



Examples of using spatial information technologies for mapping and modelling mosquito-borne diseases based on environmental, climatic and socio-economic factors and different spatial statistics, temporal risk indices and spatial analysis: A review

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Abstract

The best way to avoid the impact of mosquito-borne diseases (MBDs) is to control and monitor their vectors and their environmental conditions. Spatial information technologies (SITs) are required for forecasting, controlling, monitoring and early detection of these environmental conditions and prevention of mosquito-borne diseases. Different SITs have shown promising results in assessing the risk of various MBDs at different spatial scales. SITs such as the geographic information system (GIS) and remote sensing (RS) and their related techniques cannot identify the vectors of MBDs themselves, but they can characterise the environment in which the vectors thrive. As new tools of surveillance, SITs are powerful predictors in the mapping and modelling of the geographical limits, intensity, and dynamics of the risk of MBDs. This literature review concentrates on MBDs that are transmitted by mosquito-borne viruses. Additionally, the main aim of this review is to give overview examples of how mapping and modelling based on SITs (e.g. GIS and its related tools) approaches are used to visualise and analyse mosquito vector and epidemiologic data and to describe the factors that can help in the control of these diseases. Using spatial information technologies and other methods with climatic, socio-economic and environmental factors and mosquito distribution pattern(s), it should be possible to extract the risk-areas at a predetermined spatial scale of investigation. Also, many points that are extracted from this review described the importance of using spatial information technologies and their related spatial statistics, temporal risk indices and analyst methods. This review also highlights the knowledge gaps in this area of research.

Key words: Spatial information technologies, mosquito-borne diseases, geographic information system, remote sensing.

Introduction

Mosquito-borne diseases (MBDs) are a major world health problem, especially in tropical and subtropical areas. In some countries, particularly developing countries, many development projects are delayed as a result of the impact of mosquito-borne diseases. No medical vaccinations exist for some of these diseases; therefore, the best way to avoid their impact is to control and monitor their vectors and their environmental conditions. SITs support visualizing and analysing spatial and space-time patterns for entomological and epidemiological data and producing risk models for vector and MBDs virus exposure. Due to their capacities to link different types of information on environmental, climatic and socioeconomic factors for a given area, they can be used in different spatial statistics analysis and development of spatial databases that can be applied in a wide range of public health programs¹. However, few literature reviews have described the use of mapping and modelling approaches of spatial information technologies in the field of mosquito-borne diseases. The critically important issue of the potential of such technologies and methodologies for operational surveillance and control of MBDs in tropical and subtropical areas has not received the attention it deserves. Modification of modelling and mapping solutions for use in disease endemic environments must be made part of the new frontier in mosquito-borne diseases research. This literature review concentrates on MBDs that are transmitted by mosquito-

borne viruses. Additionally, the main aim of this review is to give overview examples of how mapping and modelling based on SITs (e.g. GIS and its related tools) approaches are used to visualise and analyse mosquito vector and epidemiologic data and to describe the factors that can help in the control of these diseases.

Using Remotely Sensed (RS) Data in the Epidemiology of Mosquito-Borne Diseases

Mosquitoes cause illness and death in more than 300 million clinical cases every year around the world. MBDs such as malaria, dengue fever (DF), dengue hemorrhagic fever (DHF), yellow fever (YF), West Nile Virus (WNV) and Rift Valley fever (RVF) are of great public concern². They have been studied using RS data. Depending on the biological criteria and environmental conditions, the mosquito density can be determined. Remote sensors can provide low or high spatial resolution imagery that can be utilised to model these conditions. The result of these models provides information on the spatial and temporal characteristics of preferred mosquito environmental settings. The potential links between remotely sensed environmental conditions and mosquito habitats are summarised in Table 1³.

Many studies suggest that remote sensing imagery is a viable predictor of mosquito-borne disease transmission. For example, some studies indicated that higher malaria incidence rates were

Table 1. Remotely sensed environmental factors and mosquito habitats ³.

Remotely sensed factors	Description	Remotely sensed factors	Description
Deforestation	Habitat creation (sunlight pools)	Vegetation/ Crop style	Breeding, resting and feed habitats
Flooded forests	Mosquito habitats	Wetland	Mosquito habitats
Flooding	Mosquito habitats	Soil moisture	Breeding habitat
Permanent water	Mosquito habitats	Canals	Dry season mosquito habitat
Vegetation green up (Response to a rainfall events)	Timing of habitat creation	Human settlements	Source of infected humans, population at risk for transmission

associated with broadleaf hill forests, agricultural land, wetland, and vegetation types, and the lower rates were related to coastal swamps, tall herbs, wetland communities, urban development, and water bodies ⁴. A correlation study of supervised land cover classification on Landsat ETM imagery and data from a ground mosquito survey showed that malaria carrying mosquito populations are prevalent in rice paddies and forest lands in Thailand and Madagascar ⁵. Also, Landsat ETM images were used to build a controlling system that was able to determine the outbreak probability of the diseases, especially the recognition of high risk malaria regions in Iran ⁶. Pope *et al.* ⁷ used Landsat TM for deriving larva habitats in surface water, vegetation, and other variables. They classified high and mixed mangroves as low producers of malaria mosquitoes, while low mangrove and salt marshes and mudflats were classified as medium producers. They also classified savannah, woodland, lower pasture, grassland, and riparian zones as high producers of malaria mosquitoes. Roberts *et al.* ⁸ used SPOT images to show the probability of malaria mosquito presence depending on the amount of forest between houses and waterways, the distance of houses from waterways, and altitudes above specified waterways. The results showed that the closest areas to the water in both distance and altitude have the highest probability of mosquito presence. Kaya *et al.* ⁹ used RADARSAT-1 data for interpreting risk areas of malaria in coastal Kenya. They produced a risk map that showed most of the population was located within two km of potential malaria carrying mosquito breeding grounds.

Many researchers ^{3, 5a, 5b, 10-13} considered vegetation indices as the most consistent predictor of mosquito-borne disease transmission; therefore, they have been widely used in epidemiological studies. The normalised difference vegetation index (NDVI), which is the measure of photosynthetic activity of vegetation, is the most common index of vegetation growth. By transforming the digital values of the visible wavelength in the red band (R) (0.58 to 0.68 μm) and near-infrared band (NIR) band (0.72 to 1.10 μm) NDVI can be determined, and through these bands the representative values of photosynthetic activity can be achieved. The NDVI is defined as:

$$\text{NDVI} = \frac{\text{NIR}-\text{R}}{\text{NIR}+\text{R}} \quad (1)$$

The result of the NDVI calculation is given as a number that ranges from -1 to 1; no vegetation gives a value close to 0, and close to 1 indicates the highest possible density of healthy vegetation. The premise behind NDVI is that a low reflectance in the visible red wavelength in the electromagnetic spectrum represents healthy vegetation because photosynthetic pigments in plant tissue absorb such light and reflect it strongly in the near-infrared wavelength, which is a phenomenon not commonly found

in other natural objects ¹⁰. According to Wilder ¹¹, “the strength of photosynthetic activity is influenced by many environmental factors including precipitation, land types, soil contamination, humidity, elevation, land surface and climatic temperature, which can account for observed differences in vegetation density, health, and evapo-transpiration rates”. Generally, at 0.4 and greater an area is thought to be almost entirely covered by forest, greenery, or other vegetation ¹², and the NDVI value of 0.5 and greater in non-forest land is typically in response to a prolonged precipitation event that can determine the development of mosquitoes. Many epidemiological studies are examples of using NDVI in MBDs. Brownstein *et al.* ¹³ studied West Nile Virus distribution in 1999 using remote sensing and geographic information system technologies. Cluster analysis revealed the presence of a statistically significant grouping of cases, which also indicated the area of probable virus introduction. Within the cluster, habitat suitability for potentially infective adult mosquitoes was measured by the amount of vegetation cover using satellite imagery. A logistic regression analysis model revealed satellite-derived vegetation abundance to be significantly and positively associated with the presence of human cases. In addition, the model showed the probability of a human case of WNV within the previously defined cluster according to mean NDVI ($p = 0.05$). As a result, the probability of a human case of WN increased with increasing NDVI up to a threshold NDVI of 0.22 and then decreased. Hay *et al.* ¹⁴ used a statistical examination of the NDVI threshold values and mean percentage of total malaria admissions in Kenya using linear regression to produce a coefficient of determination, r^2 , of 0.73 for NDVI thresholds between 0.3 and 0.4. This coefficient suggests that the range of NDVI thresholds holds a strong predictive strength of malaria risk. The study also showed that no results for NDVI threshold values were greater than 0.5, which may be explained by sustained torrential rains during the study period. It is possible that these rains destroyed mosquito larvae before they matured into adults. Monthly NDVI extracted from the Advanced Very High Resolution Radiometer (AVHRR) have been used to predict spatial dynamics of dengue mosquitoes ¹⁵. Additionally, to study the epidemiology of DHF in Thailand, Sithiprasasna *et al.* ¹⁶ used NOAA and AVHRR data to derive NDVI and variables associated with DHF transmission.

Another remotely sensed factor is soil moisture that can be used to determine suitable habitats for mosquito eggs and larvae. Different types of remote sensing sensors are used to detect soil moisture. Examples are Landsat TM, Spot, NOAA-AVHRR, ENVISAT-1 ASAR, Landsat ETM and Radarsat ³. Additionally, some models can be used to estimate soil moisture. For example, Patz *et al.* ¹⁰ used a water balance model (WatBal) to estimate weekly soil moisture. The model changed the soil moisture by taking into account precipitation, runoff, soil characteristics, and evapo-transpiration. Potential evapo-transpiration can be used

to extract water from the soil. The value of modelled soil moisture represents the percentage of maximum capacity or relative soil moisture. For instance, 0.8 means that soil moisture is at 80% of full capacity. In the area of MBDs, a small number of studies have used soil moisture as an environmental indicator to illustrate the abundance of mosquitoes. For example, Patz *et al.*¹⁰ predicted key malaria transmission factors, biting, and entological inoculation rates using modelled soil moisture in Kenya. They found that the modelled soil moisture substantially improved prediction of biting rates compared to rainfall. In addition, soil moisture lagged two weeks explained up to 45% of *Anopheles gambiae* biting variability compared to 80% for raw precipitation.

Mosquito-Borne Diseases of Urban Area and RS Data

Millions of people living in urban areas are at risk for contracting dengue fever and malaria¹⁷. High resolution images with less than 5 Mpixel size are needed to study infectious disease risks in urban areas. High resolution data is helpful in studying factors affecting reservoir distribution in urban areas. Very few studies in infectious diseases have used high resolution images such as IKONOS, Quick-bird, and SPOT. These multispectral data applications have good spatial resolution, which can lead to the identification of small areas within cities such as trees, buildings, distance between residences, and rooftops¹⁸. IKONOS images were employed in previous studies to display *Anopheles* distribution². They were also used to construct a household GIS database for health studies¹⁹. High resolution imagery has generated land use and land cover classifications for integration with a GIS to study malaria transmission risk in Thailand^{5a}. Landsat ETM+ and SPOT images were used in Korea to study *Anopheles* mosquito habitats¹¹. Also, colour infrared aerial photography was used in the forested and open wetlands, marshes and residential areas to control *Aedes* and *Culex* mosquitoes in Michigan²⁰. Troyo² observed that “some researches in the study of epidemiology of diseases in urban areas like malaria and dengue fever have begun and the application of high resolution imagery within the urban environment is yet to be analysed”. Remote sensing is a valuable tool in disease surveillance, especially in mosquito-borne diseases. RS data can help epidemiologists to derive risk areas, vector distributions, and relationships between diseases and environmental variables.

Using GIS for Mapping and Modelling Mosquito-Borne Diseases

Geographic Information System (GIS) contains useful tools for monitoring, controlling, predicting, mapping and modelling MBDs due to its capability to capture, store, retrieve, manage, integrate, analyse and display geographical and non geographical data. GIS-based MBD occurrences or risk maps and models are increasingly used in endemic areas around the world.

Examples of mapping and modelling filariasis, Lyme and West Nile Virus (WNV): Filariasis is a harbouring mosquito-borne disease; the infected person can remain asymptomatic and in many cases have no knowledge of being infected for up to 15 years. In East Asian countries such as Indonesia, China and India, filariasis has become a serious health issue²¹. India has the largest number of infected people, predominantly with *lymphatic filariasis*. Different models have been built depending on environmental and climatic parameters such as temperature, relative humidity,

rainfall, water stagnation spots, water quality, forest types and soil types. These variables were used for creating the filariasis transmission risk index (FTRI)²¹. Also, filariasis risk maps for the Tamil Nadu region of India were produced using the same variables²².

GIS has been applied to generate risk models for tick-borne diseases such as Lyme. The environmental factors for Lyme disease have been identified and located by Glass *et al.*²³, who found that eleven of fifty-three environmental factors were associated with an increased risk of Lyme disease. They subsequently built a risk model that combined GIS with logistic regression analysis.

Historically, WNV appeared in Uganda in 1937. Outbreaks have since occurred sporadically in Africa, Asia, Eastern Europe and North America²⁴. Mosquitoes are the principle transmitters of WNV. WNV requires infected animals such as birds and mosquitoes to be transmitted to human. GIS and other geographical techniques have been used to model and map WNV risk. For example, Allen and Wong²⁵ applied kernel density estimation on mosquito data and land cover to explore the spatial pattern of potential risk for WNV. They also used population data, data of facilities and positive dead bird data to identify areas of high risk intensity of WNV by creating a buffer around positive dead birds. A group at New York's Hunter College developed the Dynamic Continuous-Area Space-Time (DCAST) model to identify and monitor high risk areas for WNV in New York City²⁶. The main parts of this model are dead bird reports and a Knox Test for space time interactions²⁶. Additionally, a group of students working for NASA created a model of WNV based on suitable mosquito habitats that derived from satellite imagery. The result showed the risk location of humans 55 and older and their proximity to WNV carrying mosquito habitat²⁷.

Examples of mapping and modelling of malaria: One of the most dangerous MBDs worldwide is malaria, with cases occurring in more than 92 countries. *Plasmodium vivax*, *P. falciparum*, *P. malariae* and *P. ovale* are the causes of human malaria. In tropical and sub-tropical countries, about 70 species are vectors of malaria under natural conditions; the major vectors are female *Anopheles* mosquitoes²⁸. According to WHO²⁹ malaria has emerged as the top infectious killer and the top tropical and sub-tropical disease.

Many studies have used GIS to describe malaria epidemiology. Epidemiologists used habitat suitability models to study the distribution and abundance of several malaria species. These models were developed mainly in the fields of biogeography and conservation biology. The quantification of relations between the species and several environmental factors were the basis of these models³⁰. In mainland Portugal, Capinha *et al.*^{28b} used values of former malaria distribution and suitable habitats to produce binary maps of suitable and unsuitable areas for *Anopheles artoparvus*. The maps showed that former malaria distribution was similar to *Anopheles* distribution in Portugal, suggesting that habitat models of vectors can be good surrogates in the spatial assessment of malaria risk.

For formulating a prompt and focused malaria control strategy, an information management system based on GIS using district and block-wise malaria data was constructed to map and highlight hot spots of malaria in Madhya Pradesh in India³¹. As a result, the map displayed 58 blocks showing 25 districts as hot spots. The map helped the decision makers to keep those areas under intensive

treatment. Additionally, Bogh *et al.*³² geo-referenced a Landsat TM image that contained 10 classes of land cover to UTM zone 28 based on the 1:50,000 national survey map of Gambia. They digitised additional features including national borders, main roads, villages and edges of flood plains. They overlaid the mosquito data with the 10 classes of land cover and additional features to produce maps that showed the habitats representing suitable breeding areas for mosquitoes.

A GIS approach to map malaria risk in Africa was established by the South African Medical Research Council (SAMRC) with support from the International Development Research Centre (IDRC)³³. Statistical modelling, climatological charts, and field work were included in this project to produce a state map of malaria. In addition, the progress and current status of GIS with reference to *Plasmodium falciparum* malaria in sub-Saharan Africa was reviewed³⁴. Hay *et al.*³⁵ focused on the ecology of *Plasmodium falciparum* and its major *Anopheles* vectors to provide a background for the study of transmission processes and their environment correlates. In addition, due to the lack of spatially defined data and a clear understanding of how epidemiological variables relate to disease outcome, the limited use of epidemiological maps in malaria control in Kenya was noted³⁶.

In India, villages with unsuitable malaria conditions were determined using topographical maps, satellite generated maps, and Arc Info software³⁷. A composite map featured 13 stratification classes by sequentially integrating environmental factors such as hydro-geomorphology, water table level, water quality, soil type, and relief and irrigation channels. This study found that malaria incidence is mainly related to water table, soil type, irrigation, and water quality³¹. In China, particularly Yunan province, GIS and multiple regressions was used to determine the nature and extent of factors influencing malaria transmission. The data of 1990-1996 were collected and analysed; the results showed that the combined physical environmental effects, the presence of compatible vectors, and the degree of population mobility influence the malaria situation³⁸.

Examples of mapping and modelling dengue fever (DF): DF is a family of viruses (*DEN-1,-2,-3,-4*) that are transmitted by mosquitoes. It is an acute disease of abrupt onset that usually follows a benign course with headache, fever, exhaustion, severe joint and muscle pain, swollen glands and rash³⁹. DF attacks people who have low levels of immunity. Therefore, it is possible to get DF multiple times. An attack of dengue produces immunity for a lifetime only to that particular type to which the patient was exposed⁴⁰. Nowadays, DF is prevalent throughout tropical and subtropical regions around the world, predominantly in urban and semi-urban areas. Outbreaks have occurred in the South and South East Asia, Caribbean, the U.S. Virgin Islands, Cuba, Central America, Australia and Saudi Arabia.

GIS was applied in the study of dengue fever in a number of studies. Barrera *et al.*⁴¹ investigated stratification of a city with hyper-endemic dengue hemorrhagic fever transmission to identify hotspots for the application of surveillance and control measures. GIS also have been applied to analyse economic resources and diseases with reference to DF and malaria in Thailand. Provincial products and healthcare resources in relation to geographical distribution were examined in this study. The authors argued that, at national and multi-country levels, overall planning can be done;

they also admitted that the disease data and socioeconomic data were collected at different times and in different ways, and thus limited dynamic interpolation of the two data sets⁴².

Tran *et al.*⁴³ used the Knox test, a classic space-time analysis technique, to detect spatio-temporal clustering and demonstrated the relevance and potential of the use of GIS and spatial statistics for elaboration of a dengue fever surveillance strategy. Strickman and Kittayapong⁴⁴ identified locations with higher concentrations of the dengue vectors using spatial analysis. To visualise and map the effect of open marsh water management for mosquito vector control when merged with invasive plant and salt marsh restoration, GIS was used. The results showed a significant reduction in the frequency of finding larvae on the marsh surface leading to loss of spatial larval hotspots in the area under open marsh water management⁴⁵.

Morrison *et al.*⁴⁶ did a space-time analysis of reported dengue cases during an outbreak in Florida in 1991-1992. Pratt⁴⁷ wrote that "incorporating traditional epidemiological statistical techniques into a GIS interface allows researchers to gain a greater insight into the spatial aspect of the spread of disease". Tan and Song⁴⁸ in their study of the use of GIS in ovitraps monitoring for dengue control in Singapore, developed three models to monitor, analyse, and evaluate ovitrap breeding data to better understand the *Aedes* situation on the island for planning vector surveillance and control operations. Household surveys of dengue infection during 2001-2002, spatial point pattern analysis, and risk factor assessment were used to illustrate the spatial heterogeneity in the risk areas of dengue when using a spatial approach in a short time interval. The results pointed out that the low prevalence areas in 2001 shifted to high risk areas in the following year⁴⁹.

Schafer and Lundstrom⁵⁰ used the geographical distribution of *Aedes sticticus* and climate change data to model the future distribution of this vector. The model showed that the *Aedes sticticus* potential areas with suitable conditions would likely increase. An information value method in the GIS environment was used to analyse and obtain the influence of physio-environmental factors such as land use and land cover on the incidence of DF⁵¹. Chansang and Kittayapong⁵² integrated immature sampling methodology to GIS technology to produce spatial density distribution maps and to identify the clusters of immature stages and breeding sources for improving the surveillance and control systems of *Aedes aegypti*. This study found that water jars of various types and cement bath basin were the two main breeding sources. In the state of Hawaii, geographic analysis and GIS spatial/temporal analysis were conducted on the 2001-2002 DF outbreaks to create the dengue threat model⁵³. Takumi *et al.*⁵⁴ assessed whether *Aedes albopictus* that were found at Lucky Bamboo import companies in the Netherlands could produce subsequent generations. Based on GIS and collected climatic variables data, they located suitable and unsuitable regions for the *Aedes albopictus* species.

In Brazil's Rio de Janeiro State, maps of *Aedes aegypti* density were generated using the Infestation Index obtained from the *Aedes aegypti* Infestation Index Rapid Survey, the Breteau index, and spatial pattern analysis⁵⁵. The map represented five areas with high and medium density of positive *Aedes aegypti* breeding locations and highlighted small block clusters with high larvae density. Chaikoolvatana *et al.*⁵⁶ aimed to develop a GIS for *Aedes aegypti* surveillance and dengue hemorrhagic fever in north

eastern Thailand. The development went through three stages of collecting primary and secondary data, such as dengue vector incidence, water storage containers, and number of reported dengue hemorrhagic fever cases/100,000 population, analysing the data, searching the target location and presenting the results via figures on maps. There was an increase in the number of dengue hemorrhagic fever cases during a high disease incidence, suggesting a strong correlation between the peak rainfall, the high density of *Aedes aegypti* mosquitoes and the high incidence of DHF cases. In Singapore, people assumed that the *Aedes aegypti* mosquito breeds indoors and people are infected in their homes; however, GIS showed that the groups most infected by DF and DHF were very mobile such as teenagers and young adults who spend most of the time outdoors. The surveillance systems were changed to fortnightly checks on outdoor areas. The result of this change showed a decline in the number of dengue fever and dengue hemorrhagic fever cases⁵⁷. This study is an example of how GIS can lead to a decision that diminishes the prevalence of the diseases.

Using Spatial Statistics, Temporal Risk Indices and Analyst Methods on MBDs

Mosquito-borne disease studies have used many types of spatial statistics, spatial analyst methods and temporal indices. In their use of spatial statistical methods, many researchers used modeling spatial relationships between different variables using geographically weighted regression (GWR) to model the suitable areas of vectors to breed and the areas of disease prevalence. Mapping cluster methods also have been applied to study the presence of vectors and places under the impact of MBDs. Mapping cluster and spatial cluster methods that have been applied are K-means partitioning, space-time permutation, scan statistic, and hot spots clustering. In addition, spatial autocorrelation is used for analysing patterns of the disease. On the other hand, spatial analyst methods are used to study different sorts of MBDs. Density analysis such as kernel density estimation and interpolation methods such as IDW and kriging are the

common tools of spatial analysis. Temporal risk indices are also used to illustrate the frequency, duration, and intensity of MBDs (Fig.1). The following paragraphs provide more information about all these methods and provide some examples of their uses in MBDs.

Kernel Density Estimation (KDE)

The data on mosquitoes and MBD cases often appear as discrete events. KDE is used to create surfaces based on the discrete events to indicate the intensity of a disease or phenomenon. Using the density surface can help epidemiologists to identify MBD hot spots and cold spots. The hot spots are the number of frequency of events that are spatially clustered to a local area. The cold spots are events that occur with much less frequency in a local area. Many studies have used KDE for analyzing the prevalence of MBDs. For example, KDE was used to discover the spatial patterns of potential risk for West Nile Virus based upon positive dead bird data²⁵. Lagrotta *et al.*⁵⁵ also used KDE to analyze the spatial patterns of *Aedes aegypti* based on the data of an *Aedes aegypti* infestation index. The results allowed the researcher to determine high building infestation densities.

Spatial Interpolation

Spatial interpolation methods are widely used to predict values of unknown geographic value point data and then to interpolate new data points, filter signals from noise, or smooth data. Inverse distance weighting (IDW) and Kriging are the two common and simplest spatial interpolation methods. In IDW, neighborhoods around the interpolated points are identified, and then the weighted averages are taken from the observation values within neighborhoods⁵⁸. The kriging method is used to predict unknown point values based on surrounding and known point values. Kriging is a technique of spatial estimation that uses a weighted moving average interpolation to produce an optimal spatial linear prediction⁵⁹. It reflects the minimum square error. Therefore, it has been used in geo-statistics as an interpolation method, and it is considered the best linear estimation of the characteristics under

study. In epidemiological studies, especially of MBDs, kriging has been used widely. For instance, Ribeiro *et al.*⁶⁰ used it to illustrate the *Anopheles gambia* mosquito distribution in houses in a village in Ethiopia. Kriging also has been employed in approaches for improving malaria prediction at a local level in Mali⁶¹. Disease spread over large areas has been the subject of more recent studies that used kriging to predict the underlying spatial processes of MBD epidemics in general and MBD epidemics in particular.

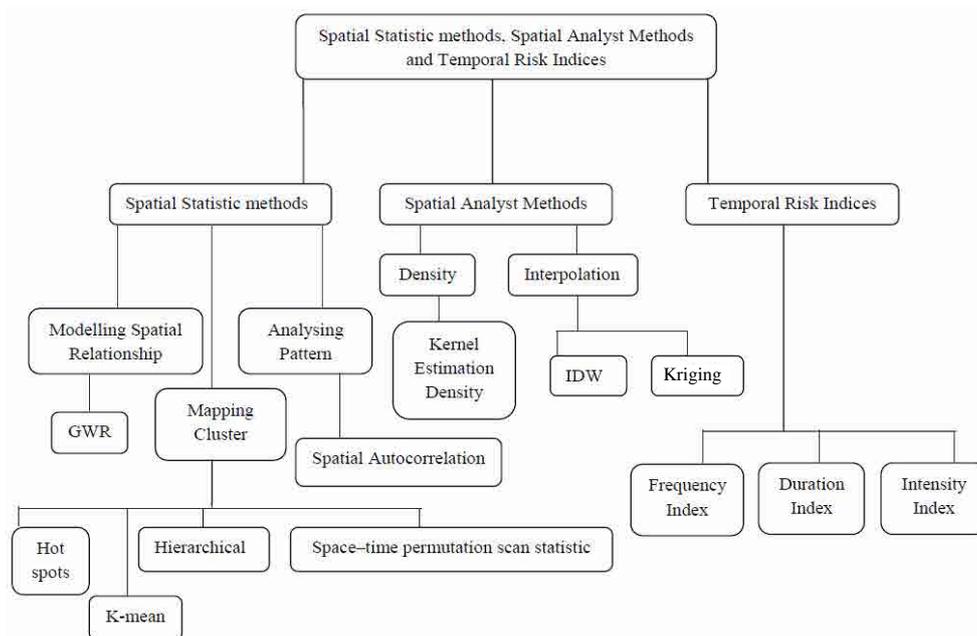


Figure 1. Representing spatial statistic methods, spatial analyst methods and temporal risk indices.

Geographical Weighted Regression (GWR)

The association between different types of factors such as environment, climate, and socioeconomics is critical. Many spatial analyses are used for that purpose. One of these spatial analyses is GWR, which was developed to measure spatial dependency of neighbours specified by distance or sample data. It provides an efficient way to analyse the point pattern at a local scale without studying the overall point pattern in the whole study region⁶². Comparison of the P-value of each variable that can be used in GWR to the critical 95% helps to determine whether an observed pattern is related to a true spatial trend or random variation in the local model. GWR analysis software can output files that can be linked to the Arc GIS for mapping purposes. GWR has a number of models such as the Gaussian model. It is an ordinary least squares regression with geographically weighted function. However, many studies have used it to describe the pattern of MBDs and the variation that can form their patterns. For example, it was applied to study the association between dengue fever cases and population density and dengue fever cases and rainfall in Johor State, Malaysia⁶³. In this study, GWR produced a set of local parameters estimated for each location as separate files. These files were used as input files to Arc GIS to visualise the spatial variability of the parameters. Then, kriging interpolation was used to generate the surface of local parameters that were estimated from GWR⁶³.

Spatial Autocorrelation (*Moran's I*)

This method measures the spatial autocorrelation of a disease based on the disease locations and the disease values, simultaneously. It assesses whether the disease pattern expressed is dispersed, clustered, or random. The *Moran's I* index value is calculated using this method, and both a p-value and Z score evaluate the significance of that index. The value of spatial autocorrelation near to -1 indicates dispersion and +1 indicates clustering. The null hypothesis indicates no spatial clustering of the values associated with geographic features in the study; as a result, the null hypothesis can be rejected⁶⁴. The spatial autocorrelation (*Moran's I*) has been used in many studies of MBDs. For example, Kitron and Kazmierczak⁶⁵ used it to identify the degree of spatial clustering of Lyme disease cases, ticks and forested vegetation, and they also used it to determine the distances where spatial effects are maximised. As a result, they assigned cases to the county level and the spatial pattern that they found indicated relatively large geographic areas (cluster of counties) as being risk areas for Lyme disease. Nakhapakorn and Jirakajohnkool⁶⁶ mapped the local indicators of spatial autocorrelation in Sukhothai province, Thailand. In this study, the local *Moran's I* reflected that the average of DF and DHF case prevalence in the northern part of the province had the highest local *Moran's I* value. Results of this type of analysis lead to more comprehensive knowledge of how spatial patterns will change from the past to the future.

Temporal Risk Indices

According to Wen *et al.*⁶⁷, the disease occurrence can be described as either a sporadic or clustering event both temporally and spatially. An intensive contact with contagion and the environmental factors or the risk factors results in an infectious disease epidemic⁶⁸. However, a number of indicators have been

used to measure the magnitude and severity of MBD, taking into account temporal factors in dealing with environmental risk identification. Firstly, the frequency index is defined as the probability of one or more confirmed cases that occur in a certain week or weeks. Epidemiologists need variables to apply the frequency index, which are the total number of weeks during the entire epidemic period (TW), and the total number of weeks in which one or more cases occurred during the entire epidemic period (EW). The frequency index can be defined as $f = EW/TW$. The frequency index value (f) ranges from 0 to 1. If the value of f is equal to or approaches 1, the possibility of disease occurrence in a certain week or weeks increases^{67,68}. Secondly, the duration index reflects the effectiveness of the prevention or control strategies used during the epidemic. Two variables are important to apply the duration index (d). These variables are the total number of weeks in which one or more cases occurred during the entire epidemic period (EW), and the total number of epidemic waves during the entire period (EV). EV is defined as the number of weeks in which cases successively occur. A larger value of (d) means the cases are less likely to disappear once they occur and there is more chance of virus mutation^{67,68}. Thirdly, the intensity index indicates the likely magnitude within an epidemic wave when more than one case occurs. The intensity index needs the application of the incidence rate during the defined epidemic period (IR), and the total number of epidemic waves during the entire period (EV). The incidence rate measures the magnitude of new cases appearing during a specified period, but it cannot measure the weekly severity during the period. The spatial temporal approach that includes the temporal risk indices has been used in MBDs. For example, these indices were applied to the DF epidemic in Taiwan in 2002 as a case study^{67,69}. These indices provided a procedure to identify spatial health risk levels with temporal characteristics. Additionally, they were used to generate spatial risk maps to improve spatial clustering analyses that focused on case-incidence data⁶⁷.

Climatic Variables and Climatic Change Impacts on Mosquito Borne Diseases (MBDs)

Temperature, relative humidity and precipitation play important roles in the mosquito density population and also in the replication and transmission of MBD. According to Wallis²⁷, mosquitoes are critically dependent on climate for their survival and development. Also, climate circumscribes the distribution of MBDs, while weather impacts the timing and intensity of outbreaks. In general, temperature ranges from 14-18°C at the lower end and 35-40°C at the upper end can lead to higher transmission occurrence⁷⁰. Development increases in warmer temperature, raising the odds of disease transmission, while the reproduction rates and replication of diseases are slower in cooler temperatures^{70,71}. In general, high amounts of precipitation lead to increases in the number of breeding sites, and humidity is often overlooked as a factor in the life cycle of mosquitoes and in disease replication and transmission. Relative humidity is increased by rainfall particularly following drought. Relative humidity strongly impacts flight and the subsequent host seeking behaviour of mosquitoes⁷². Many studies used the climate variable impact MBD distributions. For instance, Moore *et al.*⁷³ predicted *Aedes aegypti* abundance from climatological data, finding that temperature was not a good indicator of larval abundance. In their study, the amount of rainfall

and the number of rainy days were useful predictors of larval abundance. In Mexico, the average temperature during the rainy season related strongly to the estimated risk of dengue infection. In addition, there was a significant relationship between humidity and infection⁷⁴. Weekly dengue morbidity data and monthly rainfall data of Trinidad were analysed, and the results suggested that there is a significant relationship between the temperature and the dengue incidence rates with a six month time lag and a slightly negative correlation with the rainfall rate⁷⁵. Lindsay and Birley⁷⁶ developed a model to illustrate the impact of small increases in the temperature on transmission of *Plasmodium vivax* malaria. The results showed that, at low temperatures, small increases lead to large reductions in the time for malaria development and hence a disproportionate increase in transmission. They considered different aspects of the influence of global environmental change and emphasized that the direct effects of temperature increase on malaria would be most obvious in highland areas of Ethiopia, Madagascar and Kenya⁷⁷.

There is increasing scientific interest in the potential effects of global climate change on health. Global climate change re-merged recently and re-spread mosquito-borne diseases to new areas, extending the risk season for infection and maintaining a high incidence level. Spreading global warming has caused the spread of mosquito-borne diseases to new suitable habitats such as water pools. Dengue fever, Lyme disease, malaria, West Nile Virus and yellow fever are examples of MBDs that are influenced by climate change⁷⁸. Rapid climate change, e.g. the sustained global warming of 0.2°C per decade, raises many questions about how MBDs will be impacted. Recently, many studies have been conducted to answer this question. For example, Hales *et al.*⁷⁹ modelled the reported global distribution of dengue fever on the basis of vapour pressure, which is a measure of humidity. They also assessed the changes in the geographical limits of dengue fever transmission and in the number of people at risk of dengue by incorporating future climate change and human population projections into the model. Estimates of population and climate change projections for 2085 showed that 5-6 billion people would be at risk of dengue fever transmission compared with 3.5 billion people if climate change did not happen⁷⁹. Tonnang *et al.*⁸⁰ predicted and mapped malaria in a climate change scenario in Africa. The result of this study showed that western and central regions of Africa may become unsuitable habitats for mosquitoes, while the malaria vector may shift towards the eastern and southern regions of continent; therefore, the southern and eastern areas of Africa might become more favourable for the development of the African malaria vectors⁸⁰.

Conclusions

This review has shown the different application areas of spatial information technologies (e.g. Geographic Information System and remote sensing in the study of mosquito-borne diseases). Some key points emanating from this review are:

- There is an increase of using SITs such as GIS and RS in the study of mosquito-borne diseases.
- The use of spatial information technologies and their related tools with environmental and climatic factors could lead to the formulation of specific plans to manage or control MBDs.
- Techniques of spatial epidemiology used with the above factors can generate recommendations concerning target intervention and

disease prevention. Remote sensing sensors provide good data to the epidemiologist with high temporal and spatial resolution.

- Improvements in both sensor capabilities and data processing algorithms enable estimates of parameters such as rainfall, temperature, humidity, soil moisture, land cover type, vegetation cover, and other suitable mosquito habitats directly from space, and have diminished the need to use surrogate variables.
- GIS has the capability of not only mapping and modelling with high accuracy but also using satellite images, allowing it to merge ground observations of vector demographics and disease incidence more accurately.
- User-friendly SIT software supports visualizing spatial and space-time patterns for entomological and epidemiological data. SIT software also produces risk models for vector and MBDs virus exposure due to its capacities to link different types of information on environmental, climatic, and socioeconomic factors for a given area, to apply different spatial statistics analysis, and to develop spatial databases that can be applied in a wide range of public health programs.

This review also highlights the knowledge gaps in this area of research:

- The quantitative relationships between environmental, socio-economic and climatic variables and the transmission of MBD remain unclear. Further study is needed.
- Spatio-temporal models using environmental factors (e.g. vegetation cover, soil types), socio-economic factors (e.g. income, sex, age) and climatic factors (e.g. temperature, humidity, and rainfall) have not been formally attempted.
- Predictive models for manipulation of GIS, RS and applications of spatio-temporal analytic methods are yet to be developed for the surveillance and control of some mosquito-borne diseases such as DF.
- Few studies have been undertaken to look at the epidemiology of dengue fever and malaria in urban areas.
- High resolution imagery within the urban environment has not been used widely.

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