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Using the information value method in a geographic information system and remote sensing for malaria mapping: a case study from India

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ABSTRACT

Background This paper explores the scope of malaria-susceptibility modelling to predict malaria occurrence in an area.

Objective An attempt has been made in Varanasi district, India, to evaluate the status of malaria disease and to develop a model by which malaria-prone zones could be predicted using five classes of relative malaria susceptibility, i.e. very low, low, moderate, high and very high categories.

The information value (Info Val) method was used to assess malaria occurrence and various time-were used as the independent variables. A geographical information system (GIS) is employed to investigate associations between such variables and distribution of different mosquitoes responsible for malaria transmission. Accurate prediction of risk depends on a number of variables, such as land use, NDVI, climatic factors, population, distance to health centres, ponds, streams and roads etc., all of which have an influence on malaria transmission or reporting. Climatic factors, particularly rainfall, temperature and relative humidity, are known to have a major influence on the biology of mosquitoes. To produce a malaria-susceptibility map using this method, weightings are calculated for various classes in each group. The groups are then superimposed to prepare a Malaria Susceptibility Index (MSI) map.

Results We found that 3.87% of the malaria cases were found in areas with a low malaria-susceptibility level predicted from the model, whereas 39.86% and 26.29% of malaria cases were found in predicted high and very high susceptibility level areas, respectively.

Conclusions Malaria susceptibility modelled using a GIS may have a role in predicting the risks of malaria and enable public health interventions to be better targeted.

Keywords: Epidemiology, geographical mapping, malaria, public health, spatial analysis

INTRODUCTION

Malaria remains one of the greatest killers, particularly in the developing world.¹ Malaria transmission depends on diverse factors that all have an influence on the vectors, parasites, human hosts and the interactions among them. These factors may include, among others, meteorological and environmental conditions.² The most apparent determinants are observed to be the meteorological and environmental parameters such as rainfall, temperature, humidity and vegetation type and cover.^{3,4} There are only a few examples of the application of epidemiological maps in malaria control and this may be explained by a lack of suitable, spatially defined data and also by a relatively incomplete understanding of how epidemiological variables relate to disease occurrence. Recent evidence suggests that clinical manifestations of infection are determined by the intensity of parasite exposure. Developments in the area of geographical information systems (GISs) can provide new ways to represent epidemiological data spatially.⁵ GIS software is being used to correlate the climatic attributes of the collection localities with the presence or absence of various mosquitoes.⁶ This technology has been in existence for a number of years, but it is only recently that it has been widely accepted as a powerful tool to augment existing monitoring and evaluation methods.^{3,7} A GIS technique integrated with remote sensing can play a variety of roles in the planning and management of a dynamic and complex healthcare system, disease mapping, public health and epidemiology,^{8,9} although it is still at an early stage of integration into public healthcare planning.²⁰

Vegetation has often been found associated with the vector's breeding, feeding and resting locations. A number of vegetation indices have been used in remote sensing and earth science disciplines. The most widely used index is the Normalized Difference Vegetation Index (NDVI). It is defined as the difference between red and near-infrared bands normalised by twice the mean of these two bands.¹⁰ For green vegetation, the reflectance in the red band is low because of chlorophyll absorption, while the reflectance in the near-infrared band is high because of the spongy mesophyll leaf structure.¹¹

Mathematical and statistical modules embedded in GISs enable the hypotheses to be tested and the estimation, explanation and prediction of spatial and temporal trends.^{12,13} Statistical techniques model the relation between parasite exposure risk and environmental risk factors via a multivariate linear regression model. Such a model can also be used for prediction.^{14,15}

The purpose of malaria-susceptibility modelling is to examine the long-term parameters, and to define their relations to malaria occurrence in the studied area. The primary goal has been set for assessment and appraisal of important parameters for incidence of malaria disease in the study area and, then, selection of the most determinant parameters. The study area is Varanasi district, Uttar Pradesh, India, extending between 25°10' N and 25°37' N latitude and 82°39' E and 83°10' E longitude. The main expanse is towards the west and north of Varanasi city and spreads over an area of 1454.11 km² (Figure 1). Administratively, the study area comprises two tahsils, namely Pindra and Varanasi Sadar, which are further sub-divided into eight development blocks, namely Baragaon, Pindra, Cholapur, Chiraigaon, Harhua, Sevapuri, Araziline and Kashi Vidapeeth, consisting of 1336 villages altogether.

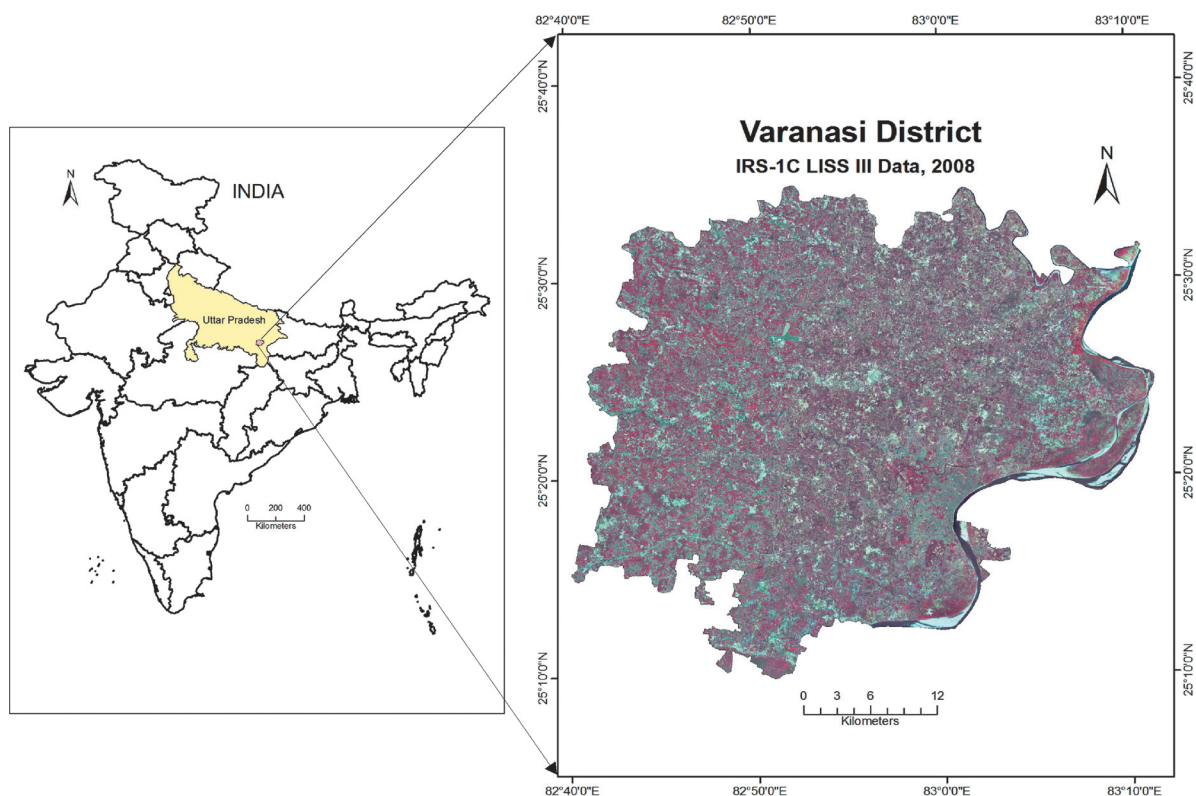


Figure 1 Study area as viewed on satellite data (IRS-1C LISS III)

OBJECTIVE

The main aim of the study was to develop a malaria-susceptibility model using the information value (Info Val) method with the help of remote-sensing data and GIS techniques.

METHODS

A number of thematic maps (referred to as data layers in GIS) were generated on specific parameters related to the consequences of malaria, that is land use, NDVI, distance to water bodies (such as ponds, rivers etc.), roads and health centres, rainfall and temperature data and projected population density in the year 2009. In this study, Ilwis Version 3.4, ArcGIS Version 9.3 and ERDAS Imagine Version 9.1 software as well as the statistical software SPSS Version 16 were used to produce the layer maps, which help in the production of the malaria-susceptibility maps. We used a 1:50,000 scale topographical map of the study area to digitise the district and development block boundaries. The coordinates of important geo-reference points such as road junctions, malaria-prone areas and existing healthcare facilities were measured during field surveys using global positioning system (GPS) technology. During measurement, one receiver served as a base station, while the other collected GPS data at the selected ground control points. To establish the relationship between object space and image space, ground control points selected in the model area to conduct all measurements in the National Coordinate System. The vector maps were developed from the IRS-1C LISS-III 2008 remote sensing data and Survey of India (SOI) topographical map. A land use map, NDVI and vector layers of water bodies and other important parameters were delineated in ERDAS Imagine Version 9.1 and ArcGIS Version 9.3 software. A geo-referenced digital map of the development blocks of Varanasi district was used on the GIS platforms.

The Info Val method was used in this study to produce a malaria-susceptibility zone (MSZ) and malaria-susceptibility index (MSI). Other influential parameters considered in this study for optimum zonation and modelling of the study area were rainfall (Rf), temperature (Temp), population density (Pd), distance to river (Dri), distance to road (Dro), distance to health facilities (Dhf), land use/land cover (Lc) and NDVI.

These parameters have been used in all three of the methods mentioned above to produce MSZ of the study area.

Info Val

The Info Val method for MSZ considers the probability of malaria occurrence within a certain area of each class of a thematic.¹⁶ In this model, weights of a particular class in a thematic are determined as

$$W_i = \ln \left(\frac{Densclas}{Densmap} \right) = \ln \frac{Npix(S_i)/Npix(N_i)}{\sum_{i=1}^n Npix(S_i)/\sum_{i=1}^n Npix(N_i)} \quad (1)$$

where W_i is the weight given to the i th class of a particular thematic layer, $Densclas$ is the malaria density within the thematic class, $Densmap$ is the malaria density within the entire thematic layer, $Npix(S_i)$ is the number of malaria pixels in a certain thematic class, $Npix(N_i)$ the total number of pixels in a certain thematic class and N is the number of classes in a thematic map. The natural logarithm is used to take care of the large variation in the weights. Thus, the weight is calculated for various classes in each thematic. The thematic is overlaid and added to prepare a MSI map. For near-equal subdivision of the MSI, the cumulative frequency curve was categorised into five zones based on malaria susceptibility (that is very high, high, moderate, low and very low). Information analysis includes two specific steps, that is bivariate analysis and multivariate analysis (Figure 2).

Bivariate analysis

In this analysis, two ratios are used:

- a) P is the ratio of malaria area and study area

$$P = \frac{M}{N} \quad (2)$$

where M is the number of the malaria cases in the study area and N is whole of the study area;

- b) P_i is the ratio of the malaria area in the individual parameters:

$$P_i = \frac{M_i}{N_i} \quad (3)$$

where M_i is the number of the malaria cases into the i th variable and N_i is whole of the study area including the i th variable.

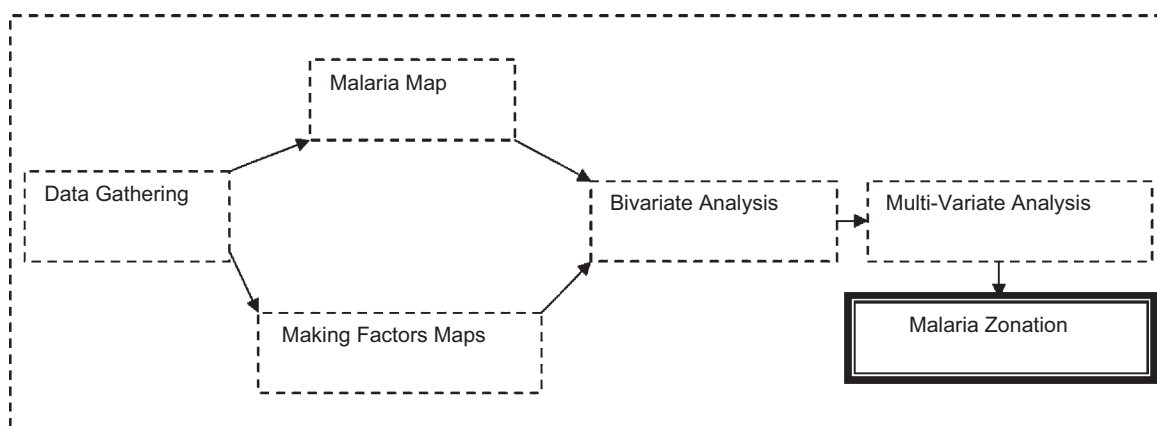


Figure 2 Different stages involved in constructing the malaria-susceptibility zone (MSZ) map using the information value (Info Val) method

Then the relation between these two values, the P_i/P information value, can be calculated from the i th variable in the predicted malaria potential characterised with M_i :

$$M_i = \frac{P_i}{P} = \frac{M_i/N_i}{M/N} \quad (4)$$

Then for each variable and its sub-group, the M_n of each M_i , which indicates positive and negative zones, has been calculated. If the calculated M_n are positive, this indicates that the pixels including the i variable have a greater incidence of malaria than mean of the study area. This indicates the susceptibility of these parameters to instability. Negative values indicate stability, meaning no presence of malaria pixels.

Multivariate analysis

After producing thematic maps by interpolating the results of each variable information value, we divided the maps into sample areas of 200×200 pixels. Then the numerical values results, which included 38,622 samples, have been transferred to EXCEL software and the final information value has been calculated as follows:

$$I_j = \sum x_{ji} \cdot I_i = \sum x_{ji} \cdot \frac{M_i/N_i}{M/N} \quad (5)$$

where $j = 1, 2, \dots, n$ indicate the number (area) of networks, $i = 1, 2, \dots, n$ indicate the number of variables, x_{ji} is the quantity of the i th variable in the j th indicator, where $i = 1$ means malaria is present $i = 0$ indicates no malaria, and I_i is the information values resulting from the i th variable.

After statistical calculation of the model, information resulting from the model is transferred to the GIS (ILWIS 3.4) and the MSI map was created.

The next step in this method is to determine the quantities of crucial information values and to divide the map according to the degree of susceptibility, which is based on the calculated values.

Malaria inventory map

A malaria inventory map identifies definite and probable areas of existing malaria prevalence and is a basic requirement for MSZ. The malaria inventory map shows the spatial distribution of malaria as points or to scale.

Malaria inventory maps are often used as the basis for other MSZ techniques or as an elementary susceptibility map. Village-wise malaria location data were collected from each primary health centre (PHC) and then the locations were determined using GPS. GPS location data related to malaria prevalence were imported into the GIS platform and 500 m buffer zones were created around each point (Figure 3). On the basis of these malaria pixels falling in the study area, the pixels from the whole study area were assigned one of two values, that is 0 (no malaria pixels) 1 (where malaria pixels are present).

RESULTS

Malaria-influencing data layers and their map preparations

A representation of the malaria database is shown in Figure 4. The following layers, that is rainfall (Figure 4(a)), average

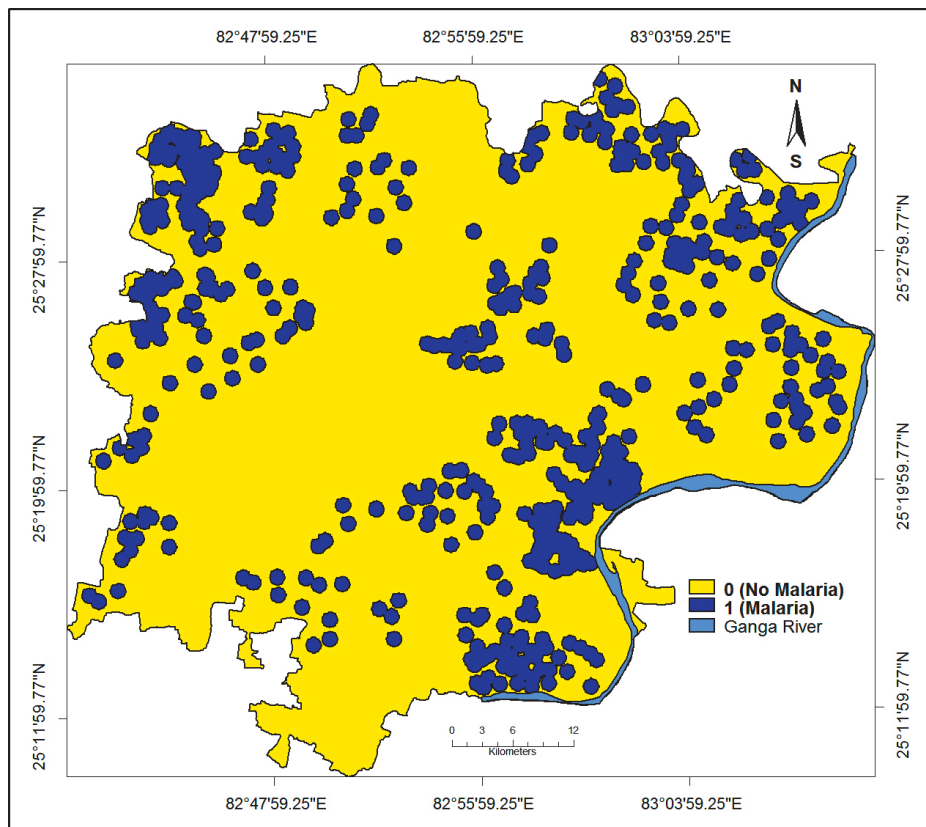


Figure 3 Buffer zones (500 m) around the location of each point of malaria prevalence

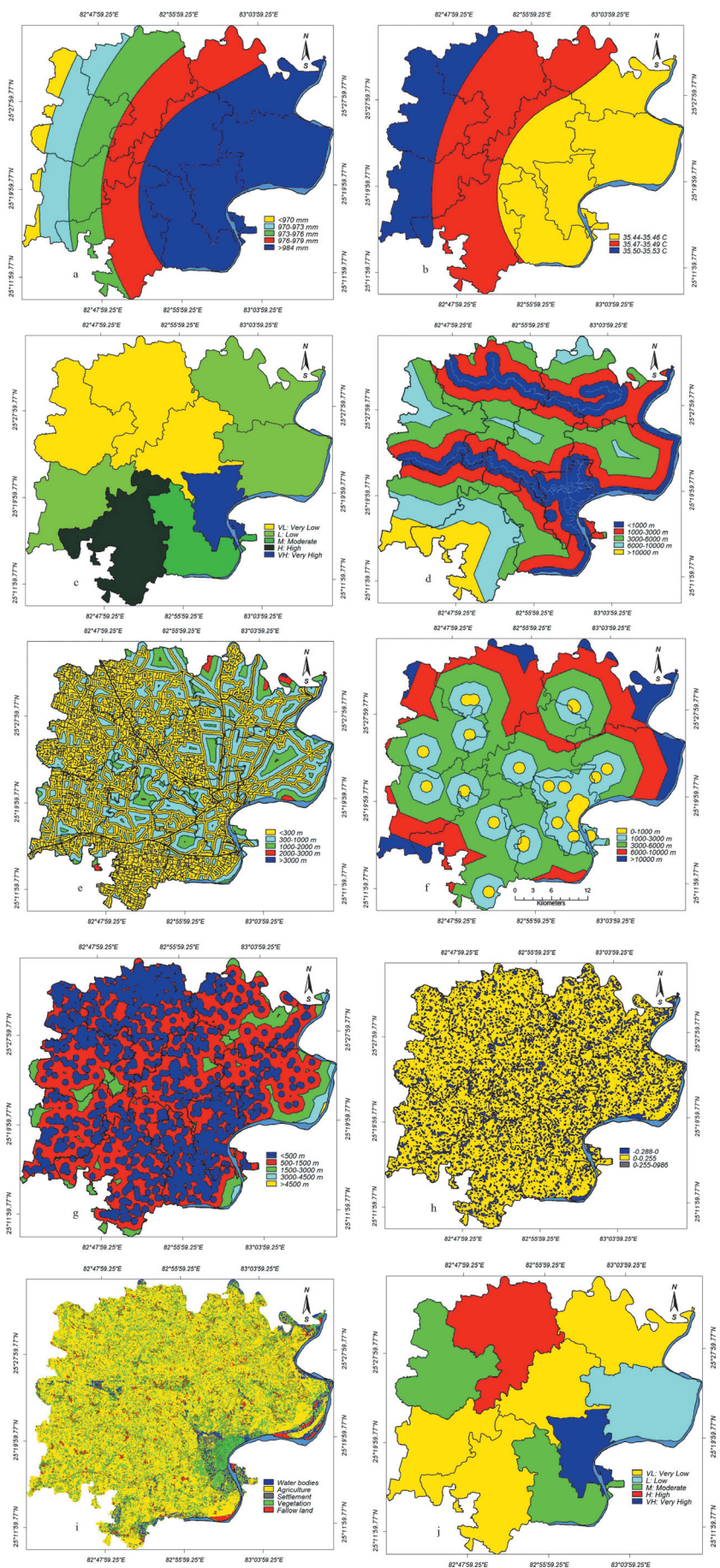


Figure 4 Representation of the malaria database: (a) rainfall; (b) average temperature; (c) population density; (d) distance to rivers/streams; (e) distance to roads; (f) distance to healthcare facilities; (g) distance to ponds; (h) NDVI; (i) land use; (j) and status of malaria in 2009

temperature (Figure 4(b)), population density (Figure 4(c)), distance to rivers/streams (Figure 4(d)), distance to roads (Figure 4(e)), distance to healthcare facilities (Figure 4(f)), distance to ponds (Figure 4(g)), NDVI (Figure 4(h)), land use (Figure 4(i)) and status of malaria in 2009 (Figure 4(j)), are used to produce the malaria-susceptibility model map.

Rainfall

Rainfall is considered to be the most important malaria-triggering parameter causing soil saturation and a rise in pore water pressure. However, there are not many examples of the use of this parameter in stability zonation, probably due to the difficulty in collecting rainfall data for long periods over large areas.

After interpolation between the amounts of annual rainfall in the study area stations, the isohyets map was created. Finally, this map has been grouped into five classes to prepare the rainfall data layer (Figure 4(a)). It is verified that approximately 57.77% of the malaria cases occurred in areas with >984 mm rainfall, but in areas with <970 mm rainfall only very low and moderate zones of malaria were found, with only 3.19% of cases. From this we can conclude that increasing amounts of rainfall increases the malaria breeding sources (Table 1, under column A).

Temperature

To take into account the relationship between temperatures and malaria transmission, the temperature data are gathered for different periods. The temperature distribution map has been grouped into three main classes, that is 35.44–35.46°C, 35.47–35.49°C and 35.50–35.52°C (Figure 4(b)). In Table 1, under column B, it is found that in the study area malaria vectors were highly developed in the 35.44–35.46°C temperature category: 56.50% of the malaria-prone area pixels were found in this category, whilst only 20.04% of malaria-prone area pixels were found in the 35.47–35.49°C category.

Population density

The overall population distribution in the district is closely related to the physical and sociocultural factors. Population distribution is a dynamic process which manifests the varying nature of man's adjustment to physical resources. Population density has been encountered under various typological purviews to reveal different aspects of population distribution. Census data from the year 2001 is also used and using this population data, the projected population for the year 2010 was calculated which used to calculate population density, with the area divided into five categories on the basis of this population density, that is very low, low, medium, high or very high (Figure 4(c)). In Table 1, under column C it is found that in very low and low population density areas especially in the rural parts of Varanasi district very high malaria prevalence (33.74%) is identified, but where population density is high and very high, only 4.83% and 14.23% respectively of the malaria area pixels were found. Most of the very high malaria zone is found in the Varanasi city area where the projected population density is very high.

Distance to rivers/streams

One of most important parameters that contribute to an increase in malaria parasites and malaria disease is the distance to rivers/streams. The proximity of the populated area to drainage structures is an important parameter for malaria vector breeding sources. Streams may also adversely affect those in low-lying areas, especially villages and settlement areas near the Varuna River. A thorough field investigation was carried out to determine the effects of rivers/streams on malaria prevalence. The malaria area percentage in each buffer zone is given in Table 1, under column D. This shows that 23.23% of the malaria area is closely located within the <1000 m buffer zone (Figure 4(d)). We identified 31.32% of the malaria area pixels in the buffer zone of 3000–6000 m. In this study, we found that 3.56% of the malaria area pixels are found >10,000 m from a river/stream and in this zone only very low and moderate categories are available, which is mainly because of the influence of some of the other indicators/variables, so at this distance malaria indicators or breeding sources have little influence on people.

The important thing result found in this study is that as the distance to rivers/streams increases, the percentage of malaria-affected area pixels decreases.

Distance to roads

The distance to roads is also an important parameter as it can be used as an estimate of the access to existing healthcare facilities in the study area. Different buffer areas are created on the path of the road to determine the effect of the road on malaria prevalence (Figure 4(e)). The malaria area pixel percentage in each buffer zone is given in Table 1, under column E and shows that 65.84% of the malaria area pixels are closely located within the <300 m buffer category, whereas only a very nominal 0.92% of the malaria area is found in the buffer zone of 2000–3000 m. Only 0.41% of malaria pixels are located in the >3000 m buffer category. Here it can be seen that as the distance to roads increases, the malaria area percentage shows a decreasing trend.

Distance to health facilities

The health facilities of Varanasi district are based on mainly modern allopathic treatment methods. To find the distributional pattern of healthcare facilities, data has been collected from the chief medical officer (CMO) office and government hospitals located in rural areas of Varanasi district. The existing health facilities both in rural and urban areas were surveyed with the help of a differential global positioning system (DGPS). There are different categories of health centre providing infrastructure and treatment in the district. The PHC's are dotted around the district located at an interval of 10–20 km and the tahsil hospitals are located about 50 km apart. The hierarchical distribution of medical centres in the district bears a close relationship with the hierarchy of central locations and the population size of the settlement. In addition, the transport network has also influenced the growth of healthcare facilities. The percentage of malaria area pixels is very much related to the distance from healthcare facilities.

Table 1 Malaria database showing the characteristics of malaria based on different parameters

Parameters for malaria mapping	Number of malaria pixels	Total number of pixels	Malaria pixel area (%)
A. Rainfall class			
<970	7897	19,519	6.38
970–973	19,682	68,937	15.89
973–976	9542	99,487	7.7
976–979	15,175	143,285	12.25
>984	71,547	280,162	57.77
B. Temperature class			
35.44–35.46°C	69,974	266,938	56.5
35.47–35.49°C	24,812	234,152	20.04
35.50–35.53°C	29,057	110,300	23.46
C. Population density			
Very low	41,787	222,199	33.74
Low	41,584	212,569	33.58
Moderate	16,861	53,352	13.61
High	5985	84,805	4.83
Very high	17,626	38,460	14.23
D. Distance to rivers/streams			
<1000 m	28,766	132,325	23.23
1000–3000 m	36,354	173,300	29.35
3000–6000 m	38,783	184,054	31.32
6000–10,000 m	15,533	80,756	12.54
>10,000 m	4407	40,955	3.56
E. Distance to roads			
<300 m	81,541	390,258	65.84
300–1000 m	34,954	177,295	28.22
1000–2000 m	5706	38,918	4.61
2000–3000 m	1134	3499	0.92
>3000 m	508	1420	0.41
F. Distance to healthcare facilities			
0–1000 m	8158	29,136	6.59
1000–3000 m	21,720	145,065	17.54
3000–6000 m	43,515	242,719	35.14
6000–10,000 m	39,376	147,357	31.8
>10,000 m	11,074	47,113	8.94
G. Distance to ponds			
<500 m	67,032	27,0681	50.45
500–1500 m	48,608	283,869	36.58
1500–3000 m	15,909	39,612	11.97
>3000 m	1319	17,228	0.99
H. NDVI			
–0.288	23,909	115,299	19.31
0–0.986	99,934	496,053	80.69
I. Land use class			
Water bodies	2690	19,282	2.17
Agriculture	65,188	330,581	52.64
Settlement	25,810	114,660	20.84
Vegetation	21,595		17.44
Fallow land	8544	46,601	6.9

In Table 1, under column F, it is found that 6.59% of malaria area pixels belong in the 0–1000 m buffer distance to health-care facilities and 35.14% of malaria area pixels are found in the 3000–6000 m buffer distance (Figure 4(f)).

Table 1, under column F shows that as the distance to healthcare facilities increases, the malaria prevalence also increases, except in >10,000 m buffer zone (8.94% malaria area pixels). In these areas it may be that malaria breeding sources are not as developed as in other areas.

Distance to water ponds

The locations of water ponds in the study area were extracted with the help of IRS-1C LISS III satellite data from 2008. Five different buffer areas were created for the water ponds to determine the effect of the distance to water ponds on malaria prevalence (Figure 4(g)). In Varanasi, there used to be many ponds and tanks dating back to ancient times. In addition to serving as the holy places for holding Hindu religious rituals, they also played an important role in rainwater collection and thereby served as sources for ground water replenishment.¹⁴ However, due to the rapid increase of the population, most of these ponds have been wiped off the map of Varanasi completely or are rapidly deteriorating. The main source of pollution in the ponds is heaps of garbage. The solid and liquid wastes generated from household and industrial activities are dumped and released into uncontrolled sites. These sites leak into the low-lying areas where the tanks and ponds are located and due to this malaria vectors develop very easily and many cases of malaria are found near to these polluted ponds. We found that 50.45% of malaria area pixels occurred in the <500 m buffer category of ponds and only 0.99% of malaria area pixels were found in the zone of >3000 m buffer category of ponds. Table 1, under column G reveals that as the distance to ponds or water bodies increases, the percentage of malaria area pixels decreases.

NDVI

Vegetation is often associated with vector breeding, feeding and resting locations. Because malaria is vector-borne, there are many remotely sensed abiotic and biotic environmental variables that are relevant to the study of malarial transmission and habitat niches of the vector. A number of vegetation indices have been used in remote sensing, but the most widely used index to enhance the vegetation areas and crop fields is NDVI. NDVI values range from -1 to +1, with higher values indicating denser vegetation. The higher the NDVI value, the denser the vegetation. Many diseases and their causative agents possess environmentally linked attributes that must be present for transmission or infection to occur. NDVI and remotely sensed variables provide additional methods of exploring and better defining these attributes. Distributions of diseases associated with arthropod and gastropod vectors, classifiable as either intermediate or definitive hosts depending upon the presence or absence of sexual reproduction of the agent while hosted, are definable by their landscape features such as land use, land cover and proximity to aquatic habitats.

The NDVI map has been grouped into three main classes and in this study it is found that 19.39% of malaria area pixels are found in the -0.288 to 0 categories (Figure 4(h)). In Table 1, under column H, it is shown that 80.69% of malaria area pixels are found in the 0–0.986 category, which is the class of agriculture, vegetation and fallow land.

Land use/land cover

Land use/land cover information is also a very important parameter used to calculate the malaria-susceptibility map and calculate the MSZ using a multilinear regression model.¹⁴ The land use/land cover map of the study area has been prepared from the IRS-1C LISS III remote-sensing data from 2008. The land use map is prepared in the image processing platform to highlight five main classes that is agricultural fields, settlement, vegetation, water bodies and fallow land. In this study we found that agriculture and vegetation are very important parameters and play important roles as malaria vector breeding sources. Areas which include dense vegetation provide favourable conditions for malaria vectors. The presence of crop fields, especially in those areas where rice cultivation is dominant, is also crucial as a malaria vector breeding source. Many parts of Varanasi district have fertile agricultural fields and wherever irrigation facilities are very good, farmers cultivate rice.

This area, with good crop fields, should be prone to the occurrence of malaria in some cases (Figure 4(i)). When using land cover and malaria maps to determine the distribution of malaria, according to the land cover classes, 52.64% of malaria affected pixels out of the total pixels occurred in the agriculture class whereas 20.84%, 17.44%, 6.90% and 2.17% of the malaria area pixels occurred in the settlement, vegetation, fallow land and water bodies categories, respectively (Table 1, under column I).

Summary of results

As shown in Figure 5(a), the distribution of malaria area pixels in the information value 0.1–0.6 is looking sensitive: 29.73% of the pixel area has quantities greater than this amount, so this value can be defined as a crucial value for malaria. Pixel networks having information values of more than 0.1 based on malaria area percentages have been divided into two groups, that is high and very high susceptibility, and pixels having lower than 0.1 information value are divided into three levels of low, very low and moderate susceptibility (Table 2 and Figure 5(b)). Table 2 also highlights that 3.87% of the malaria area pixels are in very low malaria susceptibility level whereas 39.86% and 26.29% of the malaria area falls into the high and very susceptibility levels respectively.

DISCUSSION

Principal findings

By applying and integrating the Info Val weights using ArcGIS and ILWIS software, a continuous scale of susceptibility index is generated with which the study area can be divided into five classes of malaria susceptibility. A reliable and accurate susceptibility map depends on the inclusion and proper determination

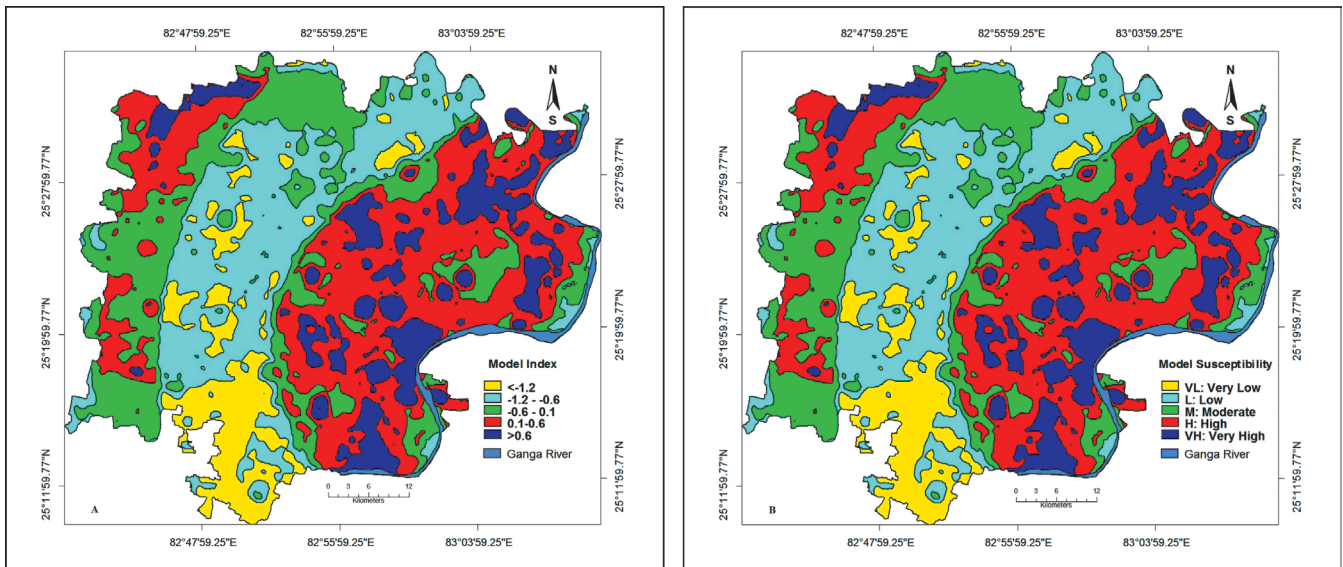


Figure 5 (a) Malaria-susceptibility index (MSI) and (b) malaria susceptibility zone (MSZ) based on the information value method

Table 2 Status of malaria area percentage versus malaria level based on the information value method

Malaria level	Total number of pixels	Pixel (%)	Malaria area (km ²)	Malaria area (%)
Very Low	58,782	9.61	47.95	3.87
Low	143,609	23.49	149.61	12.08
Moderate	149,494	24.45	221.53	17.89
High	181,759	29.73	493.70	39.86
Very High	77,746	12.72	325.64	26.29
Total	611,390	100	1238.43	100

of the role of these parameters. Info Val is used for malaria modelling and to calculate the optimum model for the MSI and for identifying MSZs. The distribution of malaria areas with the information values of 0.1–0.6 is sensitive, as 29.73% of malaria areas have quantities greater than this amount, so this value can be defined as a crucial value for malaria. Also, whilst 3.87% of the malaria pixel area has very low malaria susceptibility, 39.86% and 26.29% of the malaria pixel area falls in the high and very susceptibility classes respectively.

Implications of the findings

The aim of malaria susceptibility modelling is to use known risk factors and their relations to define malaria occurrence in the study area. This method may be helpful in improving access the healthcare facilities in areas affected by malaria. Early detection and prompt response measures may be facilitated though improved surveillance and allow timely remedial measures to be used.

Comparison with the literature

GIS will continue to play a significant role in the reorganisation of public health and disease planning, especially in response to the sweeping changes taking place in the handling of the health-related information.¹⁷ It has been noted that GIS and remote sensing play important roles in the clear interpretation of the malaria-related parameters used in this

study. GIS has shown its capability to answer a diverse range of questions relating to the key goals of efficiency, effectiveness and equity in the provision of public health services.^{18,19}

Limitations of the study

Accurate data collection related to healthcare facilities and disease data from the government hospitals are the major problems faced in this study. The probability values estimated in these kinds of predictive methods are not absolute and represent a relative degree of susceptibility. However, they can provide an appropriate and valid measure of malaria with the limitation that knowledge of past malaria information affects the final probability values calculated by this method. It is possible to use other statistical methods for model validation.

Call for further research

There is clear evidence that the application of GIS and remote sensing integrated with statistical methods for health and disease mapping can play a major role in public health management and disease surveillance. Statistical methods like multiple linear regression, heuristic approach, and logistic regression methods can also be used for further malaria mapping and to calculate the optimum model for MSI and MSZ. Based on the optimum model for MSI and MSZ, we can also calculate the hospital requirement index (HRI) and hospital requirement zones (HRZ).

CONCLUSION

GIS tools can help predict where malaria is more or less likely to occur. The results provide face validity for known predictors of the disease. Such tools might be used by public health agencies to focus on where interventions are most likely to be needed.

REFERENCES

1. Kaya S, Pultz TJ, Mbogo CM, Beier JC and Mushinzimana E. The use of radar remote sensing for identifying environmental factors associated with malaria risk in coastal Kenya. *International Geoscience and Remote Sensing Symposium*, Toronto, ON, 2002.
2. Saxena R, Nagpal BN, Srivastava A, Gupta SK and Dash AP. Application of spatial technology in malaria research and control: some new insights. *Indian Journal of Medical Research* 2009;130(2):125–32. PMID:19797808.
3. Connor SJ, Flasse SP, Perryman AH and Thomson MC. The contribution of satellite derived information to malaria stratification, monitoring and early warning. *World Health Organization mimeographed series*, WHO/MAL/1997; 1079.
4. Craig MH, Snow RW and Le Sueur D. A climate-based distribution model of malaria transmission in sub-Saharan Africa. *Parasitology Today* 1999;15:105–11. [http://dx.doi.org/10.1016/S0169-4758\(99\)01396-4](http://dx.doi.org/10.1016/S0169-4758(99)01396-4).
5. Omumbo JA, Hay SI, Snow RW, Tatem AJ and Rogers DJ. Modelling malaria risk in East Africa at high spatial resolution. *Tropical Medicine and Internal Health* 2005;10(6):557–66. <http://dx.doi.org/10.1111/j.1365-3156.2005.01424.x>. PMID:15941419; PMCID:PMC3191364.
6. Mullner RM, Kyusuk C, Croke KG and Menash EK. Geographical information systems in public health and medicine. *Journal of Medical Systems* 2004;28(3):215–21. <http://dx.doi.org/10.1023/B:JOMS.0000032972.29060.dd>. PMID:15446613.
7. Sudhakar S, Srinivas T, Palit A, Kar SK and Battacharya SK. Mapping of risk prone areas of kala-azar (Visceral leishmaniasis) in parts of Bihar state, India: an RS and GIS approach. *Journal of Vector Borne Disease* 2006;43:115–22. PMID:17024860.
8. Joyce K. To me it's another tool to help understand the evidence: Public health decision-makers' perceptions of the value of geographical information system (GIS). *Health and Place* 2009;15:831–40. <http://dx.doi.org/10.1016/j.healthplace.2009.01.004>. PMID:19268622.
9. Rytönen Mika JP. Not all maps are equal: GIS and spatial analysis in epidemiology. *International Journal of Circumpolar Health* 2004; 63:9–24. PMID:15139238.
10. Messina JP and Crews-Meyer KA. The Integration of remote sensing and medical geography: process and application. In: Albert DP, Gesler WM and Levergood B (Eds), *Spatial Analysis, GIS, and Remote Sensing Applications in the Health Sciences*. Chelsea, MI: Ann Arbor Press, 2005, 156.
11. Hoek W, Konradson F, Amersinghe PH, Perara D, Piyaratne MK and Amerasinghe FP. Towards a risk map of malaria in Sri Lanka: the importance of house location relative to vector breeding sites. *International Journal of Epidemiology* 2003;32:280–5. <http://dx.doi.org/10.1093/ije/dyg055>.
12. Kulldorff M. Spatial scan statistics: model, calculations and applications. *Scan Statistics and Applications* 1999;15:303–302. http://dx.doi.org/10.1007/978-1-4612-1578-3_14.
13. Lawson AB. Disease mapping: basic approaches in new developments. In: Maheswaran R and Cragilla M (Eds), *GIS in Public Health Practice*. New York: CRC Press, 2001; 31–49.
14. Rai PK, Nathawat MS and Onagh M. Application of multiple linear regression model through GIS & Remote Sensing for malaria mapping in Varanasi district, India. *Health Science Journal* 2012;6(4):731–49.
15. Riedel N, Vounatsou P, Miller JM, Gosoni L, Chizema-Kawesha E, Mukonka V and Steketee RW. Geographical patterns and predictors of malaria risk in Zambia: Bayesian geostatistical modelling of the 2006 Zambia national malaria indicator survey (ZMIS). *Malaria Journal* 2010;9:37. <http://dx.doi.org/10.1186/1475-2875-9-37>. PMID:20122148; PMCID:PMC2845589.
16. Saha AK, Gupta RP and Arora MK. GIS based landslide hazard zonation in Bhagirathi, Ganga valley, Himalayas. *International Journal of Remote Sensing* 2005;23:357–69. <http://dx.doi.org/10.1080/01431160010014260>.
17. Donald PA, Wilbert MG and Barbara L. *Spatial Analysis, GIS and Remote Sensing Application in the Health Sciences*. Chelsea, MI: Ann Arbor Press, 2006, 185.
18. Boscoe FP, Ward MH and Reynolds P. Current practices in spatial analysis of cancer data: data characteristics and data sources for geographic studies of cancer. *International Journal of Health Geography* 2004;97:14041–3.
19. Kleinschmidt I, Bagayoko M, Clarke GPY, Craig M and Le Sueur D. A spatial statistical approach to malaria mapping. *International Journal of Epidemiology* 2000;29:355–61. <http://dx.doi.org/10.1093/ije/29.2.355>. PMID:10817136.
20. Sweeney AW. A spatial analysis of mosquito distribution. *GIS Use* 1997;21:20–21.

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