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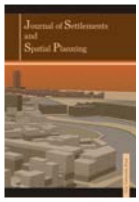

# Identification and Mapping of Dengue Epidemics using GIS-Based Multi-Criteria Decision Making. The Case of Delhi, India

**Seema SAHDEV*[1], Manish KUMAR[2]**

* *Corresponding author*

[1] *University of Delhi, Department of Geography, Kalindi College, Delhi, INDIA*

[2] *Central University of Haryana, School of Basic Sciences, Department of Geography, Mahendergarh, Haryana, INDIA*

*E-mail:* seemasahdev@yahoo.com, manish.ks1@gmail.com

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**K e y w o r d s:** *Geographic Information System, Pairwise Comparison Matrix, Analytic Hierarchy Process, Dengue epidemics, Health Care Management System*

**A B S T R A C T**

The identification and mapping ofdengue epidemics is one of the critical issues in providing better health services and policy development. In this process, multiple physiographic and socio-economic criteria have been taken into consideration. The proposed approach of this paper is to provide a framework for integrating the strengths of Geographic Information System (GIS) based Multi-Criteria Decision-Making (MCDM) to reach the most appropriate spatial solutions for the decision-makers. In this paper, the National Capital Territory (NCT) of Delhi was considered for mapping the potential sites for the development of dengue epidemics. For this purpose, various thematic layers were prepared using QGIS software. Five parameters (spatial analysis of Dengue Cases, land surface temperature, landfill sites, water logging, land use/land cover) were examined for mapping dengue epidemics vulnerable zones. The final dengue epidemics vulnerability assessment map reveals that the study area was divided into three different vulnerability regions namely high vulnerable regions - 326.24 sq.km (20.55%), moderate vulnerable regions - 674.25 sq.km (42.48%) and low vulnerable regions - 586.56 sq.km (36.95%). In this paper, the integrated approach of GIS based MCDM is showcased as a major contribution towards the development of effective health care management system (HCMS). This study also provides a new approach for decision-makers in order to decrease the spatial extent of this chronic disease and also reduce the human health hazard.

## 1. INTRODUCTION

Epidemics prone area identification and mapping can be used to pinpoint the areas where outbreaks originate and effectively target high-risk areas for early prevention and control (Ali, et al., 2003). By using GIS to determine the spatial characteristics of a disease have made it possible to detect the clustering of cases and link clustering dynamics with geographical locations that carry certain risk factors favorable for the sources of infection (e.g., mosquito breeding sites) and for the spread of infection (e.g., vector exposure) (Lai et al. 2004; Cockings et al. 2004; Dunn et al. 2001). Recent studies have mapped risk areas over different defined time periods to describe the temporal dynamics of epidemics (Tran et al. 2004; Harrington et al. 2005; Morrison et al. 1998; Siqueira et al. 2004; Getis et al. 2003). However, few studies have integrated spatial and temporal factors to differentiate the risk patterns of an epidemic.

Dengue infection has been known to be endemic in India for over two centuries as a benign and self-limited disease. Since the mid-1990s, epidemics of dengue have become more frequent in many parts of India. In recent years, the disease has changed its course manifesting in a more severe form and with increasing frequency of outbreaks (Gupta et al., 2006). India contributed with around 34% (33 million infections) to the global dengue cases in 2010 (Bhatt et al., 2013). Dengue has been considered an urban disease, but it has now spread to rural areas of India, as well (Arunachalam et al., 2004). A total of 82,327 dengue cases were reported during 1998–2009 and 213,607 cases were observed from 2010 to 2014. Thus the number of dengue cases has increased tremendously during last five years.

The rise of these dengue cases are driven by complex interactions between hosts, vectors and viruses that are influenced by environmental, climatic, demographic and socio-economic factors. Apart from this, other determinants in dengue fever emergence are human population growth, accelerated urbanization, increased international transport, lack of proper public health infrastructure as well as the lack of effective vector control and disease surveillance system (Rigau-Pérez et al., 1998; Gubler, 2002b; Hales et al., 2002; Mackenzie et al., 2004; Chaturvedi and Nagar, 2008).

GIS-based studies have mapped spatial clustering patterns of dengue cases, have analyzed the association between these patterns and relevant entomological factors and environmental conditions and have identified the spatial–temporal diffusion patterns of dengue and vector distributions (Gubler and Meltzer, 1999; World Health Organization, 2006; Bohra and Andrianasolo, 2001; Cummings et al. 2004). Although these studies helped us understand the mechanism of dengue epidemics, none, to the best of our knowledge, have analyzed the different spatial–temporal conditions. Kamali et al. (2017) proposed a combination of a Delphi-analytical hierarchy process approach and geographical information system methodology in order to find the optimum sites for the large extractive industrial units in Iran. Savargaonkaret al. (2018) examined the epidemiology of dengue with reference to serological, demographic profile, spatio-temporal distribution, vectors, circulating serotypes and co-infections.

The study emphasized the need of epidemiological and entomological surveillance to monitor trends in dengue distribution, seasonal patterns and circulating serotypes to guide dengue control activities. Mutheneni et al. (2018) conducted a study on epidemiology and spatial distribution of dengue, a retrospective surveillance study was conducted in the state of Andhra Pradesh, India, during 2011–2013. District-wise disease endemicity levels were mapped by employing GIS tools. Spatial statistical analysis such as Getis-Ord Gi was performed to identify hot spots and cold spots of dengue disease. Similarly, self-organizing maps (SOM), a data mining tool was also applied to understand the endemicity patterns in study areas. Marti et al. (2020) studied the relationships between landscape factors and urban dengue cases considering household, neighborhood and administrative levels. They found that the landscape mapping linked to human dengue infection was mainly guided by (i) vector ecology-based considerations through vegetation and water surface mapping and (ii) human presence and activities deducted from the settlement typology.

In the present study dengue epidemics vulnerability assessment map was elaborated using GIS based multi-criteria decision making approach. In order to deveop the final dengue epidemics vulnerable assessment map, various criteria maps were prepared and analysed.

### 1.1. Study area

Delhi is located in the fertile alluvial plains of Northern India as a riparian city of the River Yamuna, extending from 28° 23‘ 17” N to 28° 53‘ 00” N and 76° 50‘ 24” E to 77° 20‘ 37” E. The National Capital Territory of Delhi covers an area of 1484 km$^2$. According to the 2011 Census of India, the population of Delhi is of 16, 753,235 people and it is further estimated to 19.5 million people in 2020. The population density was of 11,297 persons per square km, with a sex ratio of 866 women per 1000 men and a literacy rate of 86.34%. Due to the migration of 6.87 lakhs (approx.) people from 2001 to 2011, the population of Delhi has increased, and this has made it one of the fastest growing cities in the world. The total dengue cases recorded in Delhi was 548 in 2007, 1312 in 2008, and 1153 in 2009, while in 2017 the number of dengue cases rose to 4,645.

Although the entire city of Delhi is suffering from environmental fever, urban informal settlement areas are more seriously affected environmentally. At a certain level of exposure, contaminants in the air, water, food and soil in Delhi are causing a variety of adverse health effects, because the physical environment in which people live is an important determinant of health.

The aim of our study was to find the significant relationship between environmental problems and human health in Delhi. Respondents were also able to correlate the incidence of diseases with the environmental problems. However, respondents did not think that the individual household would have a significant role in improving their environment, a role, they think, should be taken by the government.

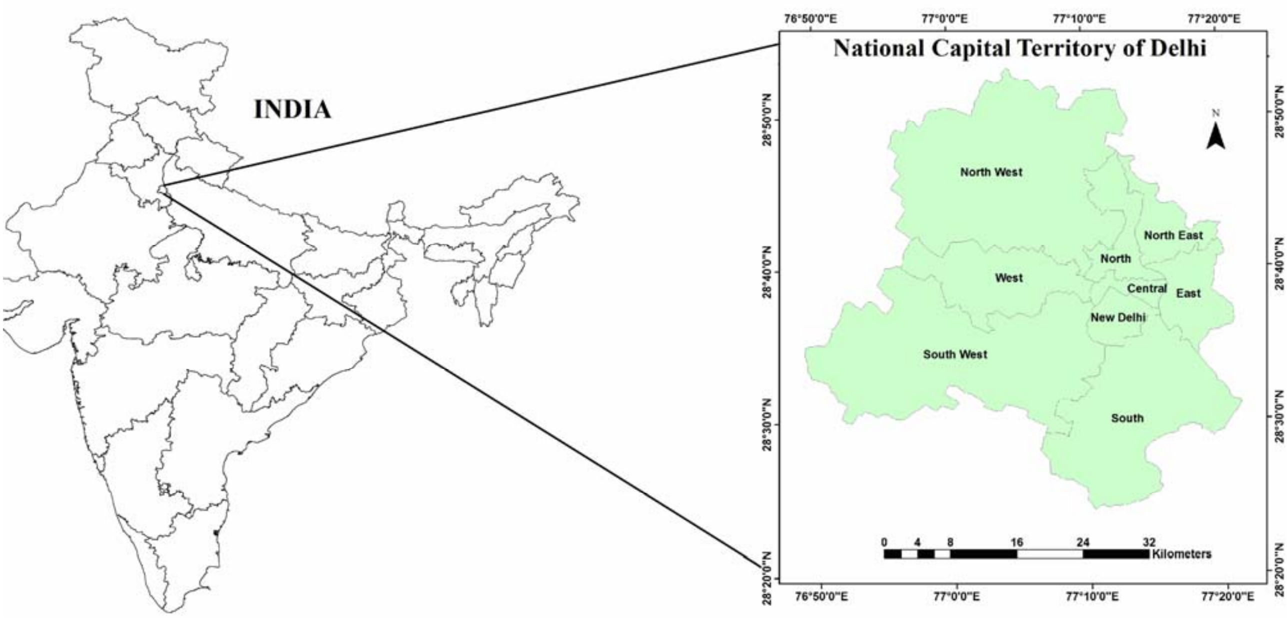


Fig. 1. Location map of the study area.

## 2. THEORY AND METHODOLOGY

### 2.1. Data collection and integration

In order to develop the epidemics vulnerability assessment map caused by water borne diseases, various thematic layers were generated using QGIS 3.12 Software. Dengue cases, land surface temperature, landfill sites, water logging, land use/land cover were obtained from various sources such as Satellite data, i.e., Landsat 8; Delhi Traffic police data; Government Hospitals of Delhi; Delhi Municipal Corporation etc. All these information layers were integrated and analysed in ArcGIS environment.

#### *2.1.1. Selection and preparation of criteria maps*

In the present study five criteria were selected. The main criteria used for the spatial analysis were the number of dengue cases, land surface temperature, landfill sites, water logging, land use/land cover (Fig. 2 to 6) These criteria were used in the preparation of criteria maps (Sumanasinghe et al., 2016). .

#### *2.1.2. Suitability scoring /ranking and development of pairwise comparison matrix*

For epidemics vulnerability assessment mapping it is necessary to assign some scores to each of the criteria as per their suitability for urban development. For this purpose, the pairwise comparison matrix using Saaty's nine point weighing scale was applied (Table 1). To develop a pairwise comparison matrix, different criteria are required to create a ratio matrix. These pairwise comparisons are taken as input and relative weights are produced as an output.

Table 1. Nine-point weighting scale for pairwise comparison.

| Intensity of importance | Description |
|---|---|
| 1 | Equal importance |
| 2 | Equal to moderate importance |
| 3 | Moderate importance |
| 4 | Moderate to strong importance |
| 5 | Strong importance |
| 6 | Strong to very strong importance |
| 7 | Very strong importance |
| 8 | Very to extremely strong importance |
| 9 | Extreme importance |

*Source:* Saaty 1980; ESRI 1996.

#### *2.1.3. Computation of the criterion weights*

After the formation of pairwise comparison matrix, the computation of the criterion weights was performed.

The computation involves the following operations:

a). Calculating the sum of the values in each column of the pairwise comparison matrix;

b). Division of each element in the matrix by its column total (the resulting matrix is referred to as normalized pairwise comparison matrix);

c). Computation of average of elements in each row of the normalized matrix that is dividing the sum of normalized scores of each row by the number of criteria. An estimate of the relative weights of the criteria, in comparison, is provided by the average values (Sahdev and Kumar, 2020).

#### *2.1.4. Rasterization of criteria maps*

In raster data format, computation is less complex than in vector data format, therefore different criteria maps were transformed into raster data environment for further investigation (Chang, 2006).

#### *2.1.5. Integration of maps*

These raster maps were combined using weighted overlay techniques in raster calculator after rasterization in ArcGIS software and, by multiplying with weightage, the final epidemics vulnerability assessment map was prepared (Sahdevand Kumar, 2020).

#### *2.1.6. Preparation of vulnerability assessment map*

A pairwise comparison matrix was developed with the help of the existing criteria. All criteria were normalised by using the ratio matrix and multi-criteria decision making weights were computed for each criterion (Table 2 and 3). The final epidemics vulnerability assessment map was prepared by using the following formula:

***Epidemics Vulnerability Index*** = ([Dengue Cases]*weights) + ([Temperature]* weights) + ([Landfill sites]* weights) + ([Water logging]* weights) + ([Land use/cover]* weights)

Table 2. Pairwise comparison matrix.

| Criteria | Dengue cases (a) | Temperature (b) | Landfill sites (c) | Water logging (d) | Land use/cover (e) |
|---|---|---|---|---|---|
| Dengue cases | 1 | 2 | 4 | 5 | 7 |
| Temperature | 0.5 | 1 | 2 | 4 | 5 |
| Landfill sites | 0.25 | 0.5 | 1 | 2 | 4 |
| Water logging | 0.2 | 0.25 | 0.5 | 1 | 2 |
| Land use/cover | 0.14 | 0.2 | 0.25 | 0.5 | 1 |
| Total | 2.22 | 4.09 | 7.95 | 12.75 | 19.5 |

Table 3. Normalized pairwise comparison matrix and computation of criterion weights.

| Criteria | Dengue Cases (a) | Temperature (b) | Landfill sites (c) | Water logging (d) | Land use/cover (e) | Weights (a+b+c+d+)/5 |
|---|---|---|---|---|---|---|
| Dengue Cases | 0.45 | 0.49 | 0.50 | 0.39 | 0.36 | 0.42 |
| Temperature | 0.23 | 0.24 | 0.25 | 0.31 | 0.26 | 0.26 |
| Landfill sites | 0.11 | 0.12 | 0.13 | 0.16 | 0.21 | 0.15 |
| Water logging | 0.09 | 0.06 | 0.06 | 0.08 | 0.10 | 0.09 |
| Land use/cover | 0.06 | 0.05 | 0.03 | 0.04 | 0.05 | 0.05 |
| Total | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |

## 3. RESULTS AND DISCUSSION

For dengue epidemics vulnerability assessment mapping, the effective criteria are briefly described below, with their individual importance.

#### *3.1.1. Land surface temperature*

Land surface temperature is regarded as one of the most important abiotic environmental factors affecting biological processes of mosquitoes, including interactions with arboviruses. Seasonal and geographic differences in temperature and anticipated climate change undoubtedly influence mosquito population dynamics, individuals' traits related to vector biology (lifespan and vector competence for arboviruses), and disease transmission patterns. The ideal temperature for Mosquitoes breeds is of about 24°C to 28°C. For this purpose, land surface temperature of the study region was calculated by using LANDSAT 8 satellite imagery (Fig. 2).

#### *3.1.2. Frequent water logging in urban areas*

Urban development and construction have led to the expansion of impervious area, reduced surface infiltration and reduced recharged groundwater, increased runoff, and increased peak flow, and increased peak flow in advance. With urbanization, the impervious surface areas of the city increases continuously. However, urbanization triggers decreases in the natural vegetation, changes in the surface material, and adds pressure to the bedding surface, and reduces the amount of surface runoff. The rainfall cannot not be well drained, leading to frequent water logging. A frequent water logging location has been identified and mapped (Fig. 3).

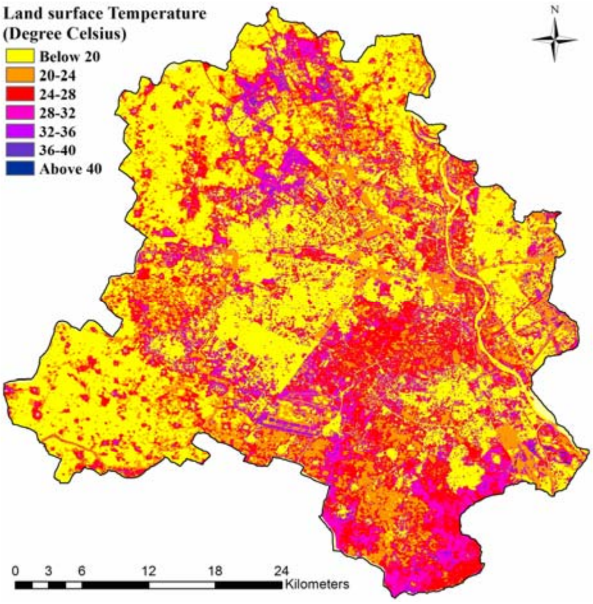


Fig. 2. NCT of Delhi. Land surface temperature (LST). *Source: Landsat 8, 2017.*

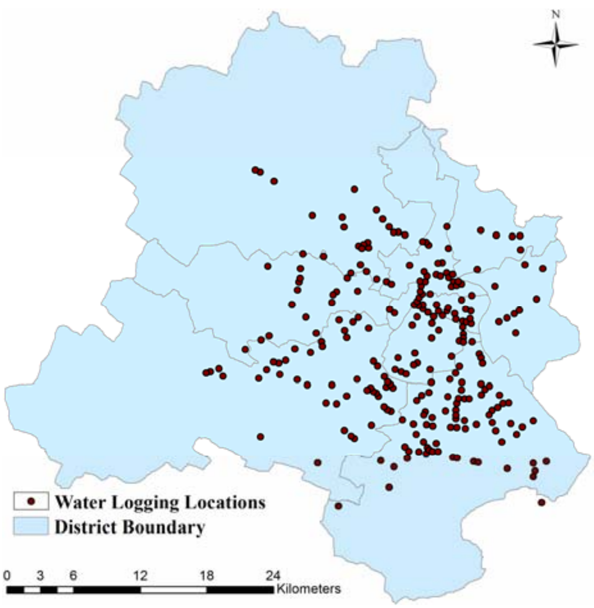


Fig. 3. NCT of Delhi. Frequent water logging locations. *Source: Delhi traffic police data, 2017.*

### *3.1.3. Land use and land cover*

Land use and land cover such as water bodies or certain agricultural practices were identified as likely risk factors for dengue because of the suitable habitats for the vector. In this study, a relationship between land use factors and dengue and other water borne epidemics for NCT of Delhi was analysed. This study aimed to identify different land use factors such as human settlements, agricultural land use, water bodies and forest, further analysed in association with reported dengue cases (Fig. 4).

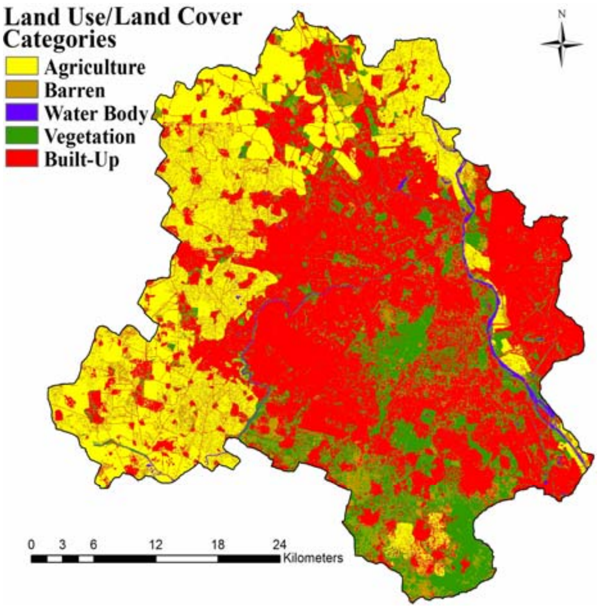


Fig. 4. NCT of Delhi. Land use and land cover. *Source: Landsat 8, 2017.*

### *3.1.4 Landfill sites*

The solid wastes which are frequently dumped in urban and industrial areas are creating not only soil pollution but also act as potential health hazards because many of these waste materials may serve as mosquito breeding sources after accumulations of rain water in these containers (Fig. 5).

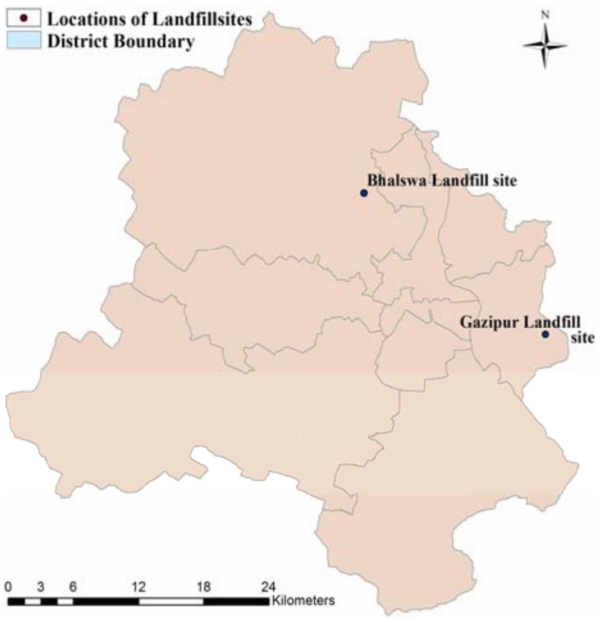


Fig. 5. NCT of Delhi. Landfill sites.

The resurgence of malaria and other mosquito borne diseases like dengue in recent years has created concern. In this study two landfill sites, namely Bhalwas landfill site and Gazipur landfill site were taken into consideration as potential ground for mosquitos breeding locations.

### 3.1.5. *Dengue cases*

Dengue is emerging as an important mosquito-borne arboviral disease in the world. Once known to occur sporadically, epidemics of dengue have now become a regular occurrence. Data on probable dengue patients was provided by various government hospitals over a period of 5 years (2012–2017) and used for studying the dengue cases (Fig. 6).

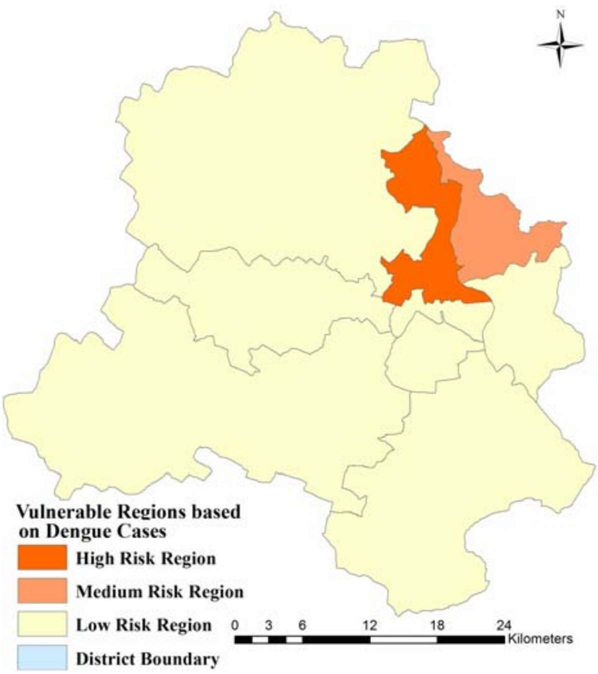


Fig. 6. NCT of Delhi. Landfill sites. Vulnerable regions based on data reflecting the number of dengue cases. *Source: Goverment Hospital, Delhi (2006-2010).*

### 3.2. Integration of weights in GIS

Integration of weights in GIS is commonly employed to solve a particular problem. The integration of these two techniques transforms and combines geographical data and value judgments to obtain information for decision-making.

The computed weights were integrated in GIS environment and vulnerability map and their areas were calculated by pairwise comparison method.

All five criteria maps were converted into raster format, so that for each pixel, a score could be determined. All criteria maps were integrated and overlapped and the final epidemics vulnerability assessment map was prepared (Fig. 7) by the following formula:

***Epidemics Vulnerability index*** = ([Dengue Cases]*0.42) + ([Temperature]*0.26) + ([Landfill sites]*0.15) + ([Water logging]*0.09) + ([Land use/cover]*0.05)

To understand dengue epidemiology, proper surveillance studies, analysis of epidemiological data, prediction of outbreaks and hot spot analysis are of critical importance. In this study, we examined hot spot and spatial distribution of dengue potential areas through cluster analysis in the NCT of Delhi, India. Our case study revealed the dengue epidemics hot spot regions from high vulnerable regions to moderate and low vulnerable regions and these results were similar to other studies (Hazrin et al., 2016; Majid et al., 2019; Respati et al., 2017; Edirisinghe et. al., 2017). The final dengue epidemics vulnerability assessment map reveals that the study area was divided into three different vulnerability regions. The area under high vulnerable regions, moderate vulnerable regions and low vulnerable regions stands at 326.24 (20.55%), 674.25 (42.48%) and 586.56 (36.95%) respectively (Table 4).

Table 4. Area under different suitability categories.

| Vulnerable regions | Area ($km^2$) | Area (%) |
|---|---|---|
| High vulnerable regions | 326.24 | 20.55 |
| Moderate vulnerable regions | 674.25 | 42.48 |
| Low vulnerable regions | 586.56 | 36.95 |

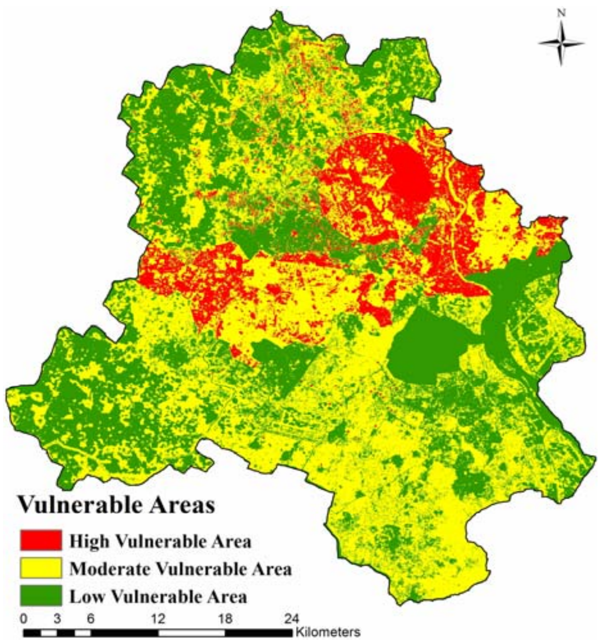


Fig. 7. NCT of Delhi. Landfill sites. Dengue epidemics vulnerable areas.

It is observed that a large area falls under moderate vulnerable regions and a less extended area falls under high vulnerable regions. The medium area is found to fall under low vulnerable regions. In India, dengue cases are increasing gradually, year by year. This method also can be utilized to identify the distance between the high risk to the low or moderate risk areas, and can be analyzed in association with the nearest health services to improve the accessibility of health services in various areas. In order to inhibit the reoccurrence and the spread of the dengue disease the concern authority in administration and health sector are expected to make proper planning during the decision-making process and implement the preventive measure in the nick of time.

## 4. CONCLUSION

The present research will provide an emergency response system at the time of health hazard that will help decision-makers and planners manage their resources effectively and efficiently. In this paper, the integrated approach of GIS based multi-criteria decision making is showcased as a major contribution towards the development of an effective health care management system. This study also provides a new approach for decision-makers in order to decrease the spatial extent of this chronic disease and also reduce the human health hazard. In this study, the spatial extent of dengue epidemics and hot spot regions were identified for the NCT of Delhi.

The identification of spatial clusters of dengue epidemics is an essential tool in policy development and for providing a suitable healthcare management system. These spatial clusters will also be helpful in informing and supporting highly effective, locally tailored interventions for dengue disease, which is a highly and spatially heterogeneous infection. Similarly, this study also suggests that spatial analyses would be helpful in managing the vector-borne diseases such as dengue, by highlighting where and when limited public health resources should be concentrated.

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