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ORIGINAL ARTICLE

Spatial susceptibility analysis of vector-borne diseases in KMC using geospatial technique and MCDM approach

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Abstract

The prevalence of vector-borne diseases (VBDs) like malaria and dengue claims many parts of the capital city Kolkata. Although the frequency of affects has been declining, still several cases are still reported from different parts of Kolkata Municipal Corporation. The present study aimed to apply multi-criteria decision making (MCDM) approach along with geospatial technique to map susceptible areas of vector-borne diseases. For growing vectors and transmitting diseases, there are always many factors responsible instead of a single factor. Hence, the present work was carried out in multiple stages. Initially different susceptible factors to vector-borne diseases like environment, demography, epidemic and related to suitable breeding sites were selected. Analytic hierarchy process as a technique of MCDM was considered and pair-wise comparison matrix (PCM) was established for each selected factor. Synergistically, weight-based single layer of susceptible zonation was developed and finally, GIS integration was performed for susceptible map of VBDs. The decision-making process was judged by consistency measurement and result shows that the consistency ratio of each selected factor ranged between 0.02 and 0.07, i.e. < 0.1 which is acceptable. Geospatial technique offers space to apply statistical method and analytical technique to acquire information. With the help of remote sensing data and spatial information, GIS tool was utilised to analyse spatial susceptibility of vector-borne diseases. The study revealed that spatial location of water bodies is the most responsible factor with highest weight among all selected factors and concomitantly, moisture content, surface temperature, proximity to waste storage bins, and reported dengue and malaria cases also share influential contributions in prevalence of vector-borne diseases. The present result shows the high applicability of geospatial technique in epidemic diseases' zonation which may considered helpful for applying in different fields of research.

Keywords Vector-borne diseases · Kolkata Municipal Corporation · Multi-criteria decision-making approach · Geospatial analysis · Susceptibility analysis

Introduction

Growth and development of vectors are the main causes of transmission of vector-borne diseases. It is always considered that suitable breeding sites for vector carrying insects is the main factor in transmission of such type of diseases. Hence, it is essential to know what is vector and how diseases are transmitted. Vectors are living organisms that can spread infectious diseases between individuals or from animals to humans, i.e. transfer virus and pathogens from one infected person or animal to another, causing serious health problems in human populations. These vectors may be bloodsucking insects like mosquitoes, which swig disease-generating microbes and virus during a blood meal from an infected host, i.e. animal or human and later inject this infected blood into a new host during their subsequent blood meal (WHO 2017). Therefore, vector-borne diseases are not possible till it is transmitted by any vector from an infected host to another. Excluding mosquitoes, others vectors are ticks, sand-flies, flies, fleas, triatomine bugs and some freshwater aquatic insects. Chikungunya, dengue fever and dengue haemorrhagic fever, Japanese encephalitis, Kala-azar, filariasis, and malaria are considered as the main vector-borne diseases.

The spatial distribution of vector-borne diseases is determined by different dynamic factors like demography, environment and social factors. Unexpected urbanization,

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urban growth and climatic factors including climate change, variation in temperature and rainfall, variation in moisture contents can influence vector breeding and growth (Morin et al. 2013; Hii et al. 2016). Moreover, various environmental factors such as changes in local land use, local sanitation conditions, drainage facility and improper management of generated waste in and around households can also affect the transmission of vector-borne diseases due to availability of suitable sites for breeding and can render large populations in towns and cities at risk of viral disease spread by mosquitoes (Rattanarithikul et al. 1995; Mushinzimana et al. 2006; Ayele et al. 2012).

As far as Kolkata Municipal Corporation is considered, malaria and dengue are found as major vector-borne diseases. The proportion of Chikungunya and filariasis is limited and found in a little frequency. Japanese encephalitis and Kala-azar are rarely found here (Chatterjee 2017). The prevalence of malaria is much more in comparison to dengue (Sharma et al. 2014). Although the degree of malaria cases has been reducing from 96,909 in 2010 to 4769 in 2017 with no more deaths from 2011, the cases of dengue have also fallen down from 3546 in 2005 to 662 in 2017 although the deaths in dengue cases reoccur year after year. Malaria and dengue are an ever-seen and common public health problem in Kolkata. *Anopheles stephensi* is the chief source of malaria transmission in Kolkata and dengue is transmitted by *Aedes aegypti* (*Aedes albopictus*).

Recently, KMC has launched different initiatives to reduce vector-borne diseases from the capital city including establishment of mosquito research laboratory, establishment of dengue detection centre, dissemination of dengue report through SMS Alert, disease surveillance system strengthening, plying of speedboats along canals for destruction of mosquito larvae, larvicidal spray along canals using rowing-boats as transport, formation of 21 rapid-action teams for vector control, efficient non-medical staff assigned with vector control responsibilities etc. Along with such type of initiatives some micro-level initiatives are also taken including localised vector detection centres, multilingual leaflets, multi-coloured flex-banners, multi-coloured hoardings, awareness meeting, comprehensive booklet, documentary film, auto-miking and house visit etc. for awakening the residents to lessen the extent of risk of vector-borne diseases.

But the best prevention method of vector-borne disease is to detect and destruct considerable suitable breeding site of vector-carrying parasites. Recently, remote sensing (RS) and geographical information system (GIS) prove their efficiency in detecting and recognising the suitable breeding sites of vector-carrying parasites, susceptible risk zones and area under prone to risk using geospatial technique and spatial analyst tool (Nazri et al. 2012; Ahmad et al. 2017; Ali and Ahmad 2018, 2019). The use of spatial tools in GIS for public health is a significant technique to find spatial association and integration (Richardson et al. 2013). Remote sensing and geographical information system provides up-to-date information on environmental parameters of a particular region or location that influence the vector-borne disease transmissions (Nazri et al. 2009). Instead of considering one single factor, the result becomes weighted on considering multiple factors (Wondim et al. 2017; Ali and Ahmad 2018). Hence, the present study punctuates multi-criteria decision making (MCDM) tool for considering the parameters and making decision towards susceptibility of vector-borne diseases and mapping of risk zonation. The fundamental functioning principle of any MCDM process is same: selection of weighted criteria, selection of alternatives or sub-criteria, selection of aggregation, methods, and ultimately rank of alternatives based on weights or outranking (Majumder 2015). Decision making is based on various data relating to the study problem. It has been suggested that 80% of data used by decision makers are geographical, i.e. spatial in nature (Rikalovic et al. 2014). Decision problems that involve geographical data are denoted as geographical or spatial decision problems (Malczewski 2004).

Several research works have been carried out using RS and GIS in malaria susceptibility, dengue risk zonation and analysis of other vector-borne diseases over time (Nazri et at. 2012; Sarfraz et al. 2014; Tu et al. 2014; Ahmad et al. 2017; Wondim et al. 2017; Ali and Ahmad 2018). Digital elevation model, satellite data and location of GPS superior spatial analysis were utilised for current environment strategy in urban areas (Dongus et al. 2009). Geospatial technology was applied to identify and demarcate malaria-susceptible areas (Delgado et al. 2011). Satellite images with various resolutions, i.e. IRS LISS I, LISS II and WiFS were utilised to recognise suitable vector habitats and susceptible areas (Sharma et al. 1996; Palaniyandi 2004; Palaniyandi and Mariappan 2012). It is always required to rely on authentic and accurate data sets for vector-borne diseases' control and management to predict susceptible areas and project risk mapping (Robert et al. 2003; Palaniyandi 2013). Mosquito-producing fields were identified in California through correlating Anopheles larva density with reflectance of canopy growth in early season using Landsat TM imagery and GIS technique (Wood et al. 1992). Detection of many vector diseases is directly not possible through field visit and observations, thus Multi-criteria analysis (MCA) along with GIS and AHP technique was applied by integrating various thematic layers for malaria risk mapping West Singhbhum district of the Jharkhand, India (Ahmad et al. 2017). Various socio-economic, geographic and epidemiological factors were integrated to familiar with malarial hotspots (Qayum et al. 2015). Moreover, there are different studies in different geographical locations of earth which have shown the capability of RS and GIS technique in detecting vector-borne diseases (Nakhapakorn and Tripathi 2005; Rochon et al. 2010; Hongoh et al. 2011; Khormi and Kumar 2011; Yadav et al. 2012; Walker et al. 2013; Nazri et al. 2016; Ali and Ahmad 2018, 2019).

The present study also highlights the application of RS data and GIS technique along with analytic hierarchy process as a multi-criteria decision-making tool for identifying susceptible areas and hotspot mapping of vector-borne disease. Thus, present study aimed to use GIS tools and other primary and secondary data for measuring the weight of various environmental, demographic and epidemic factors to make interrelationships towards vector-borne disease and to map susceptible areas. Such mapping of VBDs can provide assistance to health authorities to understand spatial distribution under risk as well as temporal outbreak of such diseases. Risk maps have prepared for public health and decision making because this will help in preventing measure and also provide guideline for implementing control programs and preparing health facilities based on spatial information of area under risk.

Study area

Kolkata is the capital of the Indian state of West Bengal which is located on the east bank of River Hooghly. As a typical riverine city, Kolkata in earlier days was surrounded by marshes, tidal creeks, mangroves, swamps, and wetlands. But now all these have changed with time. Kolkata Municipal corporation (KMC) is the largest urban agglomeration of West Bengal which is located in UTM Zone 45°N with geographical extension of 22°28′ 00″N–22°37′30″N and 88°14′30″E–88°25′30″E (Fig. 1). The KMC has an area of 205.07 Km^2 which is divided into 16 administrative Boroughs and, respectively, 144 wards. The mean elevation of the city is 1.5 m–16 m above MSL. Many parts of the city were originally wetlands which were reclaimed over the time to house the bourgeoning population. The annual mean temperature over Kolkata Municipal Corporation is 26.8 °C or 80.24 °F. Monthly mean temperature ranges between 19 and 32 °C. Summers are hot and humid with temperature 34 °C, during May and June the temperatures often exceed 40 °C.

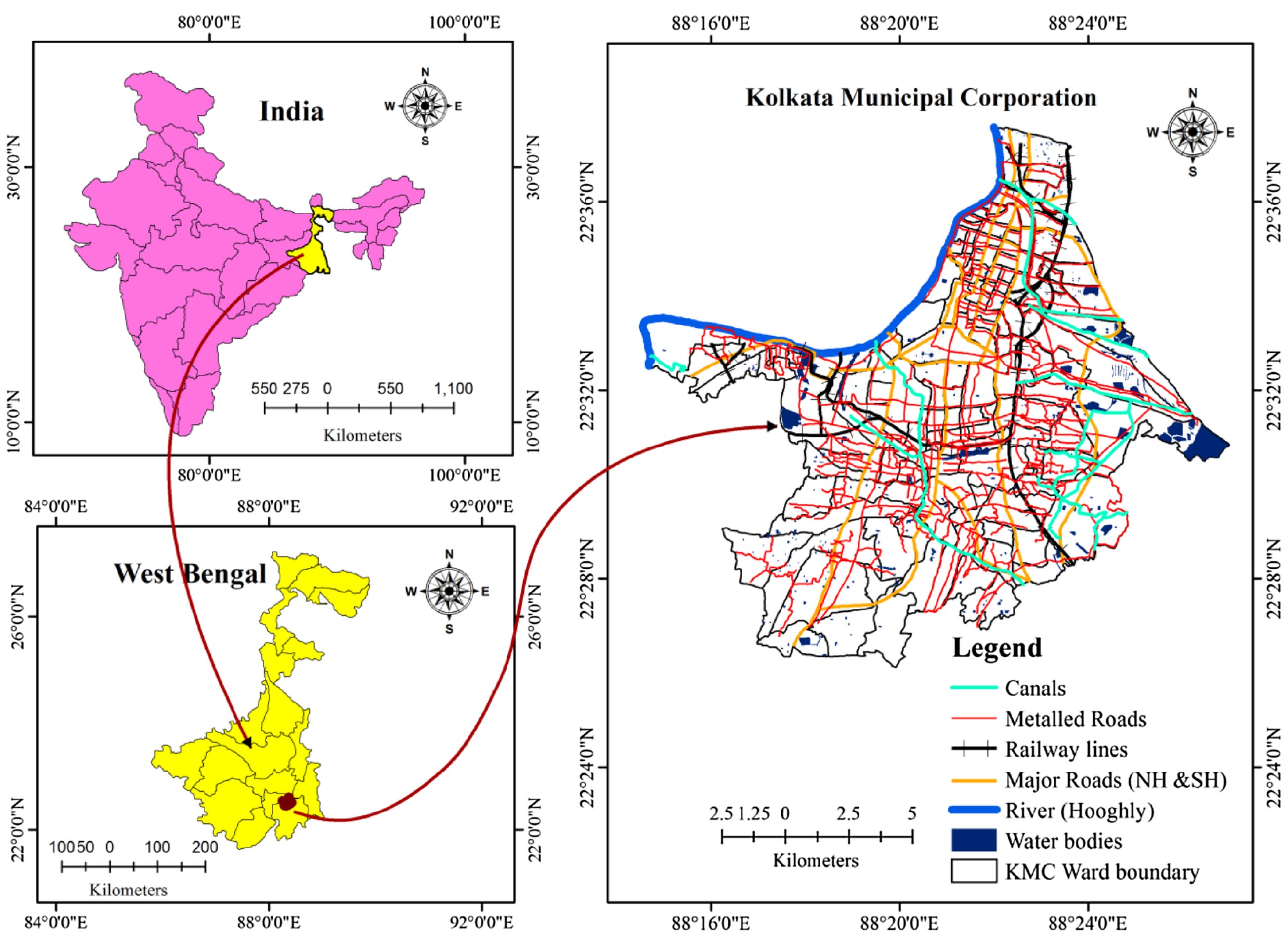


Fig. 1 Location of the study area

Winter or mild winter lasts for highly 2 and half month with lowest temperature between 9 and 11 °C in December and January. The annual average rainfall is near about 1600 mm and highest rainfall occurs during the month of August. According to latest population data (DSH 2014-15) the city has a population of 4,496,694 and 1,024,928 households. The population density of KMC is about 24,306 persons per km^2 where, household density ranges between 755 and 23,237 households per km^2 by making KMC as India's third largest metropolitan city as well as the world's eighth largest urban agglomeration.

Materials and method

Data sources

Different types of satellite data were collected looking towards requirement of the study. Landsat 8 OLI and TIRS data were used for deriving Land Surface Temperature (LST) which is an important factor for growing disease-carrying mosquitoes. The Landsat OLI and TIRS, 30 m resolution data with UTM projection by default (Path: Row 138/44) were collected from United States Geological Survey (USGS) earth explorer portal and thermal bands were obtained looking towards purpose of use. The Sentinel-L2A data were utilised for preparing Land Use Land Cover (LULC), Normalized Difference Vegetation Index (NDVI) and Normalized Difference Moisture Index (NDMI). Sentinel-L2A data (45QXE & 45QXF) with 10 m and 20 m spatial resolution along with WGS 1984 projection by default were collected from Sentinel Hub EO browser (Table 1).

Excluding satellite data, GPS field location, information from Google Earth, demographic data and epidemic data were also used in this study. The demographic data including population, household and literacy were collected from District Statistical Handbook, Kolkata 2015. The densities were calculated by dividing with respective area. To consider suitable breeding sites for vector-borne transmitting agents, GPS locations were collected which were further processed and accuracy measured in Google Earth. These locations include waste bins, open vats of waste, compactor stations and water bodies. These locations were used for proximate analysis. Furthermore, spatial epidemic data were collected from KMC and interpolation was run to determine area under high and low risk. Finally, all these input layers were processed in GIS environment with equal projections and cell size for further processing and analysis.

Study plan

Multi-criteria decision making (MCDM) is considered in present study to analyse susceptibility of vector-borne diseases. The multi-criteria decision making or multi-criteria decision analysis is a decision-making method that helps in structuring, measuring, and judging a decision problem. As a part of MCDA, it is always required to select multi-criteria and prefer more weightage criteria through different techniques. Analytical hierarchy process (AHP) is a widely used MCDA method. Hence, AHP was used

Table 1 Sources of data collection and their use in mapping of vector-borne diseases

Data set	Date	Source	Uses in VBDs susceptibility	Data type	Method used
Landsat-8 (OLI and TIRS)	14/04/2017	USGS-earth explorer portal	LST	Raster	Raster calculator: convert into TOA, reflectance value and brightness temperature
Sentinel-L2A	11/03/2018; 17/10/2017	Sentinel Hub EO browser	LULC, NDMI and NDVI	Raster	Supervised classification; standard equation for moisture and vegetation index
Demographic data	2015	District Statistical Handbook, Kolkata	Population density, household density, and literate population	Vector; converted to Raster	Data-based classification using Choropleth
Suitable breeding sites	2018	Field visit and GPS	Proximate analysis	Vector; converted to Raster	Multiple ring buffers
Epidemic data	2013–2017	KMC, Govt. of West Bengal	Mapping of malaria and dengue prevalence	Vector; converted to Raster	IDW interpolation
Base map	2011	The Kolkata Gazette, Govt. of W.B	Georeference; delineation of outer boundary, ward and borough map	Vector	Simple digitization

in present study. It is a multi-step plan including selection of relevant criteria/factors, data inputs, data processing, analysis, and making accurate decision. Kolkata Municipal Corporation was chosen to carry out such type of study, because the prevalence of vector-borne diseases like dengue and malaria is seen every year from early August to late October and claims many lives year after year. Thus, proper susceptibility zonation of VBDs can enhance better surveillance to reduce the impacts.

The methodology to carry out the study is presented in the following figure (Fig. 2). The important factors (considered as decision criteria) that associated to VBDs occurrence were chosen looking towards the aim of the study. First of all, 13 associated factors were chosen and included them into three categories, i.e. environmental factors, demographic, and epidemic factors and factors related to suitable breeding site. To cheek the decision accuracy, Consistency Ratio (CR) of each selected decision factor was calculated using Saaty's method. For spatial analysis, the spatial database of each factor was created in GIS Environment. GIS integration was run using weighted linear combination (WLC) to prepare spatial susceptibility map of VBDs.

Determination of decision criteria: data selection and preparation

Environmental factors

Land use land cover (LULC)

Different type of land cover has significant role in providing sites for suitable breeding environment. The incidence of vector-borne disease like chikungunya and malaria is related with water bodies and land under low area (Sheela et al. 2017). Alterations of land-use type including impoundments, dams, irrigation and draining systems that create shelters for the carrying agents have potential effect in transmitting vector-borne diseases like malaria, dengue, and filariasis (Norris 2004). Thus, preparation of LULC map is crucial to classify major area under different land cover and their uses to understand those areas susceptible to mosquitoes' breeding site.

The LULC map was prepared using Sentinel-2 dataset. Primarily band combination was performed with Near Infrared (Band 8), Red (Band 4), and Green (Band 3) to make false color composite (FCC) infrared. Secondly, object-based

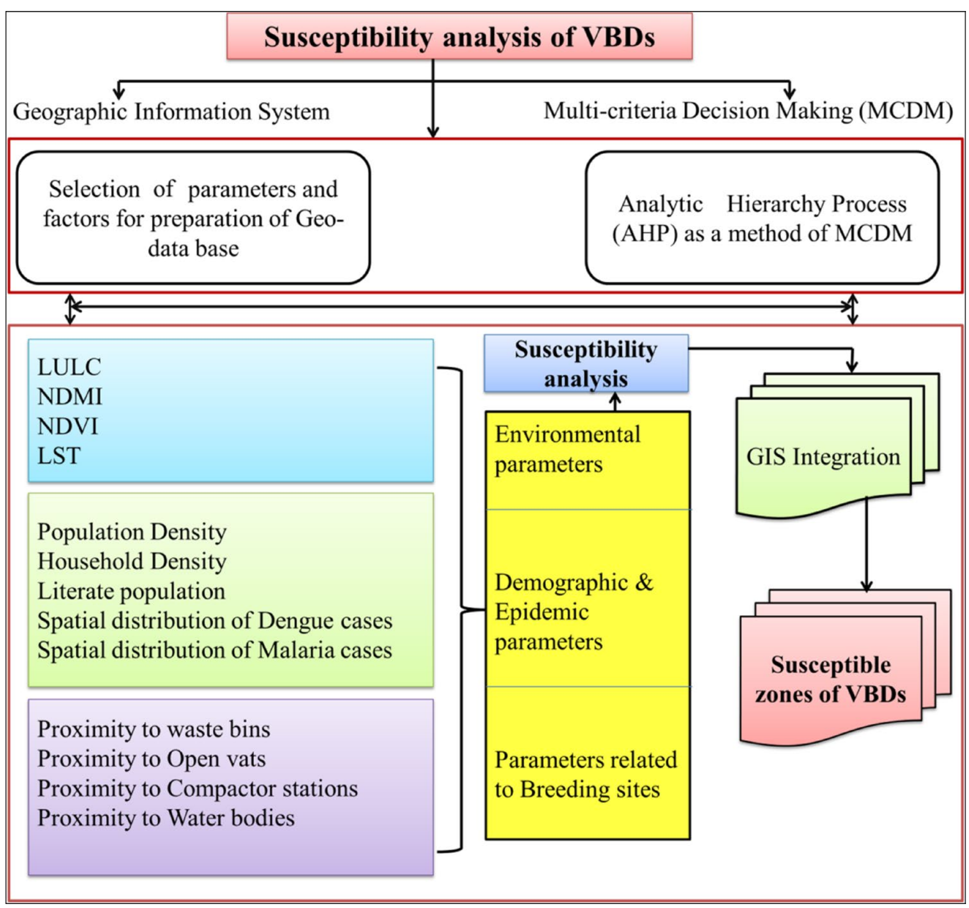


Fig. 2 Chart showing the methodology used for analysing VBD-susceptible zonation in KMC

signature file was created to run supervised classification and finally, the entire area was classified into five major land-use types and susceptible risk was considered based on classified category (Fig. 3a).

Normalized difference moisture index (NDMI*)*

The Moisture Index was calculated using NIR and SWIR Bands of Sentinel-2. Many variables are interrelated and correlated with each other. Like the wet areas have high moisture content and concomitantly high vegetation. NIR is useful for classifying the vegetation and SWIR is good for measuring the moisture content of soil and vegetation, i.e. the reflectance in the NIR band is influenced by the leaf's internal structure and the SWIR reflects the changes in vegetation water content. In SWIR, a darker area highlights higher water content. The following equation was used to estimate moisture content;

$$\mathrm{NDMI} = (\mathrm{NIR} - \mathrm{SWIR})/(\mathrm{NIR} + \mathrm{SWIR}),$$

where NIR is for the Near infrared (Band 8A) and SWIR is the Short-Wave Infrared (Band 11). For Sentinel-2 data, these bands are with 20 m spatial resolution. NDMI have a values ranging from -1 to $+1$, where -1 indicates very bad moisture level and $+1$ indicates very high moisture level (Fig. 3b).

Normalized difference vegetation index (NDVI)

Mosquito-borne diseases were found in highest proportion in areas with low land and lowest forest cover (Sheela et al. 2017). Many researchers emphasized that NDVI is a significant factor for analysing mosquito-borne diseases. Moreover, in present day deforestation seems to be associated with the growth of mosquito and rise in mosquito-borne disease transmission (Norris 2004). Vegetation indices, specially based on the NDVI, the habitat suitability for different species of mosquitoes can be described (Kleinschmidt et al. 2000; Brown et al. 2008; Lourenço et al. 2011). The mosquito population is positively correlated with Normalized

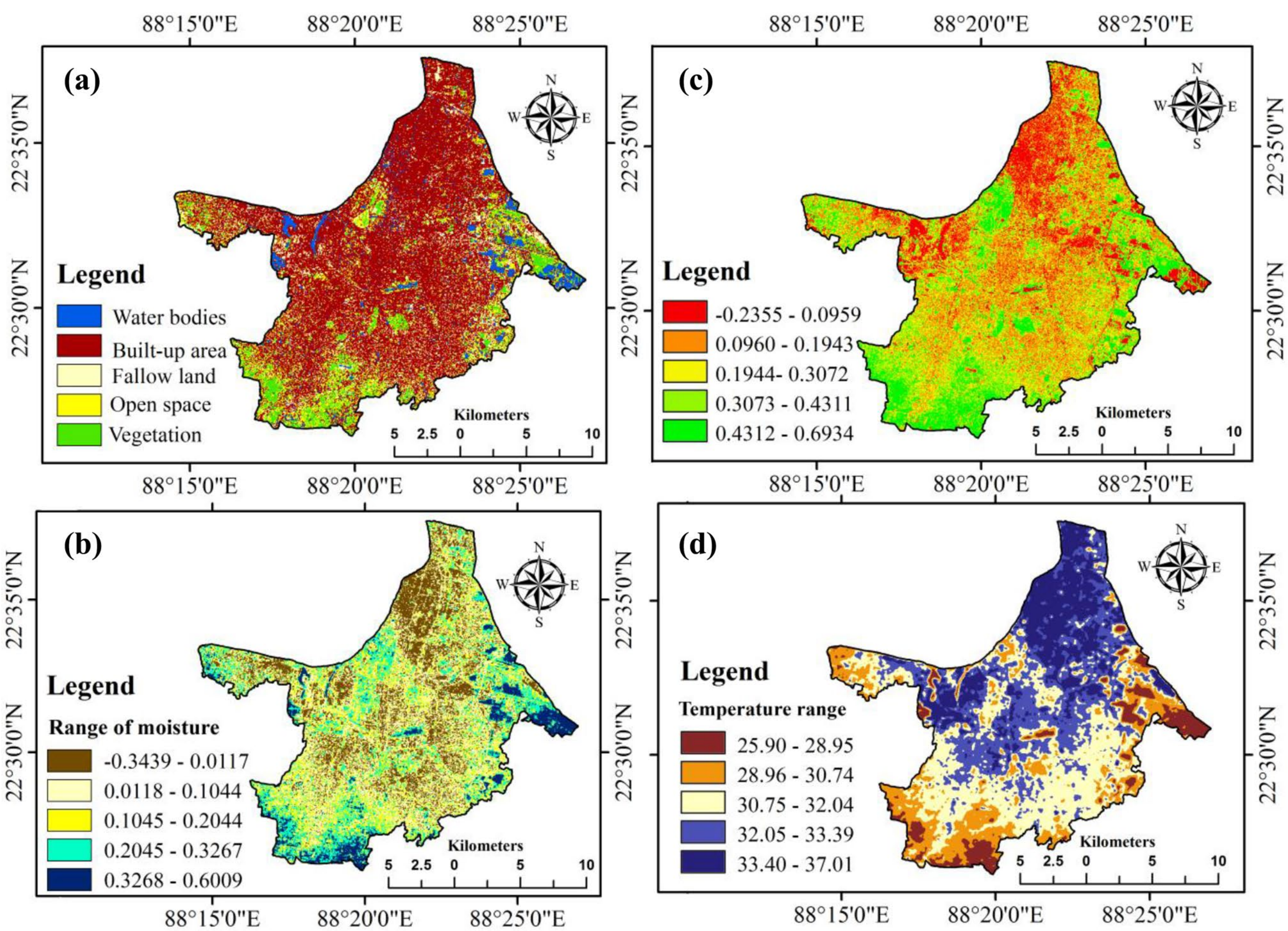


Fig. 3 Maps of four selected environmental factors which were taken as decision criteria in susceptibility analysis of VBDs; **a** land use land cover, **b** normalized difference moisture index, **c** normalized difference vegetation index and **d** land surface temperature

Difference Vegetation Index (Gemperli et al. 2006). The amount of precipitation can also be linked with vegetation index. The green vegetation is related with higher amounts of precipitation and is considered as suitable environment for mosquito habitats (Brown et al. 2008).

To know the vegetation index (VI) of KMC, NDVI was calculated (Fig. 3c). It was used for quantifying the green vegetation. NDVI normalizes the green leaf scattering in the near-infrared wavelength and chlorophyll absorption in the red wavelength. Hence, near-infrared and Red bands are required. Band 8 and Band 4 of Sentinel-2 dataset were used for this purpose and NDVI was calculated using the following equation;

$$\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{RED})/(\mathrm{NIR} + \mathrm{RED}),$$

where NIR is Band 8 and RED is the Band 4. As per Sentinel-2 EO products guideline, the value of NDVI ranges from -1 to 1. Negative values (values approaching -1) represent water bodies. Values close to zero (i.e. -0.1 to $+0.1$) mostly represent barren areas of rock, sand, or snow. Low but positive values represent shrub and grassland (mostly it ranges from 0.2 to 0.4) and high positive values indicate dense forest.

Land surface temperature (LST)

Land surface and air temperature affect the feeding behaviour of the mosquito and play an important role in the growth of mosquito larva (Sandru 2014). The survival and the life cycle of vectors are also effected by land surface temperature. Sandru (2014) found that mosquito survival is low at extreme temperatures, i.e. very high or very low temperature is harmful for mosquito's growth. The optimum temperature in which mosquito can grow and survive is found between 28 °C and 32 °C and temperatures < 5 °C and or > 40 °C are deadly for the mosquitoes.

The land surface temperature of KMC was derived from TIRS 1 (Band 10) of Landsat 8 dataset (Fig. 3d). To calculate LST using thermal infrared sensor data, first, the conversion of digital number to TOA (Top of Atmosphere) radiance is required. OLI and TIRS datasets can be converted to TOA spectral radiance using the radiance rescaling factor which is provided in metadata file of Landsat dataset. Thus following equation was used:

$$L_\lambda = M_L \times Q_{\mathrm{cal}} + A_L$$

where L_λ = TOA spectral radiance (Watts/(m^2*srad*μm)), M_L = band-specific multiplicative rescaling factor taken from metadata (RADIANCE_MULT_BAND_x, x is the thermal band), Q_{cal} = quantized and calibrated standard product pixel value and A_L = band-specific additive rescaling factor taken from metadata (RADIANCE_ADD_BAND_x, x is the thermal band).

Now, the top of atmospheric brightness temperature has to calculate from the reflectance value using the equation:

$$\mathrm{BT} = \frac{K2}{\mathrm{In}\left(\frac{K1}{L\lambda} + 1\right)} - 273.15,$$

where BT = atmospheric brightness temperature in Kelvin, which is further subtracted by 273.15 to calculate the degree Celsius, $K2$ = band-specific thermal conversion constant (K2_CONSTANT_BAND_x, x is the band number), $K1$ = band-specific thermal conversion constant (K1_CONSTANT_BAND_x, x is the band number), L_λ = TOA spectral radiance.

Finally, brightness temperature was converted to land surface temperature using the following equation:

$$\mathrm{LST} = \frac{\mathrm{BT}}{(1 + (\lambda \times BT/c2)} \times \mathrm{Ln}(e)$$

where BT = brightness temperature, λ = wavelength of emitted radiance, $c2 = h \times c/s = 1.4388 \times 10^2$ m K = 14,388 μm (h, c, and s are constant), e = emissivity which was calculated from near-infrared and Red band of the same dataset.

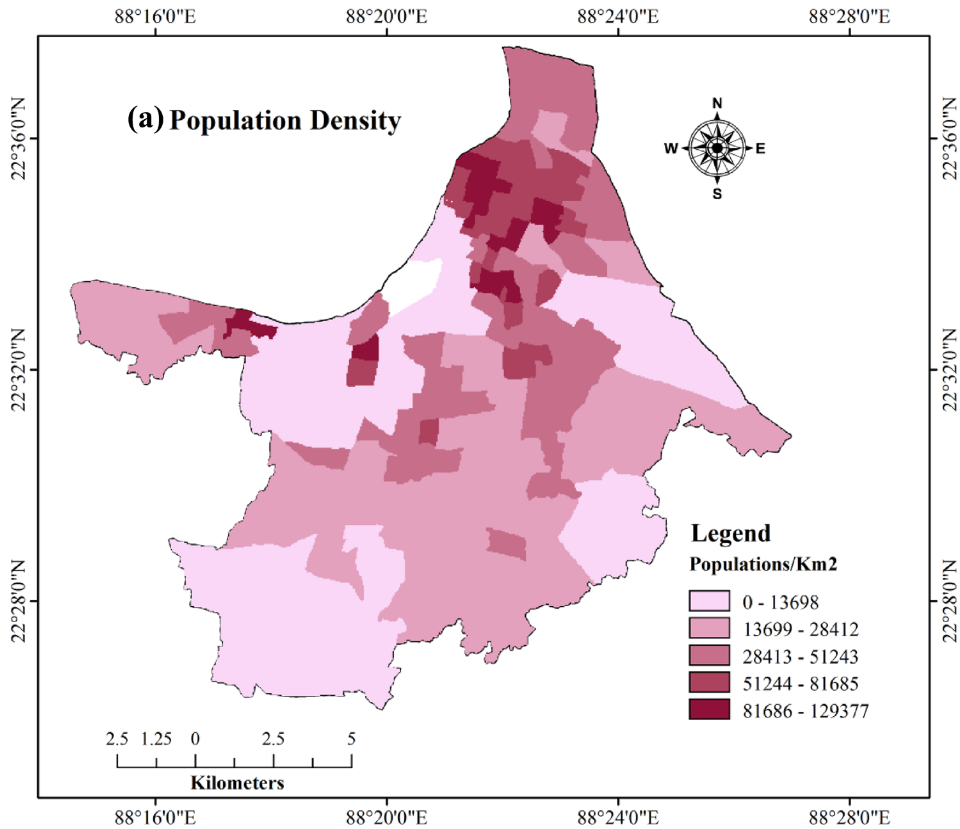
Demographic and epidemic factors

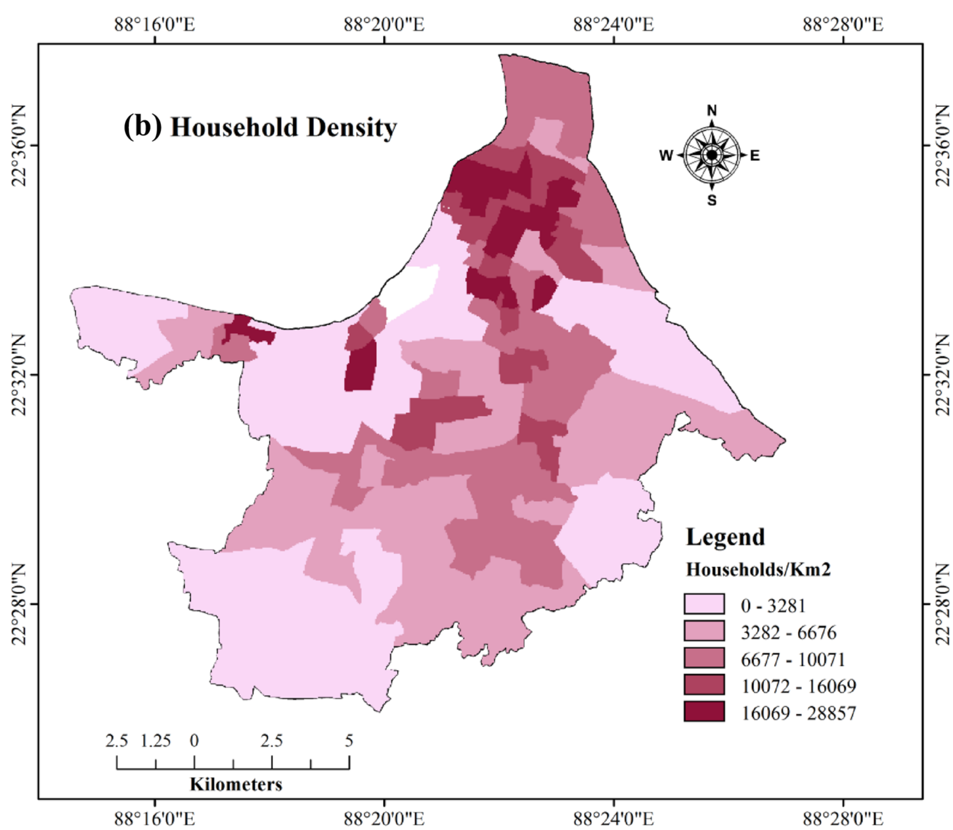
A densely populated area creates a higher chance of experiencing an epidemiological outbreak even if the vector house index is low in that area. The respective vector does not have to travel far to search for its victims (Sandru 2014). High human population density and poor water supply are regarded as major contributors to dengue epidemics (Gubler 2004; Barreto and Teixeira 2008). An unexpected range of human population densities between 3000 and 7000 person/km^2 in rural villages is prone to high dengue outbreaks (Schmidt et al. 2011). The risk of contracting West Nile disease is increased by living in low-density housing in the presence of vegetation (Sandru 2014). Household density, housing types and surrounding built-up environment have offered vital insights into the epidemiology of dengue fever and potential risk (Braga et al. 2010).

Literacy is highly related with human awareness about diseases transmission. High literate population may be well aware about the precautions and consequences of transmissible diseases and hence have low risk in contrast with low literate population. Research showed that people well conscious about the cause of malaria and found that awareness increased with the increasing literacy status and knowledge about mosquito-borne diseases were also significantly better among literate than illiterate population (Rasania et al. 2002).

Based on literature survey, the above three demographic factors (population density, household density and literacy

Fig. 4 Selected factors related with demographic and epidemic factors; **a** population density, **b** household density, **c** literate population, **d** reported dengue cases and **e** reported malaria cases





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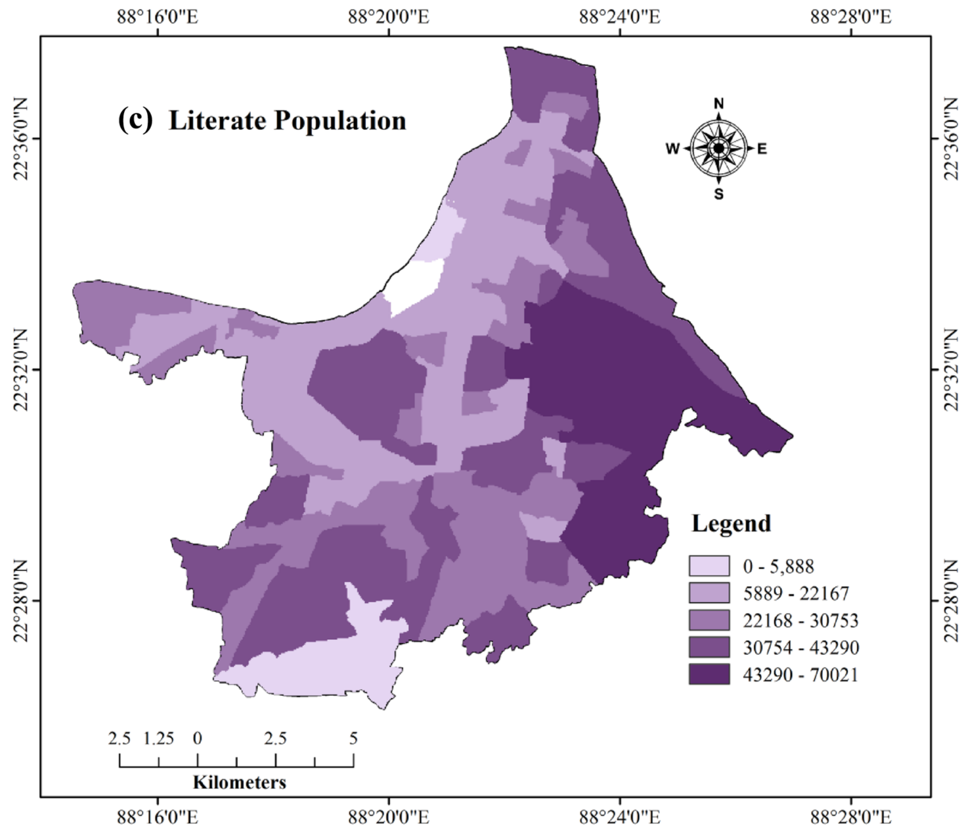

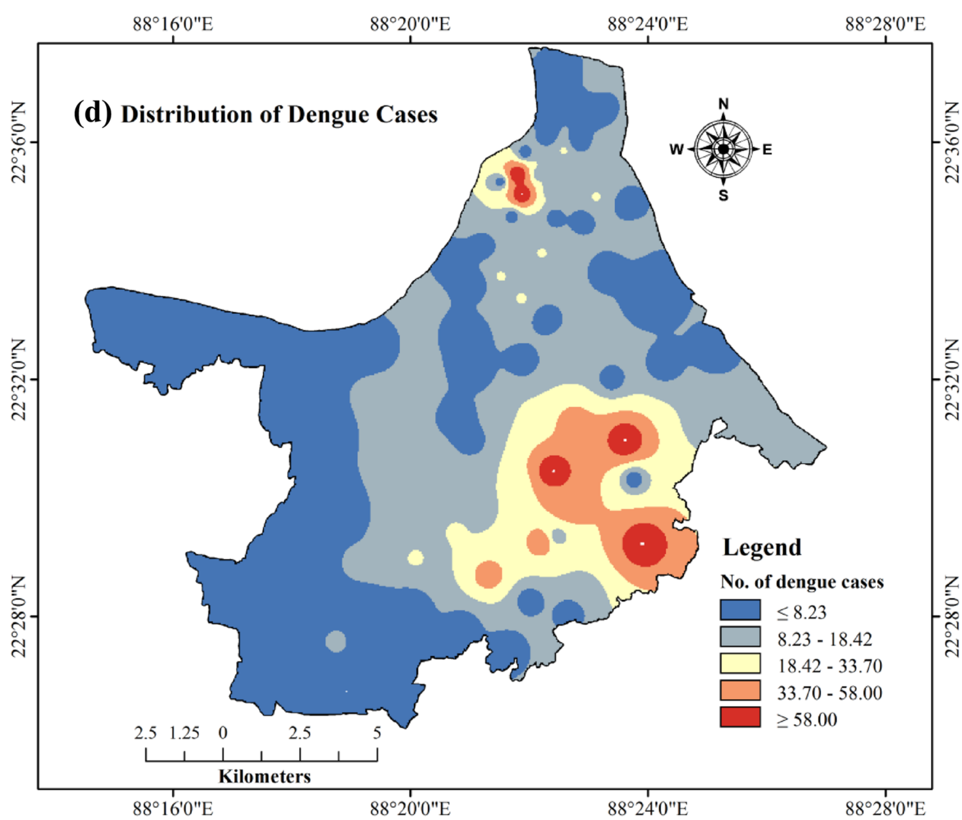

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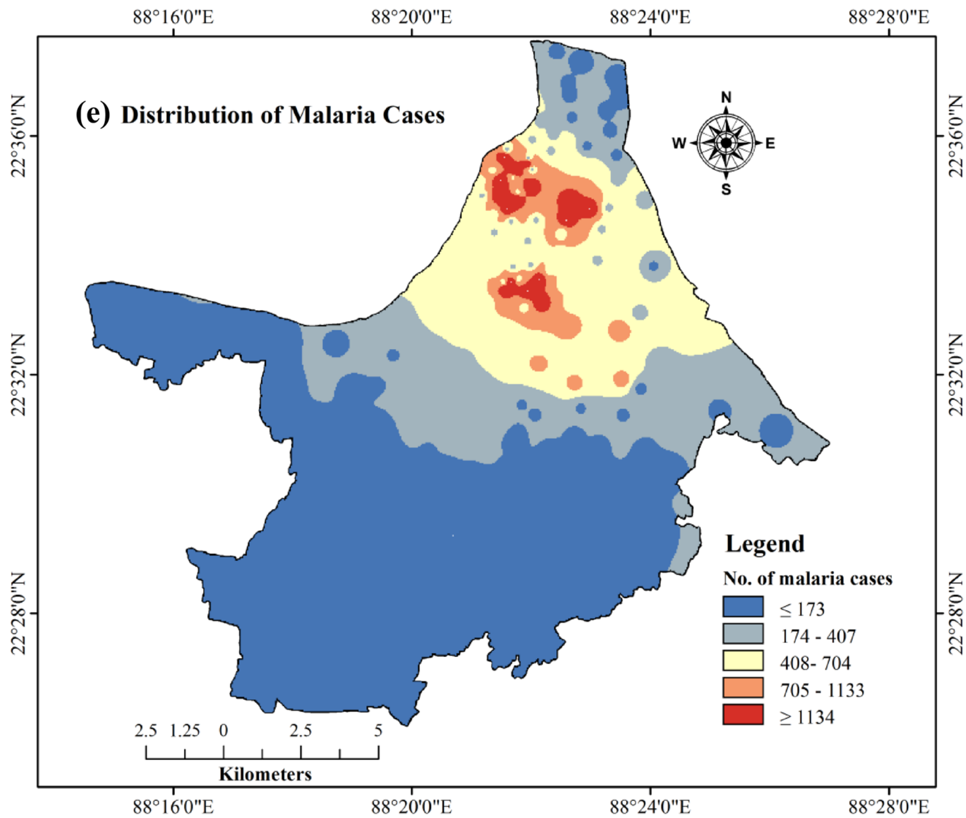


rate) were chosen in susceptibility analysis of VBDs. Data on population and literacy were collected from Bureau of Applied Economics & Statistics, Department of Statistics & Programme Implementation, Govt. of West Bengal. First of all, area of each respective wards of KMC was calculated using spatial statistical tool in GIS environment. The total number of population and household of each ward were then divided with respective area and density of population and household was calculated. The following formula was used to calculate population and household density;

$$Dx = \frac{Nx}{Ax}$$

where Dx is the density of population or Household, Nx is the total residing population or households and Ax is the area of respective ward in Km^2. Choropleth is technically a thematic areal map in which areas are shaded in color or patterned in proportion. Choropleth technique was used to prepare the literacy, population and household density map in five categories from very low to very high using natural break in GIS environment (Fig. 4a–c).

Epidemiology is the analysis of the distribution of disease conditions and public health. Dengue and malaria are considered as an endemic disease instead of pandemic as these are confined in certain places of the earth, i.e. tropical region due to availability of temperature and moisture which offers best breeding sites for the disease-carrying host. For the epidemic parameters, cases of dengue and malaria for the year of 2012–2015 were collected for spatial analysis. Dengue and malaria are main vector-borne diseases in KMC, other VBDs including West Nile Virus, Lyme disease, Japanese Encephalitis, Chikungunya etc. are not seen here. Only 2 cases of Japanese Encephalitis (JE) were found during 2014. Thus, only malaria and dengue cases were considered for present work. For spatial distribution of dengue and malaria cases, spatial interpolation was used based on given inputs on recorded dengue and malaria cases (Fig. 4d, e).

Factors related to suitable breeding sites

Places with garbage and waste accumulation, stagnant sources of water, drains, stagnant canal with garbage accumulation, in and around community waste bins and open waste dumping vats are considered as the most appropriate breeding sites for mosquitoes. Improper handling and management of waste and their unscientific disposal cause adverse impact on all components of the environment and human health. Unscientific disposal of wastes here and there and constructing built-up areas can be the reason for creating suitable sites for breeding. Disposal of garbage and dumping these into drains can also be causes of breeding grounds for mosquitoes. Hence much attention is to be paid to provide appropriate treatment and disposal of waste generated in the built-up area. In an evolving urban policy, priority is

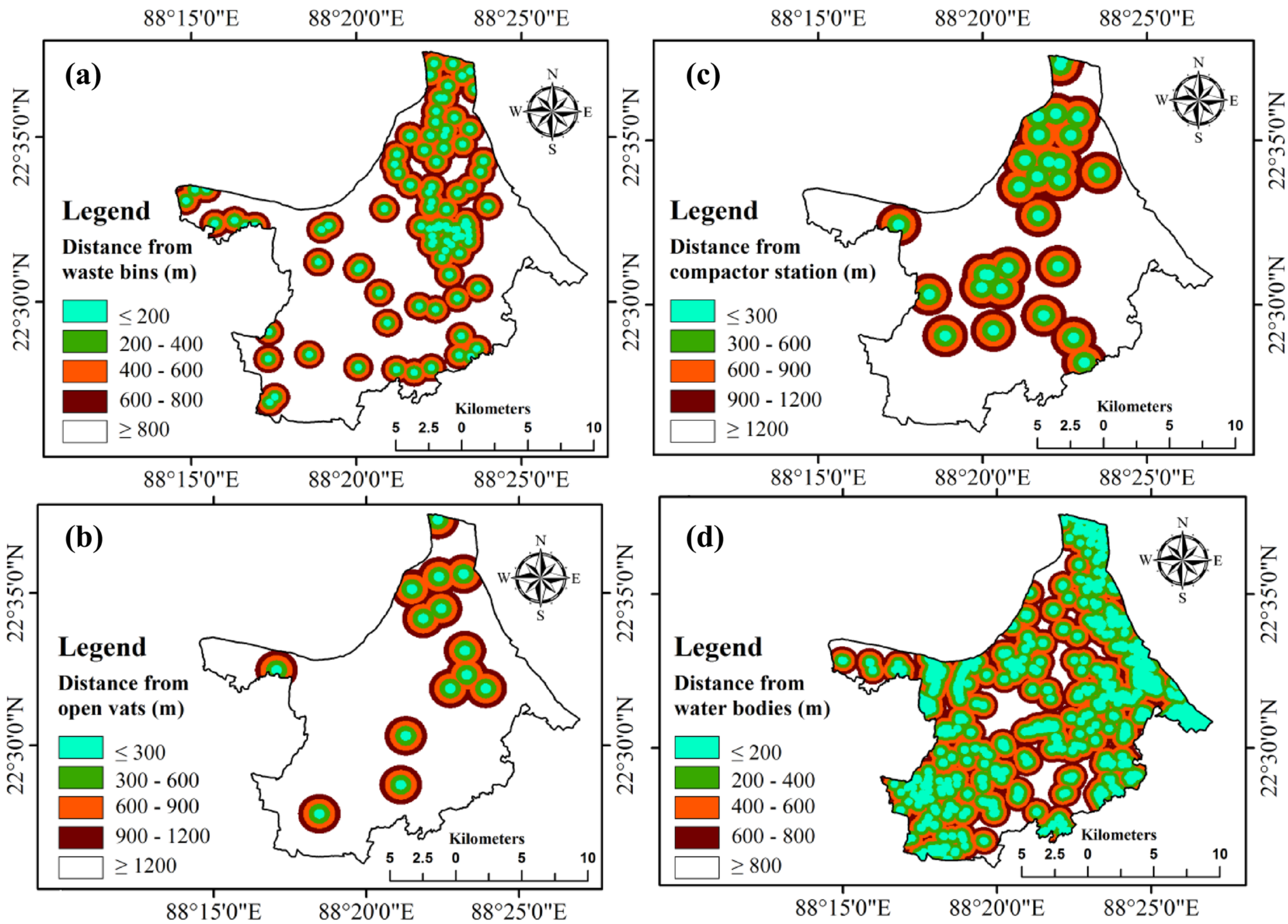


Fig. 5 Selected factors relating with suitable breeding sites responsible for vectors' growth and diseases' transmission; **a** proximity to waste bins, **b** proximity to open vats, **c** proximity to compactor stations and **d** proximity to water bodies

Table 2 Ranking scale of analytic hierarchy process adopted from Saaty to establish PCM

AHP scale of importance for PCM	Numeric rank	Reciprocal rank (decimal)
Extremely importance	9	0.11
Very strong to extremely importance	8	0.12
Very strongly importance	7	0.14
Strongly to very strongly impotence	6	0.17
Strongly importance	5	0.20
Moderately to strongly importance	4	0.25
Moderately importance	3	0.33
Equally to moderately importance	2	0.50
Equally importance	1	1.00

to be given to the installation of safe treatment and disposal facility of waste especially, sewage, sullage, and solid waste (Sheela et al. 2017).

Wastes tend to accumulate near settlements, offers breeding sites to vectors like rodents, insects and animals (Cointreau 2006). Dumping of wastes and poorly managed landfills affect the health, quality of life and impact on local environment and livelihood. The storage of waste inside the house, kitchen, room and nearby waste bins and delay of refuse trucks to collect such waste can create disease-carrying pathogens such as vector, rodent and vermin having high risk of disease spread like malaria, dengue and other viral diseases (Abdellah and Balla 2013). The vector-borne disease transmission is strongly connected with location of breeding site (Carter et al. 2000). Transmissible diseases

Table 3 Standard value of random index (RI) given by Saaty to measure consistency in judgement

N	2	3	4	5	6	7	8	9	10
RI	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

like malaria and dengue are known to be highly prevalent around specific mosquito breeding sites and they can normally be transmitted only within certain distances from the breeding sites. The range of dispersal is typically between a few hundred meters and a kilometre, but rarely exceeds 2–3 km (Kobbe et al. 2006). Land disposal facilities add to global warming and subsequently vector-borne disease abundance and pathogen survival. Proximity with landfills blurs the lines between occupational impacts on scavengers and environmental health impacts on surrounding communities (Sabesan et al. 2001; Cointreau 2006).

Keeping in mind these circumstances, four factors were chosen which are associated for providing suitable breeding sites. These factors including distance from waste bins, distance from open vats, distance from compactor stations and distance from water bodies were selected for proximity analysis. This operation was performed in two steps, i.e. GPS-based record of such locations throughout the study area was gathered during a 45 days field survey and these points were plotted in Google earth to export and create point shape files. Finally, multiple ring buffers of waste bins, distance from open vats, distance from compactor stations and distance from water bodies were created with a common interval of either 200 m or 300 m based on their extension for proximity analysis (Fig. 5a–d).

Multi-criteria decision approach

Decision-making approaches are gaining much importance as a potential tool for assessment of multifaceted real problems due to their innate ability to judge different options. Decisions about susceptibility analysis of VBDs typically involved the assessment of multiple criteria according to study objectives (Carver 1991; Eldin and Sui 2003; Malczewski 2004). Analytic Hierarchy Process (AHP) is one of the more commonly applied MCDM approach (Lootsma and Schuijt 1997). AHP allows decision makers to structure their decision criteria into a hierarchy of sub-criteria or alternatives which can then be analysed individually. Thus, in first step, the aim was defined to identify susceptible areas of vector-borne diseases. In second step, the hierarchy was constructed by the main criteria to reach the defined aim. In the present study, 13 criteria were selected looking towards their importance in VBDs susceptibility. Then in third step, selected criteria were divided into alternatives for further analysis. Then, pair-comparison matrix (PCM) was established and weights were calculated subsequently in next steps.

AHP is essentially based on pair-wise comparisons matrix of the defined criteria which are used to establish the weight to calculate the importance or performance scores for selected criteria and alternatives (Syamsuddin and Hwang 2009). PCM is a relative ranking-based matrix table used to calculate the weight value of all sub-criteria under a selected criterion in decision making process. As all the selected criteria will not have the same significance for a particular instance, hence, the significance rank of all alternatives is complimentary and divides the same alternatives in the matrix (Saaty 1990; Saaty and Vargees 2001). The AHP employs an underlying scale with values from 1 to 9 to rank the relative importance for two criteria or alternatives (Table 2). Here, extreme significance is indicated by nine and equal significance by one between criteria of the matrix (Saaty 1990; Malczewski 1999). The pair-wise comparison matrix mainly has the criteria of reciprocity which is arithmetically denoted as 1/RC, R rank of C criteria in pairwise comparison matrix (Saaty 2012). PCM gives the weights of each criterion with comparison to all others. Once the comparison rank is fitted, the weightage has to be calculated for each respective alternative to judge the consistency for considering into decision. After constructing the pairwise matrix, relative weights/eigenvectors are calculated using following equation;

$$Ax = \lambda_{\max} X$$

Table 4 Intensity of importance and respective risk value of selected environmental factors

Factors	Class	Importance given	Susceptibility category	Risk value
LULC	Water bodies	1	Very high	5
	Fallow land	0.33	Very low	1
	Open space	0.25	Medium	3
	Vegetation cover	1	Low	2
	Built-up area	0.5	High	4
NDMI	−0.3439 to 0.0117	1	Very low	1
	0.0118–0.1044	2	Low	2
	0.1045–0.2044	3	Medium	3
	0.2045–0.3267	5	High	4
	0.3268–0.6009	7	Very high	5
NDVI	−0.2355 to 0.0959	1	Very low	1
	0.0960–0.1943	2	Low	2
	0.1944–0.3072	3	Medium	3
	0.3073–0.4311	4	High	4
	0.4312–0.6934	5	Very high	5
LST	25.9021–28.9500	1	Medium	3
	28.9600–30.7402	3	High	4
	30.7502–32.0464	6	Very high	5
	32.0564–33.3901	3	Low	2
	33.4001–37.0101	1	Very low	1

Table 5 Pairwise comparison matrix along with consistency ratio of four environmental factors

	1	2	3	4	5	*w*	Ax	λ_{max}
LULC[a]								
Water bodies	1	3	4	1	2	0.3176	1.6924	5.3283
Fallow land	0.33	1	0.5	0.25	0.2	0.0643	0.3320	5.1672
Open space	0.25	2	1	0.33	0.33	0.0913	0.4748	5.2001
Vegetation cover	1	4	3	1	0.5	0.2388	1.2314	5.1573
Built-up area	0.5	5	3	2	1	0.2880	1.5196	5.2758
NDMI	1	2	3	4	5	w	Ax	λ_{max}
−0.3439 to 0.0117	1	0.5	0.33	0.2	0.14	0.0499	0.2539	5.0923
0.0118–0.1044	2	1	0.5	0.25	0.2	0.0808	0.4059	5.0259
0.1045–0.2044	3	2	1	0.33	0.25	0.1279	0.6463	5.0546
0.2045–0.3267	5	4	3	1	0.33	0.2639	1.3790	5.2255
0.3268–0.6009	7	5	4	3	1	0.4776	2.5336	5.3047
NDVI[c]								
−0.2355 to 0.0959	1	0.5	0.33	0.25	0.2	0.0624	0.3140	5.0345
0.0960–0.1943	2	1	0.5	0.33	0.25	0.0986	0.4952	5.0234
0.1944–0.3072	3	2	1	0.5	0.33	0.1611	0.8150	5.0603
0.3073–0.4311	4	3	2	1	0.5	0.2618	1.3372	5.1080
0.4312–0.6934	5	4	3	2	1	0.4162	2.1291	5.1154
LST[d]								
25.9021–28.9500	1	0.33	0.16	0.33	1	0.0723	0.3715	5.1412
28.9600–30.7402	3	1	0.33	0.33	2	0.1503	0.7700	5.1235
30.7502–32.0464	6	3	1	2	3	0.4052	2.1230	5.2391
32.0564–33.3901	3	3	0.5	1	4	0.2860	1.5013	5.2500
33.4001–37.0101	1	0.5	0.33	0.25	1	0.0863	0.4389	5.0870

[a]CI = 0.0664, CR = 0.0503
[b]CI = 0.0351, CR = 0.0313
[c]CI = 0.0170, CR = 0.0152
[d]CI = 0.0420, CR = 0.0375

Table 6 Calculation of weight value of environmental factors for overlay analysis

Environmental parameters	1	2	3	4	Weight	Ax	Weight (%)
LULC	1	0.2	0.33	0.2	0.0687	0.2753	6.8674
NDMI	5	1	3	1	0.3897	1.5854	38.9665
NDVI	3	0.33	1	0.33	0.1530	0.6172	15.3025
LST	5	1	3	1	0.3886	1.5807	38.8636

CI = 0.0147, CR = 0.0164

where A is the comparison matrix of n criteria (i.e. priority matrix), X is the Eigenvector of n criteria (i.e. priority vector) and λ_{max} is the Eigenvalue.

Calculated through,

$$\left(w_1 \times Ci_1\right) + \left(w_2 \times Ci_2\right) + \ldots \left(w_n \times Ci_n\right)$$

$$\lambda_{max} = Ax1/Wx1,\ Ax2/Wx2 \ldots Axn/Wxn$$

where $w_1 \ldots w_n$ are the weights of alternatives, $Ci_1 \ldots Ci_n$ are the ranks of alternatives and λ_{max} is the Eigenvalue.

Once the weights are calculated it is essential to check the consistency in result. As the numeric ranks are derived from the subjective preferences of individuals, it is highly possible to have some personal bias in making the final matrix of judgments. For this purpose, AHP always offers a measure of the consistency of PCM by calculating the consistency ratio (CR). Saaty (1980) provides the calculated RI value for matrices of different sizes of alternatives as given here (Table 3). The ratio is designed in such a way that if the value of the ratio exceeds 0.10, it will be considered as inconsistent for judgments and value 0 as perfectly consistent, while values 0 or close to 0 (i.e.

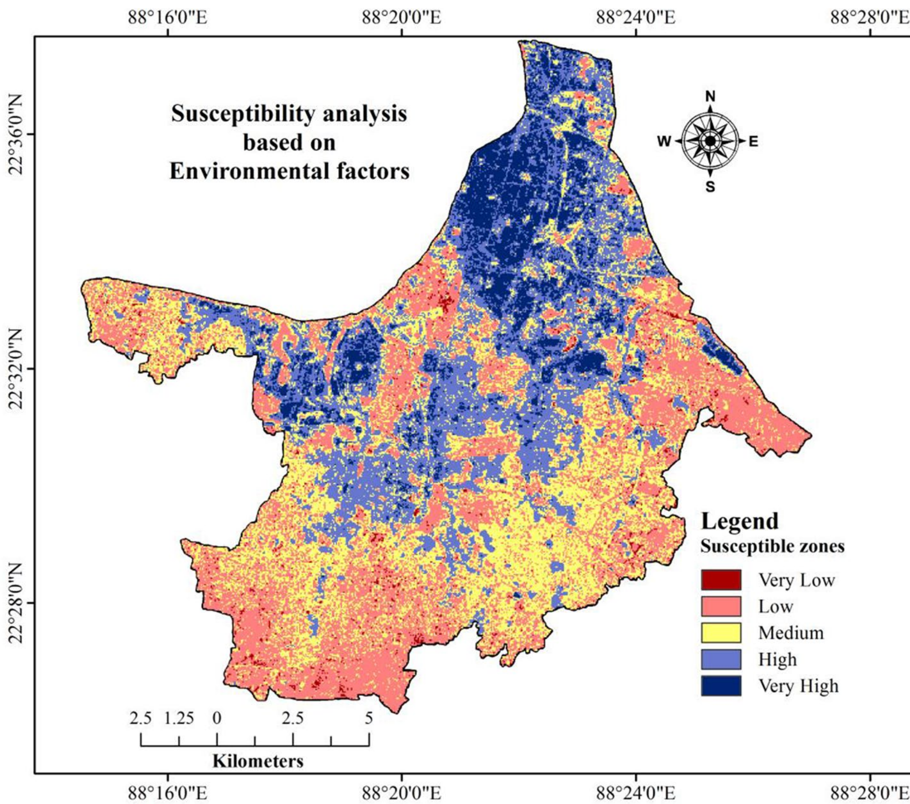


Fig. 6 Susceptibility analysis of VBDs based on selected environmental factors

0.01 or 0.03) are highly acceptable. Consistency ratio (CR) was calculated through the help of CI and RI. Mathematically, CR is expressed as;

$$\mathrm{CR} = \mathrm{CI}/\mathrm{RI}$$

CI was calculated by putting the value from above estimation by applying the following simple equation;

$$\mathrm{CI} = \frac{\lambda_{\max} - n}{n - 1}$$

CI = consistency index, $\lambda_{\max}$ = average of $\Sigma W_1 \ldots W_n$. RI depends on the number of elements being compared (i.e. number of alternatives in PCM) and if the value ranges from 0 to 0.09, the matrix will be considered as reasonably consistent and may continue the process of decision making using AHP.

Many researchers successfully used AHP as a multi-criteria decision making approach in different fields of study. Analytic hierarchy process was utilised to assess the various non-monetary criteria (Velasquez and Hester 2013). The combination of multi-criteria decision analysis and cost-benefit analysis was used for risk analysis in transport infrastructure appraisals (Ambrasaite et al. 2011). The Fuzzy multi-criteria decision-making approach and GIS were used for siting landfill in south Texas (Chang et al. 2008). The MCDM approach was used in combination with GIS to define risk zones of malaria epidemic in the central highlands of Madagascar (Rakotomanana et al. 2007). MCDM based analytic hierarchy process was applied for analysing criteria weight sensitivity to the study of spatial sensitivity in suitability evaluation (Chen et al. 2010). Several more studies applied analytic hierarchy process for analysing susceptibility, susceptibility, sensitivity and suitability (Syamsuddin and Hwang 2009; Tavares et al. 2011; Gorsevski et al. 2012; Rikalovic et al. 2014; Tu et al. 2014; Qayum et al. 2015; Eskandari et al. 2016; Nazri et al. 2016; Guler and Omralıoglu 2017; Ali and Ahmad 2018, 2019).

Susceptibility analysis of VBDs using weighted overlay analysis

Susceptibility analysis for vector-borne diseases was estimated using weighted overlay analysis (WOA). It is considered as an effective technique to resolve spatial complexity for susceptibility analysis (Kuria et al. 2011). AHP was applied to decide the more significant factors in the selected hierarchy of different inputs (Parimala and Lopez 2012). Thus, the selected thematic layers were integrated in GIS environment using linear weighted combination (Girvan et al. 2003). Susceptibility analysis of VBDs was determined

Table 7 Intensity of importance and respective risk value of demographic and epidemic factors

Factors	Class	Importance given	Susceptibility category	Risk value
Population density	0–13,698	1	Very low	1
	13,699–28,412	2	Low	2
	28,413–51,243	4	Medium	3
	51,244–81,685	5	High	4
	81,686–129,377	7	Very high	5
Household density	0–3281	1	Very low	1
	3282–6676	2	Low	2
	6677–10,071	4	Medium	3
	10,072–16,069	5	High	4
	16,070–28,857	7	Very high	5
Literate population	0–5888	1	Very high	5
	5889–22,167	0.5	High	4
	22,168–30,753	0.33	Medium	3
	30,754–43,290	0.2	Low	2
	43,291–70,021	0.14	Very low	1
Spatial distribution of dengue cases	≤ 8.23	1	Very low	1
	8.23–18.42	2	Low	2
	18.42–33.70	4	Medium	3
	33.70–58.00	6	High	4
	≥ 58.00	8	Very high	5
Spatial distribution of malaria cases	≤ 173	1	Very low	1
	174–407	3	Low	2
	408–704	5	Medium	3
	705–1133	7	High	4
	≥ 1134	9	Very high	5

based on weight calculated through AHP. All selected causative raster layers were defined with same cell size and put respective weight to combine into a single susceptibility index. The following equation was considered;

$$\mathrm{SA} = \sum_{j=1}^{n} (WjXj)$$

where Wj is the weight value of decision factors j, Xj is the selected raster input and n is the number of selected decision criteria.

Results and discussion

The prevalence of vector-borne diseases in Kolkata Municipal Corporation is seen year after year, although the frequencies of occurrence and numbers of death have reduced. Thus, effort was made to carry out a spatial analysis on susceptibility zonation of such vectors and vector-borne diseases. In this regard, a complex decision-making process was carried out through multi-criteria selecting, rating, weighting, and analysing. A total 13 factors were selected which were pre-categorised into three decision parameters. These factors are environmental parameter, demographic and epidemic parameter and parameter related to suitable breeding site. Thus, the hierarchy was constructed with three decision parameters, 13 factors and 65 alternatives or sub-factors. Primarily, after calculating the weight value of each factors and sub-factors by AHP, single layer of susceptibility map was created for each of three parameters and finally VBDs susceptible map of KMC was created using overlay of each of this single layer in GIS environment.

Table 8 Pairwise comparison matrix along with consistency ratio of five demographic and epidemic factors

	1	2	3	4	5	W	Ax	λ_{max}
Population density[a]								
0–13,698	1	0.5	0.25	0.2	0.14	0.0489	0.2463	5.0331
13,699–28,412	2	1	0.5	0.33	0.2	0.0862	0.4357	5.0531
28,413–51,243	4	2	1	0.33	0.25	0.1409	0.7128	5.0597
51,244–81,685	5	3	3	1	0.5	0.2729	1.4244	5.2198
81,686–129,377	7	5	4	2	1	0.4511	2.3340	5.1743
Household density[b]								
0–3281	1	0.5	0.25	0.2	0.14	0.0480	0.2418	5.0364
3282–6676	2	1	0.33	0.25	0.16	0.0725	0.3633	5.0126
6677–10,071	4	3	1	0.5	0.25	0.1595	0.8139	5.1044
10,072–16,069	5	4	2	1	0.5	0.2597	1.3388	5.1544
16,070–28,857	7	6	4	2	1	0.4603	2.3886	5.1891
Literate population[c]								
0–5888	1	2	3	5	7	0.4349	2.2143	5.0913
5889–22,167	0.5	1	2	4	6	0.2788	1.4148	5.0738
22,168–30,753	0.33	0.5	1	2	4	0.1574	0.7919	5.0320
30,754–43,290	0.2	0.25	0.5	1	2	0.0819	0.4112	5.0197
43,291–70,021	0.14	0.17	0.25	0.5	1	0.0469	0.2355	5.0179
Spatial distribution of dengue cases[d]								
≤ 8.23	1	0.5	0.25	0.16	0.12	0.0425	0.2149	5.0535
8.23–18.42	2	1	0.33	0.2	0.14	0.0636	0.3188	5.0113
18.42–33.70	4	3	1	0.5	0.25	0.1484	0.7576	5.1056
33.70–58.00	6	5	2	1	0.33	0.2476	1.2836	5.1841
≥ 58.00	8	7	4	3	1	0.4979	2.6198	5.2621
Spatial distribution of malaria cases[e]								
≤ 173	1	0.33	0.2	0.14	0.11	0.0356	0.1793	5.0331
174–407	3	1	0.5	0.2	0.14	0.0729	0.3683	5.0554
408–704	5	2	1	0.33	0.2	0.1253	0.6408	5.1139
705–1133	7	5	3	1	0.5	0.2887	1.5170	5.2553
≥ 1134	9	7	5	2	1	0.4776	2.5120	5.2600

[a] CI = 0.0283, CR = 0.0241

[b] CI = 0.0248, CR = 0.0221

[c] CI = 0.0117, CR = 0.0104

[d] CI = 0.0308, CR = 0.0275

[e] CI = 0.0358, CR = 0.0320

Table 9 Calculation of weight value of demographic and epidemic parameters for overlay analysis

Demographic and epidemic parameters	1	2	3	4	5	Weight	Ax	Max	Weight (%)
PD	1	1	2	0.33	0.33	0.1378	0.7040	5.1071	13.7856
HD	1	1	1	0.33	0.33	0.1128	0.5819	5.1561	11.2856
NLP	0.5	1	1	0.5	0.5	0.1221	0.6175	5.0554	12.2144
RDCs	3	3	2	1	1	0.3135	1.6235	5.1776	31.3570
RMCs	3	3	2	1	1	0.3135	1.6235	5.1776	31.3570

CI = 0.0337, CR = 0.0300

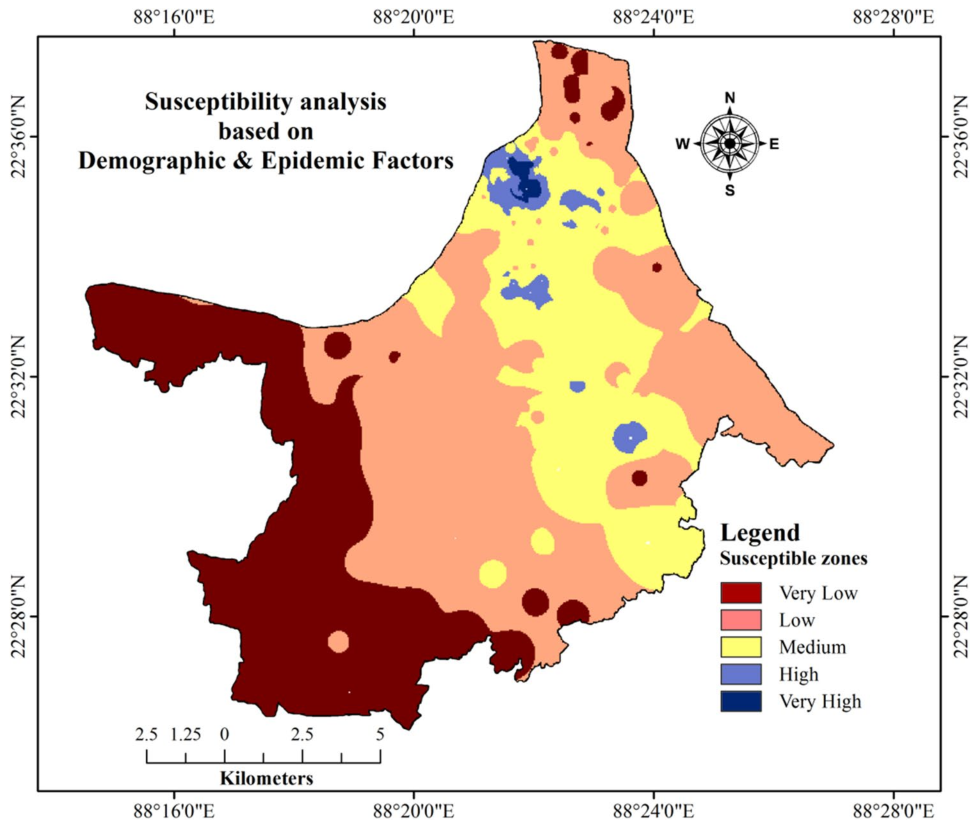


Fig. 7 Susceptibility analysis of VBDs based on demographic and epidemic parameter

VBDs susceptible zones based on environmental factor

Environmental factor is related with surrounding environmental and physical conditions. Four indicators were selected as environmental factor, including land use land cover (LULC), normalized difference moisture index (NDMI), normalized difference vegetation index (NDVI) and land surface temperature (LST). Thus, a total 20 alternatives were given risk value in a scale from 1 to 5, (5 defines very high susceptible zones and 1 defines very low susceptible zones toward VBDs) based on the scale of importance adopted after Saaty which ranges from 1 to 9. Table 4 shows 20 alternatives which were attributed by different importance from 1 (equal important towards VBDs outbreak) to 9 (Extremely important towards VBDs outbreak) and subsequently risk values were arranged to define which alternatives has greater susceptibility to VBDs (Table 4).

The main function of AHP is pairwise comparison based on their relative importance which helps in measuring quantitative judgment in new fields (Saaty 1980). Thus, choice-based intensity of importance was given to particular alternatives looking for their association towards vector-borne diseases and pairwise comparison matrix were formed to obtain the weightage value, to check the result and error of decision making and empirical bias while assigning ranks in respective field, the Consistency Index (CI) and Consistency Ratio (CR) were considered. The weights of all 20 alternatives along with CI and CR are summarized here (Table 5). Saaty suggested that if the ratio of consistency and index for the resultant random matrix is found > 0.1, the decision-making process and selection of rank will considered as inconsistent (Saaty and Vargas 2012). The result shows that the CR of all selected factors was always calculated < 0.1 (0.0503 for LULC, 0.0313 for NDMI, 0.0152 for NDVI and 0.0375 for LST). Thus, it is may considered that the selection of rank was always in acceptable choice when pairwise comparison matrix was established. Now, to derive final output layer in GIS environment, the comparison matrix of selected four factors was established (Table 6). Finally, the VBDs' susceptible zones were extracted through weight-based overlay of the chosen environmental factors using the GIS tool (Fig. 6). The result shows that the proportion of very high and very low susceptible zones-to-VBDs is limited and maximum area comes under moderate susceptible zones.

Fig. 8 Some considerable areas of suitable sites for growing vector-borne disease transmitting parasites which were identified during field visit (**a**) and **b** unclean drain in Diamond harbar Road, **c** stagnant water in drain near Nabapally, **d** drain in residential areas at Garden Reach filled with waste water and other solid waste from households, **e** dumped areas in Talata near Sealdah, **f** stagnant water body dumped with mixed waste in Tollygunge (the plastic carry bags, bottle and other such type container provides suitable places for growing diseases carrying parasites) and **f** author during discussion with a local respondent in Makaltala village near Dhapa dump site

VBDs' susceptible zones based on demographic and epidemic factor

Demographic factor is related with population, household, level of education, etc. for vector-borne diseases assessment and susceptible zonation. Demographic factors are important because humans have high potential for transmission of such kind of diseases. In this regards, three causative indicators were taken as demographic parameters based on availability of data, including population density (PD), household density (HD) and number of literate population (NLP). Along with demographic parameter, previous epidemic records were also considered. The frequency of malaria outbreak was much greater than dengue cases during last year. Here, two more indicators were taken, i.e. reported malaria cases (RMCs) and reported dengue cases (RDCs). Thus, a total 25 alternatives were given risk value in a scale from 1 to 5, based on the scale of importance of intensity which ranges from 1 to 9. Table 7 shows 25 alternatives which were rated by different importance from 1 to 9 and subsequently risk values were put to define which sub-factor has more susceptibility to VBDs (Table 7).

The choice-based intensity of importance was given to particular alternative looking at their connection towards VBDs. The pairwise comparison matrix was constructed to obtain the weight value and to check the result and error of decision making and empirical bias while assigning ranks in respective field. The weights of all 25 alternatives along with their CI and CR are summarized (Table 8). The result reveals that consistency ratio of all selected indicators was found between 0.01 and 0.03 (0.0241, 0.0221, 0.0104, 0.0275 and 0.0320 for PD, HP, NLP, RDCs and RMCs, respectively). Each alternative was arranged with risk scale on the basis of weight calculated from PCM. Now, to derive final output

Table 10 Intensity of importance and respective risk value of selected factors related to suitable breeding sites

Factors	Class	Importance given	Susceptibility category	Risk value
Proximity to waste bins	≤ 200	1	Very high	5
	200–400	0.5	High	4
	400–600	0.25	Medium	3
	600–800	0.2	Low	2
	≥ 800	0.17	Very low	1
Proximity to open vats	≤ 300	1	Very high	5
	300–600	0.5	High	4
	600–900	0.2	Medium	3
	900–1200	0.17	Low	2
	≥ 1200	0.14	Very low	1
Proximity to compactor stations	≤ 300	1	Very high	5
	300–600	0.33	High	4
	600–900	0.25	Medium	3
	900–1200	0.17	Low	2
	≥ 1200	0.14	Very low	1
Proximity to Water bodies	≤ 200	1	Very high	5
	200–400	0.5	High	4
	400–600	0.33	Medium	3
	600–800	0.2	Low	2
	≥ 800	0.14	Very low	1

layer, the comparison matrix of selected five factors was prepared (Table 9). GIS integration was created to design susceptible zones of VBDs based on demographic and epidemic parameter (Fig. 7).

VBDs' susceptible zones based on suitable breeding sites

The growth of vectors is associated with garbage damping. Wet and watery places near waste bins and open vats are highly suitable places for breeding sites (Fig. 8). Thus, proximity to spatial location of waste bins and open vats was taken and proximity to nearer locations was considered as very high to high susceptible to VBDs and vice versa. Along with these factors, proximity to compactor station was also taken into consideration because it was found during field visit that the liquid excreta is gathered into the drain after the waste compaction process which was left uncovered and this may offer suitable breeding sites for mosquitoes. One more factor, i.e. proximity to water bodies was also considered based on field visit. Thus, total of four indicators were taken as factors related to suitable breeding sites, including proximity to waste bins (PWBs), proximity to open vats (POVs), proximity to compactor stations (PCSs) and proximity to water bodies (PWTBs). Thus, a total 20 alternatives were given risk value based on same scale as used with other factors (Table 10).

After assigning choice-based intensity of importance to particular alternatives towards VBDs, PCM was constructed to obtain the weight value for checking the result. The weights of all 4 indicators along with their CI and CR are summarized below (Table 11). The result reveals that the CR values of all selected factors, i.e. PWBs, POVs, PCSs and PWTBs were calculated as 0.0511, 0.0371, 0.0508, and 0.0311, respectively. It was found that the CR was always < 0.1 for all the selected factors. Finally, same as the other factors, the VBDs' susceptible zone was designed through constructing comparison matrix of selected four indicators (Table 12). The weight-based overlay of the chosen factors related to suitable breeding sites was derived using the spatial tool (Fig. 9). The result shows that areas circulating nearest to waste bins, open vats, compactor stations and water bodies come under more susceptible zones and areas farer to these locations are come under least-risk zones.

Spatial susceptibility analysis of VBDs

After preparing individual layers based on selected factors, the final VBDs hotspot zone was created using weighted linear combination (WLC) of these individual layers in GIS environment. The weight of each parameter was assigned using AHP for integrated mapping. For creating

Table 11 Pairwise comparison matrix along with consistency ratio of four parameters related to suitable breeding sites

	1	2	3	4	5	*W*	Ax	λ_{max}
Proximity to waste bins[a]								
≤200	1	2	4	5	6	0.4358	2.3438	5.3784
200–400	0.5	1	2	4	5	0.2610	1.3961	5.3485
400–600	0.25	0.5	1	3	5	0.1710	0.9025	5.2764
600–800	0.2	0.25	0.33	1	3	0.0857	0.4353	5.0800
≥800	0.17	0.2	0.2	0.33	1	0.0465	0.2352	5.0632
Proximity to open vats[b]								
≤300	1	2	5	6	7	0.4671	2.5119	5.3778
300–600	0.5	1	2	4	6	0.2581	1.3493	5.2266
600–900	0.2	0.5	1	3	5	0.1618	0.8335	5.1515
900–1200	0.17	0.25	0.3	1	2	0.0693	0.3491	5.0337
≥1200	0.14	0.17	0.2	0.5	1	0.0436	0.2199	5.0422
Proximity to compactor stations[c]								
≤300	1	3	4	6	7	0.4838	2.6063	5.3868
300–600	0.33	1	2	4	5	0.2316	1.2460	5.3802
600–900	0.25	0.5	1	3	5	0.1629	0.8516	5.2286
900–1200	0.17	0.25	0.33	1	3	0.0795	0.4014	5.0510
≥1200	0.14	0.2	0.2	0.33	1	0.0422	0.2151	5.0923
Proximity to water bodies[d]								
≤200	1	2	3	5	7	0.4262	2.2217	5.2128
200–400	0.5	1	2	4	6	0.2713	1.4186	5.2290
400–600	0.33	0.5	1	3	5	0.1771	0.9155	5.1687
600–800	0.2	0.25	0.33	1	3	0.0837	0.4215	5.0362
≥800	0.14	0.17	0.2	0.33	1	0.0417	0.2105	5.0505

[a]CI = 0.0573, CR = 0.0511

[b]CI = 0.0415, CR = 0.0371

[c]CI = 0.0569, CR = 0.0508

[d]CI 0.0348, CR 0.0311

Table 12 Calculation of weight value of parameters related to suitable breeding sites for overlay analysis

Parameters related to suitable breeding sites	1	2	3	4	Weight	Ax	Weight (%)
Proximity to waste bins	1	0.5	1	0.33	0.1411	0.5653	14.11
Proximity to open vats	2	1	2	0.5	0.2630	1.0549	26.30
Proximity to compactor stations	1	0.5	1	0.33	0.1411	0.5653	14.11
Proximity to water bodies	3	2	3	1	0.4546	1.8276	45.46

CI = 0.0034, CR = 0.0038

spatial susceptibility to VBDs, the following equation was used (Qayum et al. 2015):

$$\mathrm{VBDsH} = H_{envp} \times H_{demp} \times H_{sbs}$$

where VBDsH = vector-borne diseases hotspot; H_{envp} = hotspot identified based on environmental factors; H_{demp} = hotspot identified based on demographic and epidemic factors; H_{sbs} = hotspot identified based on factors related to suitable breeding sites.

The final VBDs raster layer was created and reclassified according to the susceptible risk zone into 5 class, i.e. Very high (VH), high (*H*), moderate (*M*), low (*L*) and very low (VL) areas (Fig. 10). The areal proportion of susceptible zones to VBDs was estimated that 0.75%, 18.107%, 48.21%, 32.36% and 0.55% area were found under VH, *H, M, L* and VL susceptible zones to VBDs, respectively. The result of the study shows that about 81% area comes under moderate to low susceptible zones, whereas about 19% area comes under high to very high susceptible zones.

Fig. 9 Susceptibility analysis of VBDs based on parameters related to suitable breeding sites

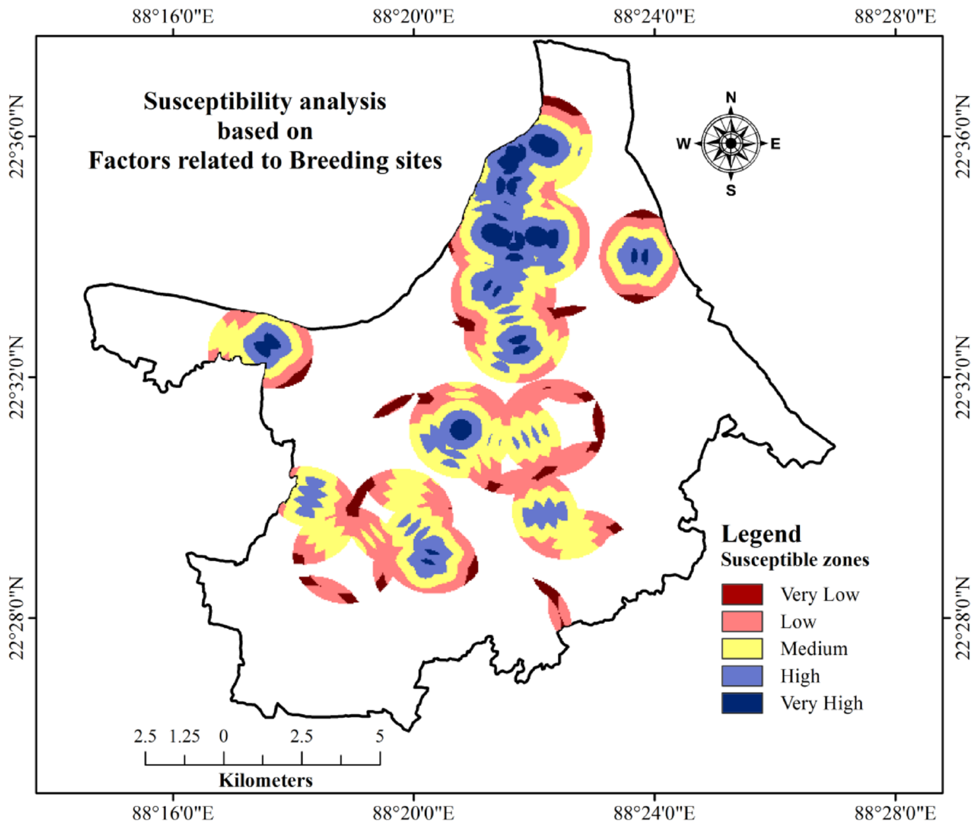


Fig. 10 Mapping of vector-borne diseases hotspot

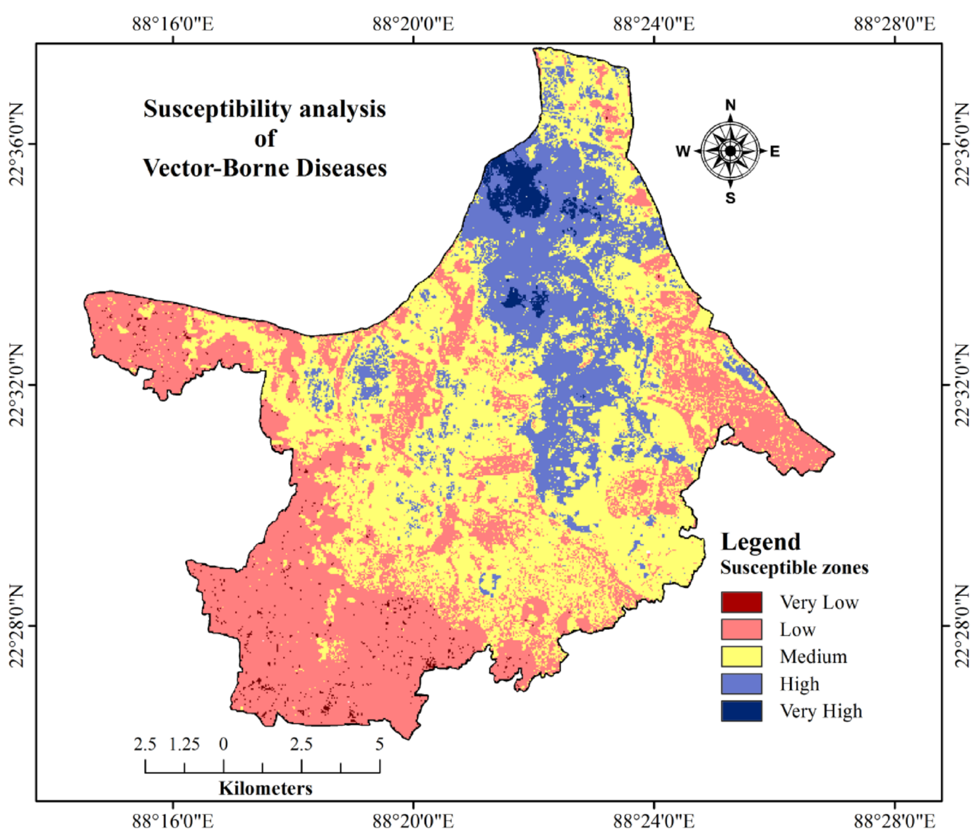
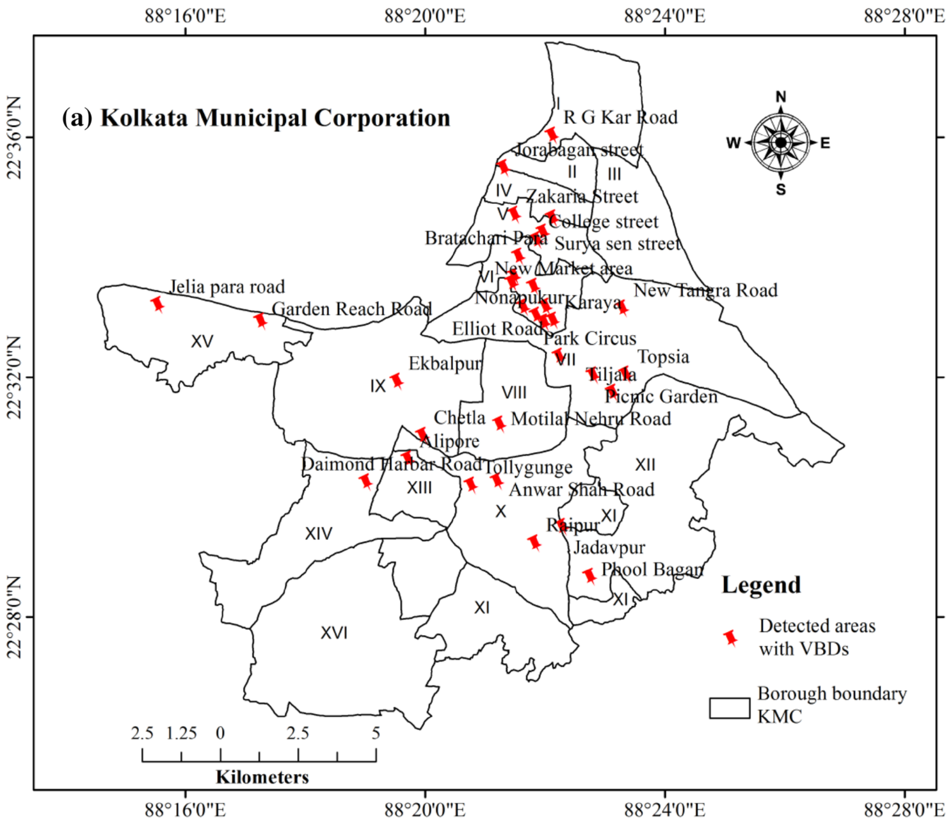
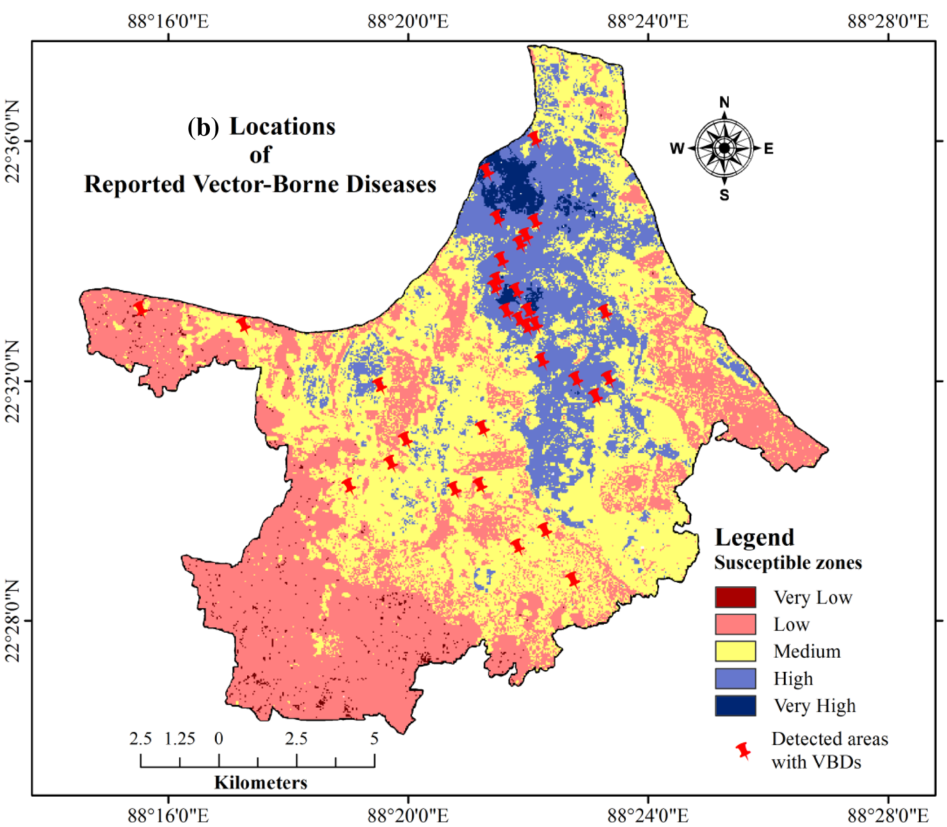


Fig. 11 Map showing assessment of accuracy (**a**) places with reported VBDs during last year (**b**) multi-criteria-based susceptible map of VBDs using geospatial technique





For the out breaking of diseases like water-borne, vector-borne or mosquito-borne are not due to any single factor. Many related factors are responsible for such. The present study tried to use such associated multi-criteria for spatial susceptibility analysis of VBDs. The result revealed that based on environmental factor, areas with water bodies, moisture content index in air > 0.33, vegetation index > 0.43 and surface temperature ranges between 30 and 32 °C has greater susceptibility to VBDs. Based on demographic and epidemic factor, areas with population density > 81,686, household density > 16,070, literate population < 5888, high reported cases of dengue and malaria has more prone to VBDs. Among suitable breeding sites, areas ≤ 200 m from waste bins, ≤ 300 m from open vats, ≤ 300 m from compactor stations and ≤ 200 m from water bodies has high susceptibility to VBDs. Out of total 13 selected criteria in this study, it was found that moisture index, land surface temperature, water bodies and nearness to open waste dumping vats have greater role in outbreak of vector-borne diseases.

Accuracy measurement

It is a very crucial task in spatial analysis, to evaluate the result with actual ground. As per KMC report in last year from January to October more than 600 dengue and more than 2000 malaria cases were reported in KMC out of which 6 were death in dengue. So, a field survey was carried out during June and July of 2018 in different wards of each 16 Borough of KMC. Looking towards surrounding settings and respondent's response on structured questions, different GPS locations were recorded. These locations were further verified in Google Earth open software and export as point locations. After sampled categorization, result found that in many areas of southern, south-eastern and western part has very low prevalence of MBDs, some areas found with no cases of such diseases, while some areas of northern and central parts has high to moderate prevalence of MBDs. Thus, some areas with very high prevalence of such diseases were plotted to merge with susceptibility analysis of MBDs (Fig. 11). The result shows that these reported areas are much uniform with final layer and constantly merged with very high to high zones as derived from spatial susceptibility analysis using geospatial technique and MCDM approach.

Conclusion

Disease-susceptibility analysis and assessment are required for better surveillance and strategy making to prevent such issues from public health. Susceptibility zonation and mapping are gaining great significant for this requirement. Materials and methods are considered as the base for logical and accepted result for this type of study. Thus looking towards research problem and main objective, geospatial technique and multi-criteria decision-making approach were used for analysing spatial susceptibility of vector-borne diseases in Kolkata Municipal Corporation. Analytic hierarchy process, as a decision-making tool of MCDM approach was selected for ranking and weighting the spatial information. AHP in combination with geographic information system offers useful result for the identification of vulnerable zones. The great advantage of AHP is the pairwise comparison matrix which helps in developing rank-based decision to judge decision criteria. Hence, wrong selection of rank or judgement of any chosen factor will offer consistency ratio of > 0.1, which is not acceptable and make decision process inconsistent. The consistency measurement of present study showed that it was always between the range of 0.01–0.07, it signifies acceptance for decision making based on intensity of importance. So, final overlay was carried out using derived weight of selected factors. The result revealed that maximum portion of study area belongs to moderate susceptible zones followed by low and high, i.e. covering about 48.21% (99.10 km^2) area under moderate, 32.36% (66.3 km^2) under low and 18.10% (37.6 km^2) under high susceptible zones to vector-borne diseases. While very little portion was found under very high and very low with areal extension of 0.75% (1.50 km^2) and 0.55% (1.13 km^2), respectively. The study result also revealed that out of all selected criteria in this study, moisture index, land surface temperature, water bodies and nearness to open waste dumping vats have greater importance in outbreak of vector-borne diseases.

Finally, the study result was evaluated through locations of previously vector-borne disease-affected areas. The assessment found that highest malaria and dengue recorded areas of previous year are closely associating with high and very high susceptible zones derived from spatial susceptibility analysis. To seek more accurate and precise result, the present research also recommends to highlight on more ground-level information, long and extensive GPS-based field study and comprehensive studies of breeding sites of mosquitoes and vectors. The present study also suggests to use very high resolution satellite data including IKONOS (1 m), QuickBird (60 cm), GeoEye-1 (50 cm), WorldView-1 (50 cm) and WorldView-4 (30 cm) which will provide more accurate result in identification of susceptible areas.

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