GeoJournal (2017) 82:1101–1111
DOI 10.1007/s10708-016-9732-0

Modelling malaria susceptibility using geographic information system

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Published online: 18 July 2016

Abstract Identifying and/or predicting the geography of malaria will help decision makers locate the particular area with the health problem, and to design area-specific interventions. Using GIS (ArcMap 10.1), a spatial analysis of environmental factors that contribute to the spread of malaria vector was conducted to develop a malaria susceptibility model that could be used in effective malaria control planning. The study first determined malaria susceptibility index and combined it with geospatial modelling to predict malaria susceptibility. Clinical malaria cases were then geocoded and tested to determine the accuracy of the prediction. The results show that 72.3, 24.5, 3.1 and 0.1 % of the clinical malaria incidence were found in areas that were predicted to have *very high, high, low* and *very low* susceptibility levels. Hence, the model, to a large extent, predicted malaria occurrences. The conclusion is that modelling such as this can help determine spatio-temporal prediction and mapping of malaria incidence to aid in the design and administration of appropriate interventions.

Keywords ArcMap · Geospatial modelling · GIS · Malaria susceptibility index · Saboba

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Introduction

In 1854, John Snow used a dot map to identify a cluster of cholera cases around a public water pump. This enabled him trace the source of a cholera outbreak in Soho, London. Snow's work inspired changes in the water and waste systems of London and other places in the world.

Since then, the importance of the geographic patterns of diseases gained importance. The geography of a health issue such as the spatial pattern of malaria is very vital for the following reasons: (1) to know the particular area with the health problem, (2) to enable us trace the source of the causative agent or variable causing the disease, (3) importantly, to be able to design area-specific interventions (Rai et al. 2013; Srivastava et al. 2009) or for identifying control interventions (Niringiye and Douglason 2010; Raso et al. 2012). Thus, knowing where a disease is prevalent or most likely to occur will enable stakeholders respond to it properly. On the other hand, not knowing the spatial pattern of a disease or where it is likely to occur will make it difficult to tackle the problem or the measures could be targeting an entire *ocean* when, in fact, the problem may only be prevalent or likely to be prevalence in a small *reef*.

Saboba district in Ghana has been hit hard with high malaria incidence. For example, between 2002 and 2005, recorded malaria cases increased by 57.5 % in the district (Kursah 2009). On a visit to the hospital and the clinics in the district, one is greeted with countless patients needing treatment; many of whose cases are diagnosed to be malaria. Despite the high rate of malaria cases in the district, very little is known about the spatial pattern or prevalence of the disease. The reasons for this, as have been argued elsewhere by Srivastava et al. (2009), are weak surveillance and lack of geo-referenced malaria data to pinpoint the trouble spots for timely intervention.

Also, there has not been any predictive model to estimate where malaria is more or less likely to occur in the district. Such modelling is a useful tool for malarial control programme (Rai et al. 2013) and this can be utilised for spatial targeting of interventions and optimal resource allocation (Raso et al. 2012). This is to say that modelling and predicting where malaria incidence is likely to be high will assist authorities to spatially target interventions according to local needs. We are also not aware whether the public health officials know the environmental dynamics of the disease. The questions this raises, which will be the guiding principle of this study are: (1) Are the public health officials aware of the environmental dynamics of malaria in the district? (2) Which areas in the district are most susceptible to malaria occurrences? (3) Can malaria occurrences be predicted in the district?

Geographic Information System (GIS) has been used in modelling and predicting spatial variables in recent times. This is because GIS is revolutionising the era of spatial data management through the integration and analysis of geographically represented data (Teshebaeva and Jain 2007). Improvement in GIS and remote sensing technology have created the possibility for predicting malaria distribution. Studies around the world have addressed the issue of spatial analysis of malaria, using a variety of approaches (Fobil et al. 2012; Ohemeng and Mukherjee 2015). However, there is scarce evidence of studies addressing the issue of modelling and predicting spatial distribution of malaria in Ghana. Exception is Akpalu and Codjoe (2013). This study fills-in this important void and paves the way for future such studies that use GIS to model and predict the spatial distribution of malaria.

The study developed a geospatial model using GIS which will serve as a decision making and planning tool for malaria control. This study first identified the peculiar environmental variables favourable for the breeding of the malaria vector in Saboba district and used this to develop malaria susceptibility index (MSI). After this, GIS is used to generate malaria susceptibility index (MSI) map. This is used to model and predict the suitability of the area for breeding the malaria vector and invariably, the occurrence of the disease. This model could be used in effective malaria control planning. Finally, clinical malaria data in the district is used to test the validity of the model prediction.

Literature review

One's location may predispose one to malaria infection. Therefore, geographical analysis of the disease is vital. For example, proximity to stagnant water bodies are generally perceived as one of the most important factors that increase the risk of malaria infection, as it serves as a vector breeding source. This section reviews literature on environmental factors suitable for breeding malaria vector and studies on modelling spatial distribution of malaria using GIS.

Environmental variables influencing malaria prevalence

The understanding of the factors that influence malaria prevalence is vital for the design of policies targeted at reducing the prevalence (Niringiye and Douglason 2010). Depending on the specific locational dynamics of an area, distance to water bodies, especially, stagnant water usually influences malaria incidence. For example, it has been found that with a decrease in distances to water bodies, the malaria incidence increased as more than half (50.5 %) of the malaria cases occurred within a buffer of less than 500 metres from watercourses in Varanasi district, India (Rai et al. 2013). Studies have also found spatial variation in the prevalence of malaria (Raso et al. 2012; Srivastava et al. 2009) and these variations have been influenced by environmental factors such as rainfall amount, temperature, humidity and elevation (Cohen et al. 2008; Gemperli et al. 2006). This is because these factors both directly or indirectly affect the development of the malaria vector (*anopheles* mosquitoes) and, therefore, affect the geographical distribution of malaria (Raso et al. 2012). Thus, to monitor malaria programmes and achieve effective control, predicting and assessment of the spatial distribution of malaria is paramount (Singh et al. 2009).

In Ghana, it has been found that humidity and rainfall predicted malaria prevalence (Akpalu and Codjoe 2013). It has also been found that rainfall and temperature are the two most important drivers of malaria prevalence while the elevation factor is largely insignificant in Côte d'Ivoire (Raso et al. 2012). This is not surprising because the study area does not vary greatly in terms of elevation to drive the spatial variation in the breeding of mosquito larvae. A Ugandan study, however, found no relationship between malaria prevalence and environmental and socio-economic variables (Niringiye and Douglason 2010). This is probably due to little variations in these environmental and socio-economic variables in the study area.

Kenea et al. (2011) sampled aquatic habitats for anopheline larvae on the one hand and the associated environmental variables such as water temperature and water current on the other hand for analysis. It was found that abundance of *Anopheles arabiensis* larvae was significantly and inversely linked to water current. Thus, the higher the water current, the lower the availability of *Anopheles arabiensis*. Therefore, dry season anopheline larval habitats such as riverine sand pools which are created and maintained by perennial watercourses and water development projects need to be factored into malaria vector control operations.

It has also been found that places with higher malaria cases are the relatively populated centres in some parts in Northern Ghana (Kursah 2009). Thus, malaria is highly prevalent in urbanised areas. This could be explained by the availability of uncontrolled dug-out pits for building houses, KVIP (a semi-closed toilet facility), culverts, the presence of empty cans and plastic materials, which collect water during rains and serve as reservoir for breeding mosquito larvae. All these variables are predominantly an urbanised problem in the district. This finding contradicts the work of Niringiye and Douglason (2010), which found no relationship between population density and malaria prevalence at district level in Uganda. The explanation could be that higher population density by itself does not trigger malaria prevalence, but the actions or inactions (such as creating stagnant water reservoirs) of that population predispose them to higher malaria prevalence.

In a Bolifamba (Cameroon) study, malaria prevalence has been found to be higher in the inhabitants of wooden plank houses than those of cement brick houses. Also, inhabitants of houses surrounded by bushes or garbage heaps and swamps or stagnant water showed higher malaria prevalence compared with those from cleaner surroundings (Nkuo-Akenji et al. 2006). Therefore, poor sanitation and housing conditions are significant susceptibility variables for malaria burden.

Studies have also found that there is no significant association between the presence of rivers and malaria prevalence (Niringiye and Douglason 2010) and between malaria cases and distances to conventional water sources such as rivers and streams in Northern Ghana (Kursah 2009). The reason is that the rivers have swift flowing current and such flows do not facilitate high breeding of mosquito larvae. Therefore, interventions that seek to spray along these watercourses will have minimal impact at best. This finding reaffirmed a general belief that stagnant water bodies which are not captured in conventional aerial GIS data, are the major sources of breeding mosquito larvae. However, the finding is contrary to Rai et al. (2013) which found a significant correlation between distances to watercourses and malaria prevalence. Also, nearness to water bodies have been found to be responsible for high malaria cases (Carter et al. 2000; Watson 1949) and marshlands and other areas of poor drainage are major sources of malaria vectors (Thompson et al. 1997). The explanation for this discrepancy is the nature of the water bodies—whether stagnant or swift-flowing, with the former facilitating breeding of mosquitoes than the latter.

GIS modelling of malaria incidence

The application of GIS can help predict where malaria is more or less likely to occur and enable health interventions to be better targeted. For example, Rai et al. (2013) used GIS to produce a malaria susceptibility map using weighting systems to generate a malaria distribution map. From this, the authors found that about 26, 40, and 4 % of malaria cases were found in areas which had been predicted to be of *very high*, *high* and *low* susceptibility levels respectively. This study is, however, deficient in accuracy as areas predicted to have *very high* malaria risk constituted only 26 % of the incidence of the disease.

Similarly, Raso et al. (2012) predicted the geographical distribution of malaria infection risk in Côte d'Ivoire to guide control interventions using geospatial model. This study was a large-scale one and local variations within areas were not fully incorporated in the analysis. Tuyishimire (2013), on the other hand, modelled spatial variation of malaria from one household to another and from one administrative unit to another using Getis and Ord statistics and found a cluster of malaria in Ruhuha in Rwanda.

Using expert knowledge, Ohemeng and Mukherjee (2015) identified specific environmental factors suitable for the malaria vector in Zambezi basin. With these factors, they used Indicator Kriging Algorithm to predict the suitability of the area for the *Anopheles* mosquito. This allowed the prediction that a particular location in the area is suitable for the survival and spread of the *Anopheles*. The clinical malaria incidence was produced, and compared with the potential vector distribution zones to determine areas with high malaria risk. While this approach yields effective outcome, the Indicator Kriging Algorithm may not be a convenient method for many stakeholders involved in public health sector at the local level due to its complexity.

To sum up, much of the existing literature has focused on identifying the association of environmental variables and malaria incidence. Studies focusing on modelling and predicting where malaria is less or more likely to occur in space is, however, scarce. Studies that have done this are outside Ghana. The exception is Akpalu and Codjoe (2013), but even that is a countrywide study which may mask localised conditions. This study fills this void in the existing literature and serves as a planning tool for malaria control. It will also pave the way for future researches in this area. The study tests the developed geospatial model, using clinical malaria data in Saboba district.

Study area

Saboba district lies at the north-eastern part of the Northern Region of Ghana (Fig. 1). The district is located between latitude 9° 20″N and 9° 70″N and longitude 0° 00″ and 0° 30″E. It covers an area of about 1775 km^2 and a population of 65,706, giving a density of about 37 persons per square kilometre. The district is thus, typically, rural in nature and settlements are very scattered. Saboba is the district's administrative and economic capital. The district is bordered by Chereponi district to the north, Gushiegu district (west), Yendi district (southwest), Zabzugu district (south) and the Republic of Togo to the east.

The relief in the district is undulating lowlands ranging between 50 and 300 m, dissected by River Oti drainage system and a few minor streams (Fig. 1). Flooding is common during the rainy seasons in the district due to spill-over water from River Oti (Kursah 2010, 2013, 2014), which serves almost as the boundary between Ghana and the Republic of Togo.

Climatically, the district is situated in the warm and dry savannah zone of Ghana with average monthly temperatures ranging from 25 to 35 °C. The north-east trade winds (*harmattan*) are common from November to February. During this period, malaria incidence is minimal because of the intense cold dry winds and lack of suitable conditions for mosquito breeding.

The district experiences low and erratic rainfall and long dry season (October to April) accompanied by intense heat and sparse vegetation. The rainfall is single-maxima type, with annual totals ranging between 750 and 1050 mm. The rains come mainly from April to September and torrential in nature. This often causes flooding and erosion leading to the formation of gullies which facilitate the breeding of the malaria vector. The monthly maximum malaria incidence is recorded within this period because of the presence of hatching grounds and conditions for breeding of the malaria vector.

Methodology

Acquiring environmental variables influencing malaria vector breeding and generating MSI was done in three stages. The model showing the workflows is shown in Fig. 2.

Environmental variables influencing malaria vector breeding

A number of environmental variables influence malaria incidences. These variables are locational specific. The first stage of the research was to identify these variables. To identify these variables,

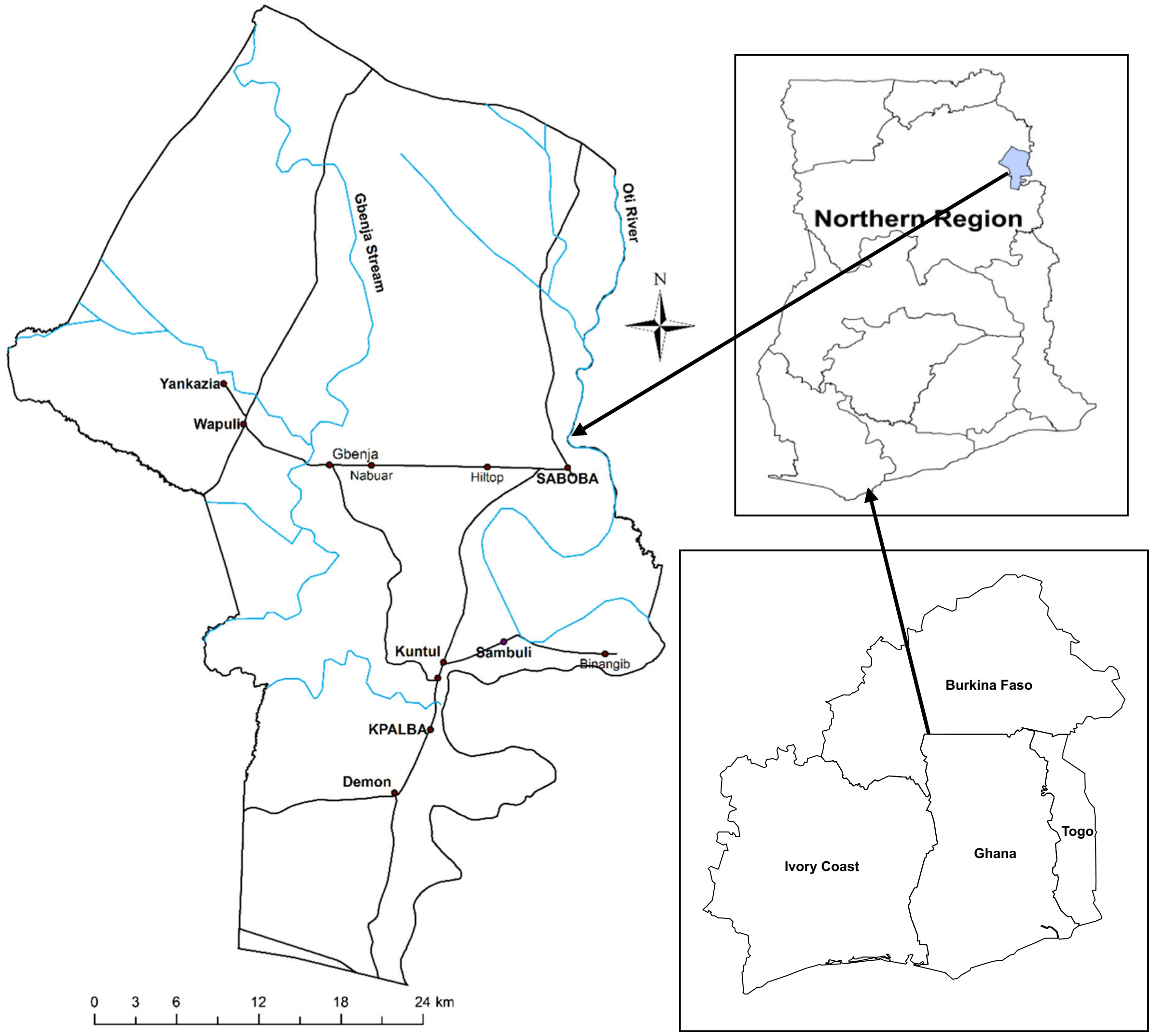

Fig. 1 Map of Saboba district

questionnaires were administered to 60 health workers in the district through a snow-ball technique. The public health workers were highly focused because they possess a lot of experience on public health issues such as malaria infections than other health workers do. They were asked to state malaria susceptibility variables in the district. Their responses were compiled to determine the peculiar environmental variables which predispose people to malaria infection in the district (Table 1). These environmental variables do not have equal importance in terms of serving as breeding grounds for malaria vector. This requires these variables to be weighted.

Weighting of variables and generation of malaria susceptibility index

Having determined the peculiar environmental variables that predispose people to malaria infection, the second stage of the administration of questionnaires began. Here, the focus was on the public health workers. Through a snow-ball technique, 30 public health workers were asked to assign scores to these variables ranging from 0 to 10, where 0 means *not important at all* and 10 means *most important* for influencing malaria infection in the district.

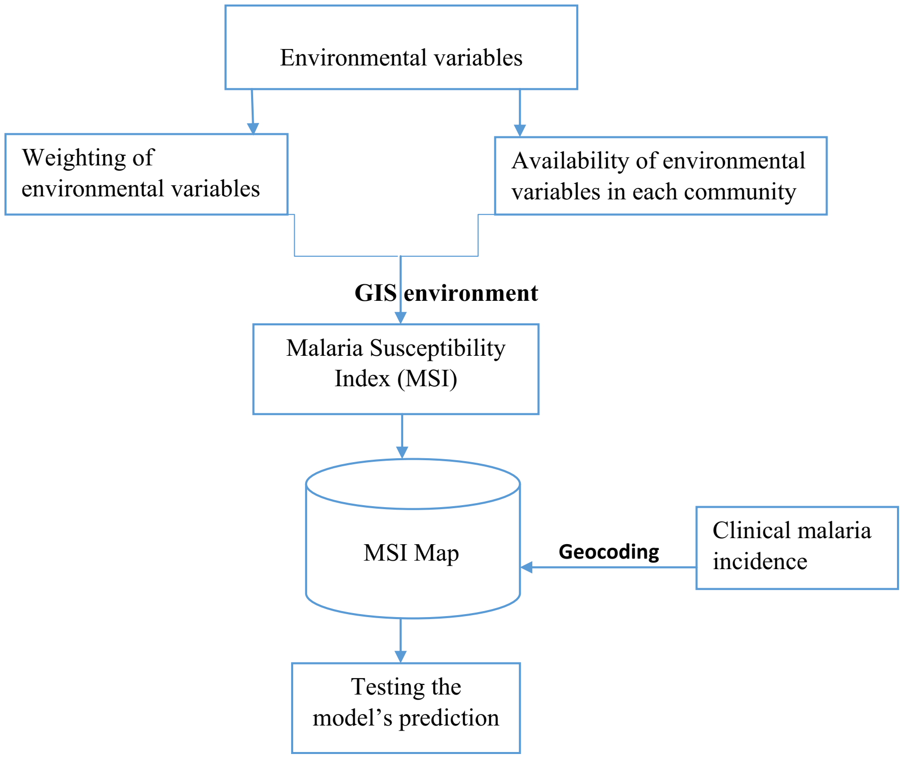

Fig. 2 The model showing the workflows of the study

Table 1 Environmental variables influencing malaria vector breeding

Environmental variables	
Sanitation factors	*Infrastructural factors*
Availability of stagnant water bodies	A lot of building and construction sites
Open pits from dugouts (for buildings) and ponds	Presence of tyre tracks, and ditches
Presence of open KVIPs	Presence of overhead tanks especially opened ones
Unclean surroundings	Defunct wells
Vegetation factors	Ground level cement tanks especially unsealed ones
Closed to swampy or marshy areas or rice fields	Presence of wooden plank houses
Presence of dead trees with trunks e.g. baobab etc.	*Elevation factor*
Behavioural factors	Located in lowlying areas
Littered tin cans, containers, and broken calabash	*Demographic factors*
Opened water storage tanks, pots etc.	Low literacy of the population
Disposed tyres, barrels etc.	High population concentration
Drainage factors	*Housing factors*
Sluggish streams/brooks with sandy margins	Houses surrounded by garbage heaps, broken walls
Presence of open gutters or drainage system	Tilled roofs
Rainwater pools and puddles	Mud houses and poorly designed windows
Close to a dam(s) and garden pools	

The third stage was to determine the availability of these environmental variables within the communities in the district. A set of another 30 questionnaires were administered to public health workers, including the District Environmental Officer to rate the availability of each variable in their communities, on a Likert-type of scale ranging from 0 to 1, where 0 means the variable is *not present at all* or *not applicable* in that community and 1 means the *variable is most present*. Multiplying the *mean score* of a variable by its *mean availability score* will give the *factor weight* (level of significance) of that variable in each community. For example, if a malaria susceptibility variable such as the presence of stagnant water is scored 10, and its availability score in community B is 0.7, then the factor weight for presence of stagnant water in community B is 7.0 (that is $10 \times 0.7 = 7.0$). However, if the same susceptibility variable has availability score in community C to be 0.2 (meaning stagnant water is not so common), then the factor weight for that variable in community C will be 2.0 ($10 \times 0.2 = 2.0$). This can be expressed as in Eq. 1.

$$\mathrm{fw} = \sum \frac{vs}{nr} \times \left(\sum \frac{vas}{nr} \right) \quad (1)$$

where fw = factor weight, vs = variable score, vas = variable availability score, nr = number of responses

The MSI, that is, summation of factor weights divided by the number of factors for each community was then determined. Since the highest possible variable score is 10, and the highest availability score is 1, then the highest possible malaria susceptibility index for any community will be 10 ($10 \times 1 = 10$). This can be expressed as in Eq. 2.

$$\mathrm{MSI} = \sum \frac{fw}{nf} \quad (2)$$

where MSI = Malaria Susceptibility Index, fw = factor weight, nf = number of factors

The MSI for each community is then geocoded and used to produce MSI map (Fig. 3).

Acquiring clinical malaria data and geocoding

For the collection of clinical malaria data for testing the model prediction, out-patient department (OPD) records of individuals (that included the type of disease the person was treated of and the place of residence of the person) were sampled from the Saboba Medical Centre (the only hospital in the district), all the health centres (in Wapuli, Sambuli and Kpalba) and all the health posts in the district. Since detailed information (especially the residence/place of the patient) is missing after data collation in the district, the raw and *hand-written* recorded cases in the health record books were used. Care was taken to include records from each month in a year. Thus, the records of the *first page* (due to the volume of work required) on the 5th, 15th and 25th day of every month (interval of 10 days) from 2012 to 2015 was scanned. If any of the dates falls on a weekend or public holiday, then the next preceding date was selected. This was to avoid using data from dates that have unusually lower hospital turn-out, with its associated imbalances. For the entry to be included in the analysis, it must fulfil the following conditions: (1) the entry has information on disease treated, (2) the entry is a malaria case, and (3) residence or place of the patient is known and traceable to a community in the district.

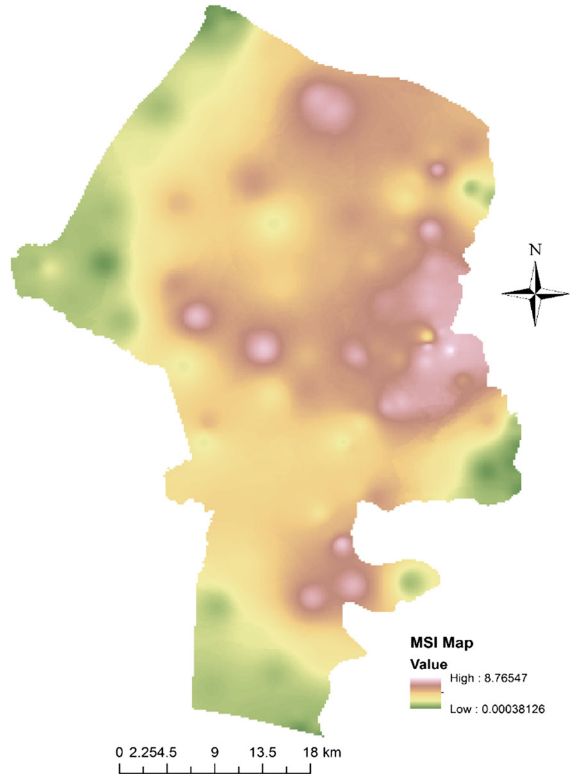

Fig. 3 Malaria susceptibility index map

Out of the sampled health records (4193), only those which were diagnosed of malaria and satisfy the two other conditions above (a total of 2776) were geocoded in ArcMap 10.1. This means that at least 66.2 % of the entries were malaria cases. This is higher than 63 % identified by Aikins and Dzikunu (2006) in the then Saboba-Chereponi district—a sign that malaria incidence is increasing in the district. A large percentage of the rejected entries were non-malaria cases such as typhoid, Respiratory Tract Infections (RTI) etc. However, few entries (approximately 0.6 %), though malaria cases were rejected because they did not meet the third condition above.

GIS analysis

GIS data and sources

The GIS data used are vector layers showing district boundaries, settlements, rivers and the roads, and these were acquired from GeoCommunity.[1] All datasets were country data and were clipped to the extent of Saboba district using the *clip* tool.

GIS data ground truthing and data preparation

To ensure the accuracy of the GIS datasets, locations of river confluences and identifiable infrastructures such as road junctions were taken using Garmin Oregon 450 GPS. These control points were used to check and adjust the positional accuracy of the datasets.

Generating malaria susceptibility index map

The malaria susceptibility index (MSI) of each community were geocoded and interpolated using *interpolation* tool in ArcMap 10.1. This generated malaria susceptibility index map (Fig. 3). The MSI map was reclassified into *very high, high, low and very low* susceptibility levels (Fig. 4) using equal intervals, that is, 0–2.5, 2.6–5.0, 5.1–7.5, and 7.6–10.

[1] http://www.geocomm.com/.

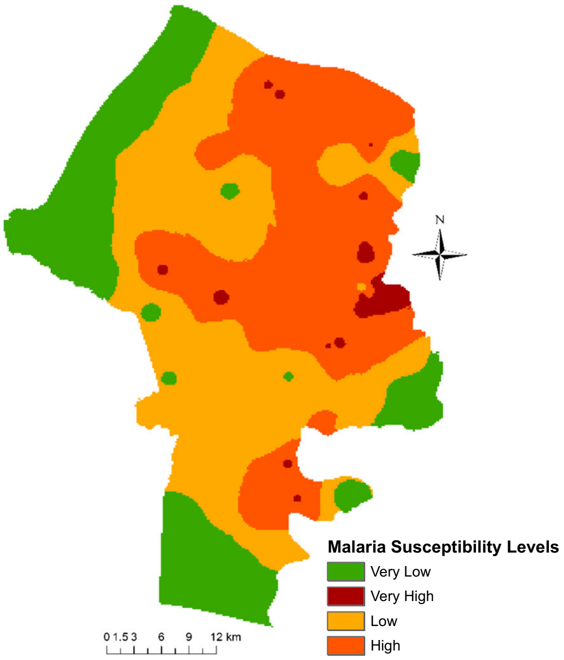

Fig. 4 Malaria susceptibility levels

Extraction of malaria cases within each susceptibility index levels and model testing

The clinical malaria incidence within each susceptibility index levels, that is, *very high*, *high*, *low* and *very low* (Fig. 4) were extracted. These were then summed to determine whether a greater portion of the clinical malaria cases were recorded in the areas predicted to have high malaria susceptibility level. The areas covered by each susceptibility level were also extracted.

Results

Table 1 depicts the 25 environmental variables (grouped into 8 thematic areas) used to generate malaria susceptibility index, and consequently for the geospatial model. These variables were generated from the first stage of the questionnaire administration.

Figure 3 shows the malaria susceptibility index (MSI) map. The brownish coloured areas indicate a higher MSI while the greenish coloured areas indicate a lower MSI. The MSI is generally higher at the east-central part, the south-eastern part, the northern part and some few areas in the central part of the district.

Table 2 Malaria susceptibility levels and its share of clinical malaria incidence

Susceptibility level	Area (m^2)	Percent (%)	Share of malaria incidence	Percent (%)
Very low	415,100	23.4	3	0.1
Low	693,500	39.1	86	3.1
High	636,200	35.9	681	24.5
Very high	30,200	1.7	2006	72.3
Total	1,775,000	100.0	2776	100.0

Figure 4 shows malaria susceptibility levels map, that is, *very high, high, low* and *very low* levels. The highest possible MSI is 10.

Table 2 depicts the malaria susceptibility levels and its share of clinical malaria incidence in the district. The area classified as *very low* susceptibility level covers about 23.4 % of the landmass in the district but only 0.1 % of the clinical malaria cases were recorded in this area. The area of the district which the model predicted to have *low* susceptibility level covers about 39.1 % of the total district's landmass, but only 3.1 % of the clinical malaria cases were recorded in this area over the study period. Areas classified by the model as *high* susceptibility level cover about 35.9 %, but contributed 24.5 % of the recorded malaria incidence over the study period. The *very high* susceptibility level areas cover only 1.7 % of the district's landmass but contributed 72.3 % of the clinical malaria cases over the study period.

Discussion

Twenty-five environmental variables were identified as affecting malaria occurrences specific to the district. Conspicuously missing in these variables are: (1) closeness to rivers, and (2) the three main climatic factors that affect malaria transmission, that is, temperature, rainfall and relative humidity. For closeness to rivers, a significant correlation has been established between distances to rivers and malaria prevalence (Rai et al. 2013). However, studies have also found that there exist no significant relationship between closeness to rivers and malaria prevalence in Uganda (Niringiye and Douglason 2010) and in Northern Ghana (Kursah 2009). What then accounts for this contrary findings? The explanation which resolves the contradictory findings is the nature of the rivers—whether stagnant or swift-flowing, with the former facilitating breeding of mosquitoes than the latter does. This explanation has been established elsewhere. Kenea et al. (2011), for example, found that there was significant inverse relationship between anopheline larvae and water current. This argument reaffirmed a general belief that stagnant water bodies, which may be too tiny to be captured in remotely sensed data, are the major sources of breeding mosquito larvae.

The three main climatic factors that affect malaria transmission, that is, temperature, rainfall amount and humidity were also not mentioned by the public health workers and not included in the model. This may seem surprising as some previous studies have found a relationship between malaria prevalence on the one hand and rainfall amount, temperature and humidity on the other (Cohen et al. 2008; Gemperli et al. 2006; Raso et al. 2012). The argument is that these factors both directly or indirectly affect the development and occurrence of the malaria vector (*anopheles* mosquitoes) and, therefore, affect the geographical distribution of malaria (Raso et al. 2012). Also, Akpalu and Codjoe (2013) found that humidity and rainfall influenced malaria prevalence in Ghana. This is, however, not surprising because the study areas for these studies are either countrywide or large-scale where the three climatic variables may vary greatly over space. Thus, any geographic study of malaria prevalence should factor in these variables when their scale may vary. However, the study area, Saboba district, is too small to cause variations in these climatic variables. It is not surprising that no single public health worker mentioned any of these climatic variables. Vegetative type or index was also not mentioned for the same reason—it does not vary greatly within the district.

Though Saboba district recorded high malaria cases (about 66.2 %), the prevalence of the disease is concentrated in few areas (1.7 % of the district's landmass) giving rise to malaria hot spots (Fig. 4) which need appropriate intervention. ArcMap application was enormously valuable in identifying and displaying these hot spots. It unmasked a profound heterogeneity in the endemic of malaria prevalence that had previously been concealed within the summary data on incidence of malaria in the district. The study also revealed how GIS can model and predict malaria occurrences. This is useful so that intervention measures can be sent to areas that need them the most. Thus, GIS, as has shown, can be used to make spatio-temporal modelling and prediction of malaria occurrences.

It is important to note that only 1.7 % of the area covered by the district (Table 2) contributed 72.3 % of the malaria cases during the study period. These areas, forming the hot spots are associated with higher concentration of the environmental variables linked to malaria transmission. Chiefly of these variables are the presence of stagnant water bodies, dug-out pits, KVIPs, swampy surroundings, and bushes or garbage heaps. This finding confirms Nkuo-Akenji et al. (2006) who found that areas with houses surrounded by bushes or garbage heaps and swamps or stagnant water showed higher malaria parasite prevalence and densities, compared with those from cleaner surroundings.

The public health workers in the districts understand the dynamics of malaria susceptibility as their weights which were used in the model, predicted malaria incidence, to a large extent, accurately. This is because 96.8 % of the clinical malaria cases came from areas which the model predicted to have *very high* (72.3 %) and *high* (24.5 %) susceptibility levels. The 96.8 % is higher than 89 % achieved by (Rincón-Romero and Londoño 2009) in a similar study. It goes to say that the public health workers are well-informed about malaria dynamics in the district.

The interpretation of the result must be done with caution, especially with lower rates in the southern part and the western "horn". This is because those areas may have very few clinical malaria cases not because of fewer malaria occurrences, but because people from those areas may seek higher rated health facilities in the neighbouring districts due to shorter distances. However, due to ethnic affinity, language barrier and the three-tier referral system within the districts, it is common to see people around these fringes coming to the district hospital in the capital, Saboba, even if they are closer to the district hospitals in the neighbouring districts.

The usefulness of GIS for modelling and predicting malaria prevalence for a focused intervention depends on the availability of accurate spatial data on malaria cases. However, such could not be said to be readily available in the district, as the data are manually recorded. It is recommended that data management system with spatial variable be implemented in the health facilities in the district, in order to make it easier to track and map malaria prevalence. Also, the habit whereby the spatial variable is dropped after the out-patient department (OPD) stage has to be discouraged, so as to allow spatial analysis of health data in the district.

Conclusion

Identifying the geography of malaria will help decision makers locate the particular area with the health problem and to design area-specific interventions. Using ArcMap 10.1, this study determined malaria susceptibility index and with geospatial modelling, predicted malaria occurrence. Clinical malaria incidence was then geocoded and tested to see the accuracy of the prediction. The results show that 72.3, 24.5, 3.1 and 0.1 % of the clinical malaria cases were found in areas that were predicted to have *very high, high, low and very low* susceptibility levels, respectively. The conclusion is that modelling such as this can help determine spatio-temporal prediction and mapping of malaria incidence. This study has shown that the public health workers truly understand the dynamics of malaria infection in the district. However, it is not clear if the other stakeholders such as NGOs and other Civil Society Organisations (CSOs), and the general public in the district understand these dynamics. It is recommended that studies be conducted using these other stakeholders to determine if their knowledge of malaria infection is adequate to predict the spatial distribution of malaria in the district. It is also suggested that further modelling of this kind be conducted periodically for temporal analysis and comparisons.

Compliance with ethical standards

Ethical approval Matthew B. Kursah declare that the manuscript has not been submitted or under consideration by any journal or institution for publication. It has not also impacted on the ethical rights of individuals in anyway

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