to focus interventions rather than covering a large area, thereby avoiding shortfall in supplies and staff. Previous studies have highlighted the importance of hotspot analysis especially in the assessment of dengue incidence by mapping the patterns, *e.g*., hotspot analysis has been used in Brazil to identify spatial clusters associated with a high risk of dengue and high numbers of *Ae. aegypti* eggs (Pessanha *et al*., 2012). In a local study conducted by Aziz *et al* (2014), this approach was utilised to visualise the density of mosquitoes and hotspots based on the highest Breteau Index, thereby providing beneficial information to the local health authorities for reducing and eradicating the mosquito distribution in high-rise apartment buildings (Focks, 2003). In a neighbouring country, such as Thailand, hotspot detection has also been applied to identify hotspots based on the number of dengue cases associated with high morbidity rates (Jeefoo *et al*., 2011).

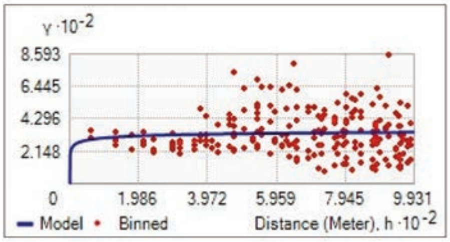
While Duncombe *et al.* (2013) reported radii up to 100 m of spatial autocorrelation for *Ae. aegypti* and *Ae. albopictus* mosquitoes caught by traditional sticky ovitraps, we found shorter distances (approximately 50 to 70 m) based on 5 monthly observations or 15 weekly ones. This information is potentially useful for vector surveillance because it confirmed that the MSOs should be deployed at least 50 m apart to provide comprehensive surveil-

Table 4. The tabulated, monthly variation of *Ae. albopictus* density among the eleven sites.

Month	High-density areas											Low-density areas										
	A	B	C	D	E	F	G	H	I	J	K	A	B	C	D	E	F	G	H	I	J	K
1 (Mar-18)	X	√	X	√	√	X	√	√	√	√	X	√	X	√	√	√	√	X	√	√	√	√
2 (Apr-18)	X	X	X	√	√	X	√	√	X	X	X	√	√	√	√	√	√	√	√	√	√	√
3 (May-18)	√	√	X	√	√	√	√	√	√	√	X	√	√	√	√	√	√	√	√	√	√	√
4 (June-18)	√	√	X	X	√	X	√	√	√	√	X	√	√	√	√	√	√	√	√	√	√	√
5 (July-18)	√	X	X	√	√	X	X	√	√	X	√	√	√	√	X	√	√	√	X	√	√	√
6 (Aug-18)	X	√	√	√	X	√	X	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√
7 (Sep-18)	X	√	X	X	X	X	X	√	X	√	√	√	√	√	√	√	√	√	√	√	√	√
8 (Oct-18)	X	X	√	X	X	X	√	√	X	X	X	√	√	√	X	√	√	√	X	√	√	√
9 (Nov-18)	X	X	√	√	X	X	√	√	X	X	X	√	√	√	√	√	√	√	√	√	√	√
10 (Dec-18)	X	X	√	√	√	X	√	√	X	X	X	√	√	√	X	√	√	√	√	√	√	√
11 (Jan-19)	X	√	√	√	X	X	√	√	X	√	√	√	√	√	√	√	√	√	√	√	√	√
12 (Feb-19)	X	√	√	√	√	X	√	√	X	√	√	X	X	X	X	X	X	X	X	X	X	X

√ √= Yes and X = No with respect to vector density.

A



B

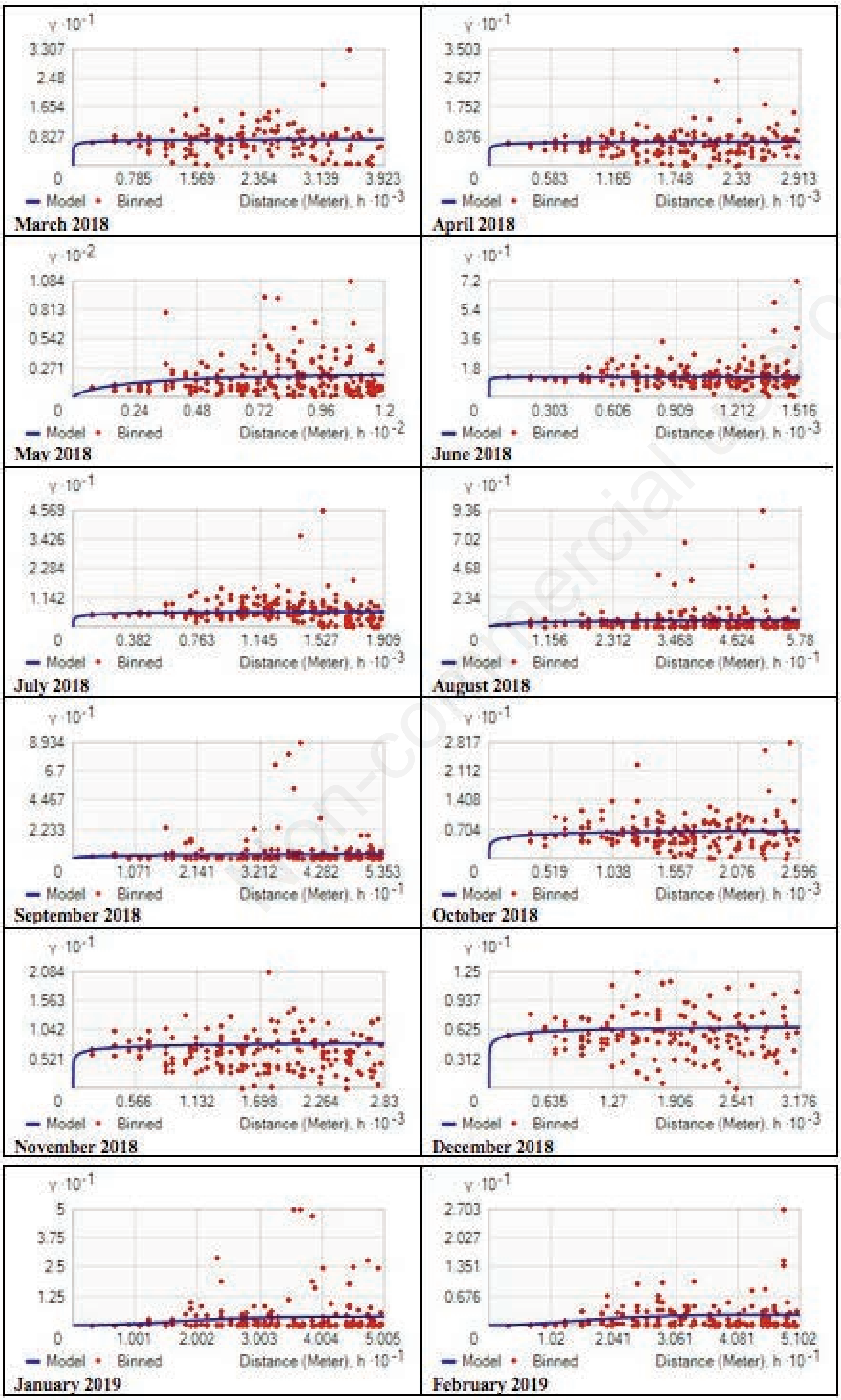


Figure 5. A) ***Ae. albopictus*** **semivariogram based on the total number of mosquitoes caught during the study year; B) Semivariograms of** ***Ae. albopictus*** **of the monthly distribution.**

lance coverage.

Interpolated vector density maps showed high densities of *Ae. albopictus* mosquitoes were predominant in site H from the first until the twelfth month, but such areas were also reported in other sites throughout the surveillance period. The spatial differences of high and low *Ae. albopictus* densities seen in 11 sites could be influenced by geographical characteristics such as vegetation, general sanitation and degree of cleanliness of each household, as well as the oviposition behaviour of the mosquito species as shown by Duncombe *et al*. (2013). As mentioned previously, interpolated mosquito maps showing high densities of *Ae. albopictus* mosquitoes in certain sites can be used to advocate for better resources and improve targeting of prevention activities. Prevention and control programmes at the household level can be conducted by public health workers with the involvement of the community especially the household residents (Arunachalam *et al*., 2010). Since the interpolated maps generated by universal kriging can also be used to identify areas with low densities of *Ae. albopictus*, valuable resources may be released from these sites and utilised in areas with high densities of the species. In addition, universal kriging is widely used by international researchers in spatial statistical studies of other mosquito species, *e.g*., it has been used to estimate the numbers of *Ochlerotatus vigilax*, *Coquillettidia linealis*, *Oc. notoscriptus* and *Cx. annulirostris* at unsampled locations caught using the CDC light traps in Australia (Ryan *et al*., 2004). Since those traps were placed in larger study sites, *i.e*. with distances of 0-1.5 km, 1.5-3 km, 3-4.5 km and 4.5-6 km, determination of spatial autocorrelation was best for only one species (*Oc. vigilax*) and the distance was 0-1.5 km. In fact, *Oc. vigilax* is commonly recognized as the vector for the Ross River (RR) and the Barmah Forest (BF) viruses in Australia (Russell and Dwyer, 2000).

Although geostatistical tools in combating vector borne diseases such as dengue are currently underutilised in Malaysia, the findings of this study suggest that the development of a spatial decision support system (SDSS) should be considered by relevant authorities for the prevention and control programs for most common mosquito-borne diseases such as dengue, malaria, chikungunya and other arbovirus diseases. SDDS has been previously established in the U. S. (Eisen and Eisen, 2011) and Vanuatu Island (Kelly *et al*., 2012). Vazquez Prokopec *et al*. (2010) reported that SDSS could improve the speed, accuracy, and efficiency of indoor residual spraying by controlling and limiting the transmission of dengue virus in Australia. In addition, Kelly *et al.* (2011) described a GIS-based SDSS that could empower and support focal indoor residual spraying (IRS) operations as part of a scaled-up campaign to progressively eliminate malaria in Vanuatu Island and Solomon Island.

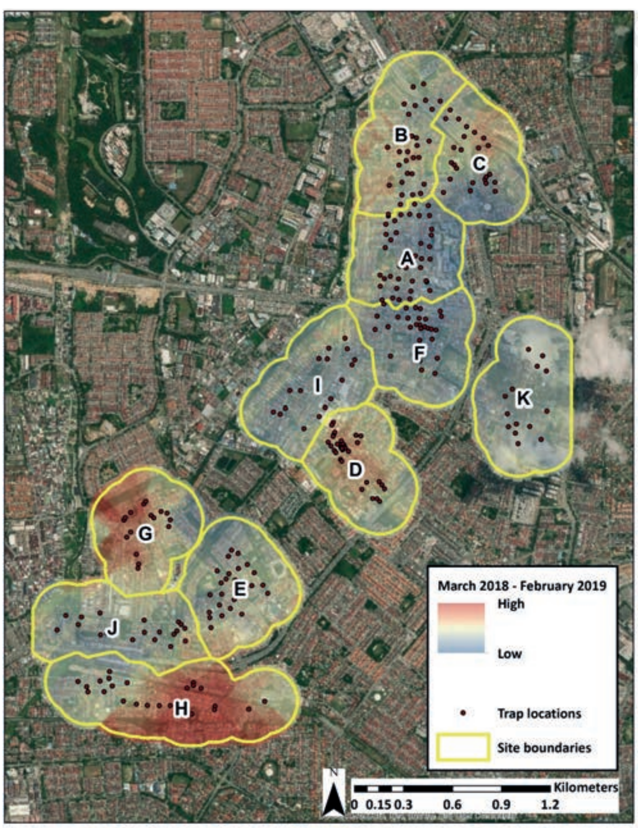


Figure 6. Interpolated maps demonstrating high and low vector densities of *Ae. albopictus* mosquitoes from March 2018 to February 2019.

Conclusions

This study demonstrated the utilisation of GIS and geostatistical methods in determining the spatial dispersal of the dengue vector *Ae. albopictus* mosquitoes captured by MSOs, a newly developed mosquito trapping device, in residential areas with low-rise buildings. The results of the study could assist health authorities in enhancing their current approach of vector control programmes by performing more targeted residual spraying of *Ae. albopictus* resting sites, especially in high-density areas of the species and where hotspots have been found. In addition, house-to-house inspection and larviciding activities can be done regularly by health personnel with community participation, especially where residents know that they live in *Ae. albopictus* high-density areas with high numbers of hotspots. Furthermore, training residents or volunteer workers with respect to technical skills and capability to supervise the prevention and control activities in the absence of health personnel should be a useful adjunct.

References

Abilio AP, Abudasse G, Kampango A, Candrinho B, Sitoi S, Luciano J, Tembisse D, Sibindy S, de Almeida A, Garcia GA, David MR, Maciel-de-Freitas R, Gudo ES, 2018. Distribution and breeding sites of Aedes aegypti and Aedes albopictus in 32 urban/peri-urban districts of Mozambique: implication for assessing the risk of arbovirus outbreaks. PLoS Negl Trop Dis 12:e0006692.

Ahmad DM, Azman A, Hafizan J, Kamaruzzaman Y, Ismail ZA, Nur HS, Mohamed AA, Romizan O, Mohd Khairul AK, Muhammad BG, 2015. Geographical Information System (GIS) for relationship between dengue disease and climatic factors at Cheras, Malaysia. Malaysian J Anal Sci 19:1318-26.

Ahmad R, Ali WN, Nor ZM, Ismail Z, Hadi AA, Ibrahim MN, Lim

LH, 2011. Mapping of mosquito breeding sites in malaria endemic areas in Pos Lenjang, Kuala Lipis, Pahang, Malaysia. Malar J 10:361.
Ali M, Wagatsuma Y, Emch M, Breiman RF, 2003. Use of a geographic information system for defining spatial risk for dengue transmission in Bangladesh: role for Aedes albopictus in an urban outbreak. Am J Trop Med Hyg 69:634-40.
Alias H, Surin J, Mahmud R, Shafie A, Mohd Zin J, Mohamad Nor M, Ibrahim AS, Rundi, C, 2014. Spatial distribution of malaria in Peninsular Malaysia from 2000 to 2009. Parasit Vectors 7:186.
Arunachalam N, Tana S, Espino F, Kittayapong P, Abeyewickreme W, Wai KT, Tyagi BK, Kroeger A, Sommerfeld J, Petzold M, 2010. Eco-bio-social determinants of dengue vector breeding: a multicountry study in urban and periurban Asia. Bull World Health Organ 88:173-184.
Azami NA, Salleh SA, Shah SA, Neoh HM, Othman Z, Zakaria SZ, Jamal R, 2013. Emergence of chikungunya seropositivity in healthy Malaysian adults residing in outbreak-free locations: chikungunya seroprevalence results from the Malaysian Cohort. BMC Infect Dis 13:67.
Aziz S, 2011. Evaluation of the spatial risk factors for high incidence of dengue fever and dengue hemorrhagic fever using GIS application. Sains Malays 40:937-43.
Aziz S, Aidil RM, Nisfariza MN, Ngui R, Lim YA, Yusoff WS, Ruslan R, 2014. Spatial density of Aedes distribution in urban areas: a case study of Breteau index in Kuala Lumpur, Malaysia. J Vector Borne Dis 51:91-6.
Aziz S, Ngui R, Lim YA, Sholehah I, Nur Farhana J, Azizan AS, Wan Yusoff, WS, 2012. Spatial pattern of 2009 dengue distribution in Kuala Lumpur using GIS application. Trop Biomed 29:113-20.
Bagny Beilhe L, Arnoux S, Delatte H, Lajoie G, Fontenille D, 2012. Spread of invasive Aedes albopictus and decline of resident Aedes aegypti in urban areas of Mayotte 2007-2010. Biol Invasions 14:1623-33.
Brassel KE, Reif D, 1979. A procedure to generate Thiessen Polygons. Geogr Anal 11:289-303.
Bonizzoni M, Gasperi G, Chen X, James AA, 2013. The invasive mosquito species Aedes albopictus: current knowledge and future perspectives. Trends Parasitol 29:460-8.
Carbajo AE, Schweigmann N, Curto SI, de Garin A, Bejaran R, 2001. Dengue transmission risk maps of Argentina. Trop Med Int Health 6:170-83.
Chang AY, Parrales ME, Jimenez J, Sobieszczyk ME, Hammer SM, Copenhaver DJ, Kulkarni RP, 2009. Combining Google Earth and GIS mapping technologies in a dengue surveillance system for developing countries. Int J Health Geogr 8:49.
Chansang C, Kittayapong P, 2007. Application of mosquito sampling count and geospatial methods to improve dengue vector surveillance. Am J Trop Med Hyg 77:897-902.
Cressie NA, 1991. The origins of kriging. Math Geol 22:239-52.
Duncombe J, Espino F, Marollano K, Velazco A, Ritchie SA, Hu WB, Weinstein P, Clements AC, 2013. Characterising the spatial dynamics of sympatric Aedes aegypti and Aedes albopictus populations in the Philippines. Geospat Health 8:255-65.
Eisen L, Eisen RJ, 2011. Using geographic information systems and decision support systems for the prediction, prevention, and control of vector-borne diseases. Annu Rev Entomol 56:41-61.
Er AC, Rosli MH, Asmahani A, Mohamad Naim MR, Harsuzilawati M, 2010. Spatial mapping of dengue incidence: a case study in Hulu Langat district, Selangor, Malaysia. Int J Human Soc Sci 5:410-4.
Flipse J, Smit JM, 2015. The complexity of a dengue vaccine: a review of the human antibody response. PLoS Negl Trop Dis 9:e0003749.
Focks DA, 2003. A review of entomological sampling methods and indicators for dengue vectors. World Health Organization, Geneva.
Getis A, Morrison AC, Gray K, Scott TW, 2003. Characteristics of the spatial pattern of the dengue vector, Aedes aegypti, in Iquitos, Peru. Am J Trop Med Hyg 69:494-505.
Hassan H, Shohaimi S, Hashim NR, 2012. Risk mapping of dengue in Selangor and Kuala Lumpur, Malaysia. Geospat Health 7:21-25.
Hazrin M, Hiong HG, Jai N, Yeop N, Hatta M, Paiwai F, Joanita S, Othman W, 2016. Spatial distribution of dengue incidence: a case study in Putrajaya. J Geogr Inf Syst 8:89-97.
Heinisch M, Diaz-Quijano FA, Chiaravalloti-Neto F, Menezes Pancetti FG, Rocha Coelho R, Dos Santos Andrade P, Urbinatti PR, de Almeida R, Lima-Camara TN, 2019. Seasonal and spatial distribution of Aedes aegypti and Aedes albopictus in a municipal urban park in Sao Paulo, SP, Brazil. Acta Trop 189:104-13.
Honorio NA, Silva W, Leite PJ, Goncalves JM, Lounibos LP, Lourenço-de-Oliveira R, 2003. Dispersal of Aedes aegypti and Aedes albopictus (Diptera: Culicidae) in an urban endemic dengue area in the state of Rio de Janeiro, Brazil. Mem Inst Oswaldo Cruz 98:191-8.
Hu W, Clements A, Williams G, Tong S, Mengersen K, 2012. Spatial patterns and socioecological drivers of dengue fever transmission in Queensland, Australia. Environ Health Perspect 120:260-6.
Jeefoo P, Tripathi NK, Souris M, 2011. Spatio-temporal diffusion pattern and hotspot detection of dengue in Chachoengsao province, Thailand. Int J Environ Res Public Health 8:51-74.
Johari NA, Voon K, Toh SY, Sulaiman LH, Yap I, Lim P, 2019. Sylvatic dengue virus type 4 in Aedes aegypti and Aedes albopictus mosquitoes in an urban setting in Peninsular Malaysia. PLoS Negl Trop Dis 13:e0007889.
Kamal M, Kenawy MA, Rady MH, Khaled AS, Samy AM, 2018. Mapping the global potential distributions of two arboviral vectors Aedes aegypti and Ae. albopictus under changing climate. PLoS One 13:e0210122.
Kelly GC, Seng CM, Donald W, Taleo G, Nausien J, Batarii W, Iata H, Tanner M, Vestergaard LS, Clements AC, 2011. A spatial decision support system for guiding focal indoor residual interventions in a malaria elimination zone. Geospat Health 6:21-31.
Kelly GC, Tanner M, Vallely A, Clements A, 2012. Malaria elimination: moving forward with spatial decision support systems. Trends Parasitol 28:297-304.
Lam NSN, 1983. Spatial interpolation methods: a review. Am Cartogr 10:129-50.
Li Z, Yin W, Clements A, Williams G, Lai S, Zhou H, Zhao D, Guo Y, Zhang Y, Wang J, Hu W, Yang W, 2012. Spatiotemporal analysis of indigenous and imported dengue fever cases in Guangdong province, China. BMC Infect Dis 12:132.
Liew C, Curtis CF, 2004. Horizontal and vertical dispersal of dengue vector mosquitoes, Aedes aegypti and Aedes albopictus, in Singapore. Med Vet Entomol 18:351-60.

Ling CY, Gruebner O, Kramer A, Lakes T, 2014. Spatio-temporal patterns of dengue in Malaysia: combining address and sub-district level. Geospat Health 9:131-40.

Lozano-Fuentes S, Elizondo-Quiroga D, Farfan-Ale JA, Loroño-Pino MA, Garcia-Rejon J, Gomez-Carro S, Lira-Zumbardo V, Najera-Vazquez R, Fernandez-Salas I, Calderon-Martinez J, Dominguez-Galera M, Mis-Avila P, Morris N, Coleman M, Moore CG, Beaty BJ, Eisen L, 2008. Use of Google Earth to strengthen public health capacity and facilitate management of vector-borne diseases in resource-poor environments. Bull World Health Organ 86:718-25.

Maciel-de-Freitas R, Neto RB, Goncalves JM, Codeço CT, Lourenço-de-Oliveira R, 2006. Movement of dengue vectors between the human modified environment and an urban forest in Rio de Janeiro. J Med Entomol 43:1112-20.

Majid NA, Nazi NM, Mohamed AF, 2019. Distribution and spatial pattern analysis on dengue cases in Seremban district, Negeri Sembilan, Malaysia. Sustainability 11:1-4.

Masnita MY, Nazri CD, Ariza Z, 2016. Spatial pattern distribution of dengue fever in sub-urban area using GIS tools. Serangga 21:127-48.

Moreno-Sanchez R, Hayden M, Janes C, Anderson G, 2006. A web-based multimedia spatial information system to document Aedes aegypti breeding sites and dengue fever risk along the US-Mexico border. Health Place 12:715-27.

Murphy A, Rajahram GS, Jilip J, Maluda M, William T, Hu W, Reid S, Devine GJ, Frentiu FD, 2020. Incidence and epidemiological features of dengue in Sabah, Malaysia. PLoS Negl Trop Dis 14:e0007504.

Nazri CD, Ahmad AH, Ishak AR, Ismail R, 2013. Assessing the risk of dengue fever based on the epidemiological, environmental and entomological variables. Procedia Soc Behav Sci 105:183-94.

Norzawati Y, Mohd Maher I, Chong JH, Husna Mahirah S, Nur Adawiyah A, Ang BY, 2015. Spatial distribution of dengue vectors in Malaysia. Med J Malaysia 70:54.

Oliver MA, Webster R, 1990. Kriging: a method of interpolation for geographical information systems. Int J Geogr Inf Syst 4:313-32.

Ord JK, Getis A, 1995. Local spatial autocorrelation statistics: distributional issues and an application. Geogr Anal 27:286-306.

Pahrol MA, Noraishah MS, Nasir RA, 2018. Spatial distribution of malaria incidence in Sabah from 2012 to 2016. Geoinfor Geostat 6:3.

Pessanha JE, Caiaffa WT, Almeida MC, Brandao ST, Proietti FA, 2012. Diffusion pattern and hotspot detection of dengue in Belo Horizonte, Minas Gerais, Brazil. J Trop Med 2012:760951.

Pfeiffer DU, Robinson TP, Stevenson M, Stevens KB, Rogers DJ, Clements AC, 2008. Spatial analysis in epidemiology. Oxford: Oxford University Press.

Richards SL, Apperson CS, Ghosh SK, Cheshire HM, Zeichner BC, 2006. Spatial analysis of Aedes albopictus (Diptera: Culicidae) oviposition in suburban neighborhoods of a Piedmont community in North Carolina. J Med Entomol 43:976-89.

Rohani A, Azahary A, Zurainee M, Wan Najdah W, Zamree I, Hanif M, Ariffin M, Zuhaizam H, Suzilah I, Lee H, 2016. Comparative human landing catch and cdc light trap in mosquito sampling in Knowlesi malaria endemic areas in Peninsula Malaysia. Adv Entomol 4:1-10.

Rozilawati H, Tanaselvi K, Nazni WA, Mohd Masri S, Zairi J, Adanan CR, Lee HL, 2015. Surveillance of Aedes albopictus Skuse breeding preference in selected dengue outbreak localities, peninsular Malaysia. Trop Biomed 32:49-64.

Russell RC, Dwyer DE, 2000. Arboviruses associated with human disease in Australia. Microbes Infect 2:1693-704.

Ryan PA, Lyons SA, Alsemgeest D, Thomas P, Kay BH, 2004. Spatial statistical analysis of adult mosquito (Diptera: Culicidae) counts: an example using light trap data, in Redland Shire, Southeastern Queensland, Australia. J Med Entomol 41:1143-56.

Sithiprasasna R, Patpoparn S, Attatippaholkun W, Suvannadabba S, Srisuphanunt M, 2004. The geographic information system as an epidemiological tool in the surveillance of dengue virus-infected Aedes mosquitos. Southeast Asian J Trop Med Public Health 35:918-26.

Tsuda Y, Suwonkerd W, Chawprom S, Prajakwong S, Takagi M, 2006. Different spatial distribution of Aedes aegypti and Aedes albopictus along an urban-rural gradient and the relating environmental factors examined in three villages in northern Thailand. J Am Mosq Control Assoc 22:222-8.

Vazquez-Prokopec GM, Kitron U, Montgomery B, Horne P, Ritchie SA, 2010. Quantifying the spatial dimension of dengue virus epidemic spread within a tropical urban environment. PLoS Negl Trop Dis 4:e920.

Vythilingam I, Lim YA, Venugopalan B, Ngui R, Leong CS, Wong ML, Khaw L, Goh X, Yap N, Sulaiman WY, Jeffery J, Zawiah AG, Nor Aszlina I, Sharma RS, Yee Ling L, Mahmud R, 2014. Plasmodium knowlesi malaria an emerging public health problem in Hulu Selangor, Selangor, Malaysia (2009-2013): epidemiologic and entomologic analysis. Parasit Vectors 7:436.

Wieczorek, WF, Delmerico AM, 2009. Geographic information systems. Comput Stat 1:167-86.