Review Article

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Application of spatial technology in malaria research & control: some new insights

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Geographical information System (GIS) has emerged as the core of the spatial technology which integrates wide range of dataset available from different sources including Remote Sensing (RS) and Global Positioning System (GPS). Literature published during the decade (1998-2007) has been compiled and grouped into six categories according to the usage of the technology in malaria epidemiology. Different GIS modules like spatial data sources, mapping and geo-processing tools, distance calculation, digital elevation model (DEM), buffer zone and geo-statistical analysis have been investigated in detail, illustrated with examples as per the derived results. These GIS tools have contributed immensely in understanding the epidemiological processes of malaria and examples drawn have shown that GIS is now widely used for research and decision making in malaria control. Statistical data analysis currently is the most consistent and established set of tools to analyze spatial datasets. The desired future development of GIS is in line with the utilization of geo-statistical tools which combined with high quality data has capability to provide new insight into malaria epidemiology and the complexity of its transmission potential in endemic areas.

Key words GIS - GPS - malaria - remote sensing - spatial epidemiology

Introduction

Malaria is a major global health problem. Worldwide malaria affects 3.5-5.0 billion people and has devastating effects on health and development with at least one million deaths taking place annually[1]. About 70-90 per cent of the risk of malaria is considered due to environmental factors which in turn influence the abundance and survival of the vectors[2]. This has motivated the World Health Organization (WHO) to pursue the development of new techniques and models in which the role of environmental is fundamental. Spatial technology helps systematic and regular monitoring of the earth's environmental conditions furnishing large amounts of spatial and temporal data. Such information together with appropriate field studies can prove very fruitful for early detection and timely response to disease management.

The powerful tools of the spatial technology have revolutionized the way the epidemiological research now being carried out. Spatial technology has clearly defined the epidemiology of disease vis-a-vis environmental factors by identifying the spatial limits of the disease prevalence and risk mapping with relevant risk factors. The relationships between the disease prevalence and vector distribution could have never been so comprehensively studied without this technology. Space based images has made getting information for vast and inaccessible areas easy and collection of data and sophisticated judgment and analysis possible. Now management of malaria is easier with the help of the generated risk maps demonstrating hot areas with risk factors.

Spatial technology is a field of information technology that acquires, manages, interprets, integrates, displays, analyzes and uses datasets focusing on the geographic, temporal and spatial reference. Spatial technology includes wide array of the technologies such as Geographic Information System (GIS), Remote Sensing (RS) and Global Positioning System (GPS).

GIS is defined as an information system that is used to input, store, retrieve, manipulate, analyze and output geographically referenced data or spatial data. All methods of collecting information about earth without touching it are forms of remote sensing. Satellites, radars and aerial photographs are the different ways of acquiring remotely sensed data. GPS is a system of twenty-four satellites that allows the co-ordinates of any point on or near earth's surface to be measured with extremely high precision[3]. GIS is an umbrella term which integrates wide range of datasets available from different sources including RS and GPS. Therefore, GIS is often termed as core of spatial technology having built-in power to analyze integrated dataset and to present the results as useful information to assist decision making.

This article attempts to present the technology of GIS and its functionalities with regard to applications in malaria research and control during the last decade. The research articles have been grouped into six categories according to the usage of the technology. Spatial data sources, mapping and geo-processing tools, distance calculation, digital elevation model (DEM), model, buffer zone, and geo-statistical analysis have been investigated in detail, illustrated with examples as per the derived results. Finally, a conclusion is drawn incorporating various aspects of malaria epidemiology covered by different tools and future prospects for better decision support.

GIS in malaria research and control

(i) Spatial data sources: Epidemiology of vector-borne diseases is changing fast with the availability of data using new methods of spatial data collection like GPS and RS. The GPS has been used mainly for field data collection and remote sensing by means of aerial photographs and satellite imageries has succeeded in providing descriptive climatic and landscape features.

RS data in GIS have been used widely for identification, characterization, monitoring, surveillance of breeding habitats and mapping of malaria risk. GIS maps developed from aerial photographs in Dar-es-Salaam, Tanzania facilitated efficient larval surveillance and complete coverage of targeted areas with larval control[4]. Remote sensing imageries in a GIS was used for identification and characterization of the habitats that produced potential *Anopheles* vector mosquitoes in the Republic of Korea[5]. Integrated use of remote sensing and GIS has been successfully demonstrated in many studies related to mapping of malaria risk in different parts of Africa[6-7].

Combined with data from surveillance activities, GIS and GPS are ideal tools for generating base maps, mapping breeding habitats and analysis of areas of high disease prevalence. Mapping of the study site, Mulago III parish - a typical urban slum located in Kampala, the capital of Uganda was done using GPS and GIS to generate a sampling frame for a longitudinal study of malaria incidence and treatment[8]. GPS data integrated into a GIS were used to map anopheline larval habitats in the Suba district in Western Kenya[9]. GPS recording of the co-ordinates and elevation of anopheline larvae aquatic sites, integrated and mapped using a GIS helped determine *An. arabiensis* breeding on the Mount Kenya highlands indicating indigenous malaria transmission in the area[10]. GPS data of *Anopheles* sp. breeding sites integrated into the digital map of Ouagadougou, Africa, helped analyze a gradient of endemicity between the urban centre and the periphery[11].

(ii) Mapping and geo-processing tools: GIS mapping and geo-processing tools have contributed immensely towards the development of spatial epidemiology of malaria. GIS has enabled data to be geo-referenced, mapped and geo-processed to carry out sophisticated analysis. Geo-processing by means of overlay and intersection has helped in building spatial analysis. Overlay combines two or more map layers within a GIS to create one or more new map layers of new information. Examples have been drawn from the studies done in various countries making use of these spatial features for deriving useful results.

GIS-based malaria incidence mapping has been used for risk assessment at national, regional, town and village level. Such mapping is considered crucial for analyzing past as well as present disease trends.

Risks maps developed on the basis of mapped malaria incidence are tools for targeted and cost-effective control of disease. Mapping of both *Plasmodium vivax* and *P. falciparum* malaria incidence distribution for 8 years (1995-2002) on the islands of Sri Lanka at sub-district resolution helped in the assessment of malaria risk in the country[12]. This mapping was updated for 10 months preceding tsunami in December 2004 to assess the post-disaster malaria situation in Sri Lanka[13]. GIS was used to perform a retrospective analysis of malaria case data for the past 37 years and district-wise malaria incidence data for past 6 years to determine the spatial and temporal dynamics of *P. falciparum* and *P. vivax* malaria incidence in Thailand[14]. GIS was introduced in Mpumalanga province of South Africa to stratify malaria risk on the basis of disease incidence at town and village level[15]. Section-wise mapping of malaria incidence from 1991-2001 helped identify malaria receptivity and trends within each paradigm of Mewat district, Haryana, India[16].

Many maps of global malaria risk distribution in space and time have been prepared using GIS. Mapping the global distribution of malaria is motivated by a need to define populations at risk for appropriate resource allocation to combat the disease. Hay *et al*[17] used GIS to overlay historical maps of malaria risk to create a single global distribution map of malaria risk which illustrated range changing from 1900 to 2002. Also overlaying of contemporaneous population surfaces helped quantify changes in the numbers of people living in areas of malaria risk. Snow *et al*[18] defined the global extent of the clinical episodes caused by *P. faliciparum* worldwide by combining epidemiological, geographical and demographic data. Guerra *et al*[19] constructed an evidenced based spatial description of the global distribution of *P. falciparum* and *P. vivax* by combing in a GIS several sources of information on malaria risk. Combining these maps with those of human population distribution enabled estimates of the global population at risk of *P. falciparum* and *P. vivax* malaria during 2005. A newly launched 'Malaria Atlas Project (MAP)' is developing global maps of malaria transmission intensity to identify the distribution of populations at risk on the basis of classified malaria endemicity based on globally generated parasite rate database[20].

Spatial analyses using geo-processing tools had assisted in establishing relationship between malaria incidence and other potentially related variables. Such studies are done to identify risk factors for high receptivity. GIS based malaria information management system developed for urban malaria scheme in India ensured that if a localized spurt of the disease occurs, it can be associated rapidly with a likely cause, a specific vector and a probable human source so that appropriate preventive action can be taken to arrest any rising trend[21].

The distribution of malaria vector mosquitoes, especially those belonging to species complexes that contain non vector species, is important for strategic planning of malaria control programmes. GIS mapping was used to produce overall distribution maps for the six species of *An. gambiae Giles* complex together with environmental parameters such as rainfall and temperature in Africa[22]. GIS was used to describe overall extent of *An. dirus* complex distribution and its distribution across Southeast Asia[23]. A map of global distribution of dominant vectors in each endemic or potentially endemic region was prepared using GIS mapping[24]. In India, GIS was used to map the distribution of three important vectors of malaria namely *An. dirus* - the vector of deep forested areas, *An. minimus* - the vector of forest fringe areas to support precision surveys and to formulate species-specific control measures[25,26].

GIS mapping has assisted in monitoring and evaluation of malaria control activities in various countries. GIS mapping based insecticide spraying operations management system in southern Africa proved useful in malaria control by monitoring spraying coverage, insecticide consumption and application rates on an ongoing basis[27]. Sub-district level mapping of the indicators for roll back malaria (RBM) like possession of bed nets, usage, re-treatment of insecticide treated bed nets, prophylaxis with antimalarials for pregnant women and prompt and affective case management of malaria were used to identify geographical disparities of core population coverage for monitoring and evaluation of malaria control goals in Malawi, Africa[28].

(iii) Distance calculation: Measuring distance is one of the most fundamental functionalities of the GIS. Euclidean/ straight line or linear distance function measures distance from one point to another on a plane. The applications of GIS-distance parameter have been substantiated by different examples depicting the growing importance of this parameter in malaria research and control.

Of the prime importance in malaria risk mapping is the association between malaria incidence and distance from houses to breeding sites which has been documented from different parts of the world where different vectors play role in malaria transmission[29-30]. This parameter was quantified by Hoek *et al*[31] suggesting the use of a distance of 750 m as cut-off point for developing a risk map of malaria in Sri Lanka.

Various aspects of malaria epidemiology have been depicted by GIS distance calculation. Use of GIS-distance parameter constituted an essential part of the methodology of the assessment of malaria situation in municipalities of Philippines[32]. Higher parasite prevalence among patients of rural Philippines could be explained as a function of distance parameter from vector larval habitats[33]. Assessment of risk factors for *P. falciparum* and *P. vivax* infections in Cambodia used distance-to-forest and distance-to-hospital parameters[34].

Entomological studies based on distance parameter have been documented from various areas. A strong association of the distance of less than 750 meters between a house and the main vector-breeding site with the presence of *An. culicifacies* in the house suggested a modification in residual insecticide-spraying programme in Sri Lanka with focus on residential areas within 750 m of streams and rivers thus making residual spraying more cost-effective[35]. In lower altitudes of western Kenya, Minakawa *et al*[36] showed that over 90 per cent of adult mosquitoes were found in houses within 300 m distance of the nearest larval habitats. Geographical variability of entomological parameters such as human biting rate (HBR) was found significantly correlated with the distance of the dwellings to the closest water point in a high transmission village of Equatorial Guinea[37]. Spatial distribution patterns of *An. subpictus* larval densities varied as a function of distance from coast to the larval breeding habitats in Sekotong district of Indonesia[38].

The concept of distance as a primary influence on malaria related hospital admissions, prevalence and mortality has been well established by various studies done in wider African settings. In Kumasi, the second-largest city in Ghana, greater distance from the health facility was one of the significant risk factors for higher prevalence of *P. falciparum* and anaemia among children[39]. Schellenberg *et al*[40] investigated in children that rate of admission of patients with severe malaria to Kilifi district hospital, Kenya, was strongly associated with the distance a child lived from the hospital and to the distance from a road. Noor *et al*[41] used GIS straight-line distance analysis to define the population's overall access to government health services as part of malaria planning and monitoring in Kenya.

Analysis of child morbidity and mortality data from large-scale insecticide-treated bed nets (ITN) trials in Africa was based on GIS measured distance function. In Ghana, Binka *et al*[42] showed that mortality rates of children living in control compounds increased with increasing distance from the nearest ITN compound. Similarly, rates of severe clinical malaria in coastal Kenya were lower in children living in houses lacking ITNs but living at distances up to 1.5 km away from houses which had nets[43]. Children residing in control villages in western Kenya but within 300 m of an intervention village had a lower risk of malaria parasitaemia, high-density parasitaemia, anaemia, and death relative to children who lived near the center of a control village[44].

Linear distance measurement has been used in various studies conducted to analyze focal nature of malaria transmission in African highlands which were previously found free from it. Decreased risk of malaria was associated with increased distance from the forest fringe and swamps and increased risk was associated with longer distance to the health center in highland areas of west Kenya[45]. Minakawa *et al*[46] demonstrated that anopheline larval habitat during the dry season was significantly more clustered compared with the rainy season at the distances up to 0.3 and 0.6 km in valley bottoms. Carlson *et al*[47] found that the houses closest to brick-making pits had malaria vectors thus identifying the latter as man-made dry season local habitats of malaria vectors in highlands of western Kenya.

(iv)Digital elevation model (DEM) : A digital elevation model (DEM) is a digital representation of ground surface topography or terrain. Elevation data are used to create DEM which may be in the form of spot heights or contours. A DEM can be represented as a raster (a grid of squares) or as a vector triangular irregular network (TIN). DEM is used to calculate derivatives such as slope, aspect, and wetness index which have been applied in many studies relating malaria to topography. Slope is a measurement of how steep the ground surface is. Aspect of land surface is the terrain orientation which is derived from slope, and wetness index is considered an approximate measure of predicted water accumulation.

Wetness index provides a meaningful description of how topography may affect malaria risk via suitability for potential mosquito breeding. In western Kenya highlands, wetness index derived from spatial modeling (DEM) was found significantly associated with the occurrence of aquatic habitats during dry and rainy seasons[48]. Also wetness index helped characterize the spatial patterns of vector breeding habitats in northwestern area of Thailand[49]. DEM based spatial modeling is an ideal tool to map and characterize vector breeding habitats. In Central Brazil, multi-temporal shoreline simulations through DEM-based GIS-analyses contributed to *An. darlingi* habitat characterization and mapping in hydropower plant reservoir area[50].

Topography is an important factor in understanding the malaria epidemiological situation at local scale. Topography and slope derived from TIN model explained the difference in the distribution of malaria and schistosomiasis in two municipal sites of Philippines[32]. In Tanzania, TIN helped identify down slope flat areas of malaria risk illustrating how topography could help identify local areas prone to epidemics in the highlands[51].

(v) Buffer zone analysis: Buffering, the most commonly defined neighbourhood function involves the ability to create distance buffers around selected features. Buffers are created as polygons because they represent an area around a feature. Some features may have a greater zone of influence due to specific characteristics, accordingly different size buffers can be generated for features within a data layer[52]. Technically buffering is a process in which a certain distance or width is selected and a zone is created physically on the map based on this distance.

Buffer zones have been used to identify disease risk areas where control activities need to be strengthened. Also quantification of the risk areas according to size or distance helps in selecting control activities. In Natroun lakes area of Egypt, GIS was used to create 2 km buffer zones around breeding habitats to delineate risk areas of mosquito nuisance and disease transmission[53]. Estimating rice in a 900-meter buffer area around the villages in Mali, Africa, resulted in the best correlation with mosquito abundance. The quantification of this relationship between *An. gambiae* abundance and rice cultivation resulted in decision support to prevent malaria in these high risk villages[54]. Buffers were constructed around two US army camps based on the flight range of *An. sinensis,* reported to be about 1 km. The sizes of all habitats inside the buffer were quantified to estimate the cost of larviciding around each of the camps thus helping in decision support of the selection of appropriate measures for malaria control for the protection of US army personnel in the Republic of Korea[55].

Buffer zone analysis has also been used to study the impact of risk factors based interventions. In an endemic region of southern Sri Lanka, poor house construction type was found to be a malaria risk determinant and exclusion of all these houses from the buffer zone of 200 m around bodies of water was estimated to lead to a 21 per cent reduction of the malaria incidence in the overall population and a 43 per cent reduction in the relocated community[56].

(vi) Geo-statistical analysis: Geo-statistics refers to the collection of statistical methods in which location data plays an important role in the study design or data analysis. Geo-statistical analysis in malaria epidemiology in relation to exploratory data analysis and disease mapping is described here. Exploratory data analysis refers to describing patterns in the distribution of a disease using location data. Kriging is one of the methods used for disease mapping. Kriging is a group of geo-statistical techniques to interpolate the value of a variable at non sampled locations based on the observations at known locations.

Exploratory data analysis for GPS generated location data linked with epidemiological information incorporates statistical methods for point pattern analysis in a GIS. These studies range from detecting high risk malarious areas, identifying the presence of spatial and spatial-temporal clusters to studying the micro-geographic variation of malaria incidence in time and space. Spatial scan and k-nearest neighbor (k-NN) statistics are the statistical methods to detect probable location and quantification of the clustering of cases in a defined geographic area. In Northern Peruvian Amazon, GIS, GPS and spatial scan statistic were used to detect spatial clusters and spatial-temporal clusters by *Plasmodium* species and to identify high risk areas to target control efforts[57]. Brooker *et al* demonstrated spatial clustering of malaria cases in children during an epidemic in a single year using geo-referenced data of the households with malaria cases in Kapkangani location of Nandi district in the highlands of western Kenya[58]. Ernst *et al*[59] identified a significant spatial cluster of malaria cases all four years in the same geographic location of Kipsamoite highland area of Nandi district of western Kenya. Individuals who lived in the area of spatial clustering had a consistently >3-fold greater risk of contracting malaria than individuals who lived outside the cluster area. Determination of imported cases of malaria in urban areas and locating clusters around large port cities of Trinidad was done by locating all malaria cases by GPS, defining attribute data in a GIS and analyzing spatial and temporal distribution with *k*-NN statistic for space-time clustering[60].

Disease mapping using interpolating estimates of disease occurrence from a regional database to a continuous surface has been done using geostatistical prediction method of kriging. Kriging significantly improved the prediction of malaria risk at local level using malaria prevalence data collated from surveys of childhood populations in Mali since 1960[61]. Space time kriging was used to predict the values of malaria cases at health facilities in Kenya where monthly records were missing in order to get reliable estimates of national outpatient malaria treatment burdens for accurate quantification for health system planning[62]. Spatially smoothed data are more appropriate for disease mapping than raw rates. Kriging was applied to the incidence data for the construction of a smoothed map of higher malaria and typhoid fever incidence areas in the slums of Kolkata, India[63].

Conclusion

The variety of analyses using different GIS tools demonstrates tremendous capabilities of the technology available to epidemiologists and researchers. Integration of GIS with remote sensing helped in identification, characterization, monitoring and surveillance of breeding habitats and mapping of malaria risk areas. GPS data in a GIS assisted in generating base map, mapping breeding habitats and analysis of areas of high disease prevalence. GIS-based malaria incidence mapping assisted in risk mapping for analyzing past as well as present trends. Mapping has been extensively used in preparing maps of global malaria risk distribution in space and time. Spatial analyses using geo-processing tools have assisted in establishing relationship between malaria incidence and other potentially related factors. GIS mapping helped determine distribution of malaria vector mosquitoes along with monitoring and evaluation of malaria control activities in various countries.

The role of GIS distance parameter in development of risk maps, assessment of malaria situation in different countries, analyzing focal nature of malaria transmission in highland areas, analysis of child morbidity and mortality data from large scale ITN trials, malaria-related hospital admission and mortality has been established by a number of studies carried out in various settings. Digital elevation modeling has helped to understand the role of topography in malaria epidemiology at local scale. Buffer zone analysis has helped to identify risk areas and the impact of the risk factors based interventions. Geostatistical analysis contributed to identify the presence of spatial and spatial-temporal clusters to study the micro-geographic variation of malaria incidence in time and space. Prediction of malaria cases at places where data were missing using kriging helped to get reliable estimates of national outpatient malaria treatment burden in time and space. The future development of GIS with the utilization of geo-statistical tools combined with high quality data has capability to provide new insight into malaria epidemiology and the complexity of its transmission potential in endmic areas.

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