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ORIGINAL ARTICLE

Mapping dengue susceptibility in Dhaka city: a geospatial multi-criteria approach integrating environmental and demographic factors

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Abstract

Dengue, a rapidly spreading mosquito-borne disease, poses a serious public health threat in tropical cities like Dhaka, Bangladesh—one of the world's most densely populated megacities. In 2023 alone, Dhaka experienced its worst outbreak, recording 321,179 cases and 1,705 deaths. This study aims to assess dengue susceptibility across Dhaka using a geospatial Multi-Criteria Decision-Making (MCDM) approach. Fourteen environmental and demographic factors were selected, and thematic raster layers were developed and weighted using the Analytical Hierarchy Process (AHP). These layers were integrated to generate spatial dengue susceptibility maps, highlighting risk zones across the city. Findings reveal that southern and southeastern Dhaka, particularly under the South City Corporation, are highly susceptible based on environmental factors. Demographic analysis shows moderate to very high susceptibility in central and southern wards, with population density and proximity to waterlogged areas identified as key drivers. The model was validated through field surveys with 80 stakeholders, with 67.5% agreeing with the susceptibility classifications. This study provides a scalable and transferable framework for dengue risk assessment and can inform targeted interventions in other endemic regions. The results offer critical guidance for urban health planning, vector control, and resource allocation to mitigate dengue and similar vector-borne diseases.

Keywords Analytical hierarchy process (AHP) · Dengue fever · Dhaka city · Geospatial analysis · Mosquito-borne diseases · Urban health

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1 Introduction

Dengue fever is one of the most common vector- and mosquito-borne diseases in the tropics and subtropics [1–3]. Dengue transmission is reported from at least 128 countries worldwide, with over 3.97 billion people at risk of exposure to dengue fever each year [4, 5]. In 2023, the World Health Organization (WHO) mentioned dengue fever as one of the biggest health concerns after the COVID-19 pandemic, while in 2019, they listed dengue fever among the top ten global health hazards [6]. Over the last 50 years, global dengue incidences have increased more than 30-fold, with approximately 50 million cases increasing each year [7, 8]. Dengue is most common in urban and semi-urban areas, where the accumulation of clear and stagnant water—often due to drainage failures—creates ideal mosquito breeding sites [9, 10]. However, nowadays, dengue cases are increasingly reported in peri-urban and rural areas due to human migration and elevated population mobility, as well as changes in local and regional climate patterns which are

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favorable for dengue outbreaks and mosquito reproduction [11, 12].

The Indian subcontinent is highly vulnerable to mosquito-borne dengue virus due to its favorable climate [13]. Dengue is a major cause of casualties and hospitalization, particularly among children in this region [14]. Bangladesh, situated in the Indian subcontinent, is highly susceptible to dengue virus transmission due to its climate, high population density, and unplanned urbanization [12]. The first recorded cases of dengue in Bangladesh date back to the 1960 s, with sporadic outbreaks until the early 2000s, when the disease became endemic [9]. By 2000–2002, Dhaka reported a significant rise in cases, marking the beginning of a persistent public health challenge. The severity of dengue in Dhaka increased dramatically after 2015, with outbreaks growing in frequency and scale. In 2019, the city accounted for 81% of Bangladesh's dengue cases [15], and by 2023, it experienced its worst outbreak on record—321,179 cases and 1,705 fatalities—surpassing the cumulative total of the past 22 years. This exponential growth aligns with rapid urbanization, climate variability, and inadequate vector control measures, creating ideal conditions for Aedes aegypti proliferation. The 2023 outbreak underscored city's status as a global hotspot for dengue, with the WHO ranking Bangladesh among the most affected countries worldwide [12]. While this study is focused on Dhaka city, the methodological framework developed here—integrating geospatial multi-criteria analysis with environmental and demographic factors—is broadly applicable to other dengue-endemic regions worldwide. Many cities in tropical and subtropical areas, such as Bangkok, Jakarta, Manila, and Rio de Janeiro, face similar challenges related to urbanization, climate change, and vector-borne disease outbreaks. Our approach provides a replicable model that public health authorities and researchers in other urban settings can adapt for spatial dengue susceptibility assessment, allowing for more effective resource allocation and vector control strategies.

Past dengue control strategies have primarily focused on vector surveillance, insecticide spraying, and public health awareness campaigns aimed at reducing mosquito breeding and disease transmission [16, 17]. While these approaches have played a vital role, they are often reactive, lack spatial precision, and fail to consider the complex interactions between environmental and demographic risk factors, as discussed in Sect. 2.1. These limitations highlight the need for more proactive and spatially targeted methods. Geospatial techniques offer a valuable alternative by enabling the identification of high-risk zones through the integration of diverse spatial datasets. By combining environmental and demographic criteria, they support more efficient resource allocation, early warning systems, and localized interventions [18]. This study builds on these needs by applying a multi-criteria geospatial analysis to assess dengue susceptibility in Dhaka city—an area particularly vulnerable due to its rapid urbanization and high population density. As dengue risk is shaped by dynamic socio-environmental conditions [19, 20], spatial susceptibility assessments can guide more effective, evidence-based decision-making for dengue prevention and control [21, 22].

Geospatial techniques, which combine geographic information systems (GIS) and remote sensing, are considered effective for managing health data, analyzing spatial distribution, anticipating trends, conducting monitoring, and managing epidemic diseases [16, 23]. Geospatial techniques have recently demonstrated their effectiveness in integrating criteria that influence dengue, mapping susceptible areas for the dengue virus, and identifying and detecting ideal breeding grounds for dengue mosquitos [2, 24]. Weighting and rankings are necessary for processing and integrating multiple criteria in spatial decision-making in dengue susceptibility assessment [5]. The analytical hierarchy process (AHP) is considered simple yet powerful tool that researchers and decision-makers widely use to integrate multiple criteria and make spatial decisions to produce susceptibility maps [17]. AHP, as part of the multi-criteria decision making process (MCDM), helps analyze spatial multi-criteria layers through pairwise comparisons based on expert opinions to derive a priority scale and determine the consistency or inconsistency in the decision-making process [25, 26].

Several studies have so far been conducted globally using geospatial techniques to map dengue virus susceptibility, assess the risk, and identify dengue infection sites [2, 7, 16, 27, 28]. Ali and Ahmad [16] performed a study on dengue risk mapping using AHP with GIS in Kolkata Municipal Corporation, India considering influencing factors in the spread of the dengue virus, while, Ghosh et al. [27] mapped the dengue disease risk in Kharagpur city, India using various variables and multiple logistic regression analysis. Another study by Atique et al. [2] investigated the spatio-temporal distribution and diffusion patterns of the dengue outbreak, focusing on the Swat area in Pakistan, applying space–time scan statistics. Akter et al. [7] identified spatial and temporal patterns of dengue infections in Queensland, Australia using, geospatial techniques. Bangladesh, although, highly susceptible to the dengue virus, very few systematic study have so far been conducted in the country [10, 12]. Kayesh et al. [10] focused on reviewing severe dengue risk in Bangladesh. On the contrary, Kamal et al. [12] attempted to establish a relationship between urban environmental components and dengue prevalence in Dhaka city. While above studies have significantly contributed to understanding dengue risk and susceptibility, there are notable gaps that this research aims to address. First, most previous studies have focused on either environmental or demographic factors in isolation, without integrating both in a single framework. Second, the application of geospatial techniques in Dhaka city has been limited, particularly in the context of dengue susceptibility mapping. Third, the use of the Analytical Hierarchy Process (AHP) for weighting and ranking criteria in dengue susceptibility studies is still underexplored, especially in densely populated urban areas like Dhaka. This study fills these gaps by developing a comprehensive spatial susceptibility model that integrates both environmental and demographic factors, applies AHP for criteria weighting, and focuses specifically on Dhaka city, which has been severely affected by dengue outbreaks in recent years.

The present study was designed to develop a novel spatial dengue disease susceptibility mapping approach using multi-criteria integrated geospatial techniques and to assess the spatial pattern of dengue disease susceptibility in Dhaka city, Bangladesh. While previous studies have utilized geospatial techniques for dengue risk mapping, this research distinguishes itself by integrating both environmental and demographic factors in a comprehensive multi-criteria decision analysis (MCDA) framework, specifically tailored for Dhaka city. Furthermore, this research employs the Analytical Hierarchy Process (AHP) to weight and rank the criteria, which has not been extensively applied in the context of Dhaka city, particularly with such a detailed set of factors. The specific objectives were: (1) to develop a spatial dengue disease susceptibility mapping approach using geospatial techniques incorporating multi-criteria; (2) to apply the developed approach for assessing the spatial pattern of dengue disease susceptibility in Dhaka city of Bangladesh; and (3) to validate the produced spatial dengue disease susceptibility results.

2 Material and methods

2.1 The study area

This study was conducted in Dhaka city, encompassing both Dhaka North City Corporation and Dhaka South City Corporation. Geographically, study area is located at 23°43′0″ north latitude and 90°24′0″ east longitude (Fig. 1). The total area of Dhaka city is 276 km^2. Dhaka experiences a predominantly tropical monsoon climate, characterized by hot, muggy summers and moderate winters [12]. The annual mean temperature in Dhaka city is recorded at 28 °C, fluctuating across the months from 20 °C in January to 32 °C in May. From May to September, around 80% of the annual average rainfall, which amounts to 1854 mm, takes place [29]. Home to 21.7 million people, Dhaka city exhibits a 3.5% annual growth tendency [30, 31]. In this city, the average annual rate of urban expansion from 1991 to 2019 reached up to 8%, and alarmingly, the periphery expanded by 43% during the same period. It is characterized by congested streets, close-knit neighborhoods, and excessive traffic, contributing to increased pollution and placing stress on the city's infrastructure. The congested condition is exacerbated by a lack of public parks and green areas. Dhaka also faces challenges in providing suitable housing and sanitary services, leading to numerous human health issues such as air and waterborne diseases. The warm and humid climate in Dhaka, compounded by the influence of climate change, fosters an environment favorable for the outbreak of vector-borne illnesses such as dengue fever, malaria, and chikungunya. These diseases rank among the most prevalent and widely spread in Dhaka [30–32].

2.2 The approach

This study used an AHP-based geospatial multi-criteria assessment approach to incorporate several environmental and demographic parameters for determining dengue susceptibility. The AHP has a significant potential for effectively integrating and aggregating multi-criteria and appropriately expressing outcomes [33]. The literature study yielded eight environmental and six demographic factors for determining environmental and demographic susceptibilities.

The procedural flowchart utilized in this study is depicted in Fig. 2.

2.3 Data set and sources

To carry out this study, various secondary sources of social and demographic data were used. Satellite images from Sentinel-2 and Landsat 8 were obtained from the Copernicus open access hub and the United States Geological Survey (USGS) Earth explorer websites, respectively. Digital elevation model (DEM) data were gathered from the Survey of Bangladesh (SOB). Rainfall and humidity data were collected from the Bangladesh Meteorological Department (BMD). Demographic information was gathered from the corresponding information authorities, including the Bangladesh Bureau of Statistics (BBS) and the Directorate General of Health Services (DGHS). Data type, sources, period and mapping output are detailed in the following Table 1.

2.4 Mapping, susceptibility evaluation criteria, and alternatives

Spatial thematic layers were created by mapping alternatives of each criterion. ArcGIS software (version 10.4) and ERDAS Imagine (version 15) were used for all geospatial tasks, and 15 m resolution was determined for each raster layer in this study.

For this study, 14 environmental and demographic criteria and their alternatives were chosen through an extensive literature and data review, justifying their direct and indirect

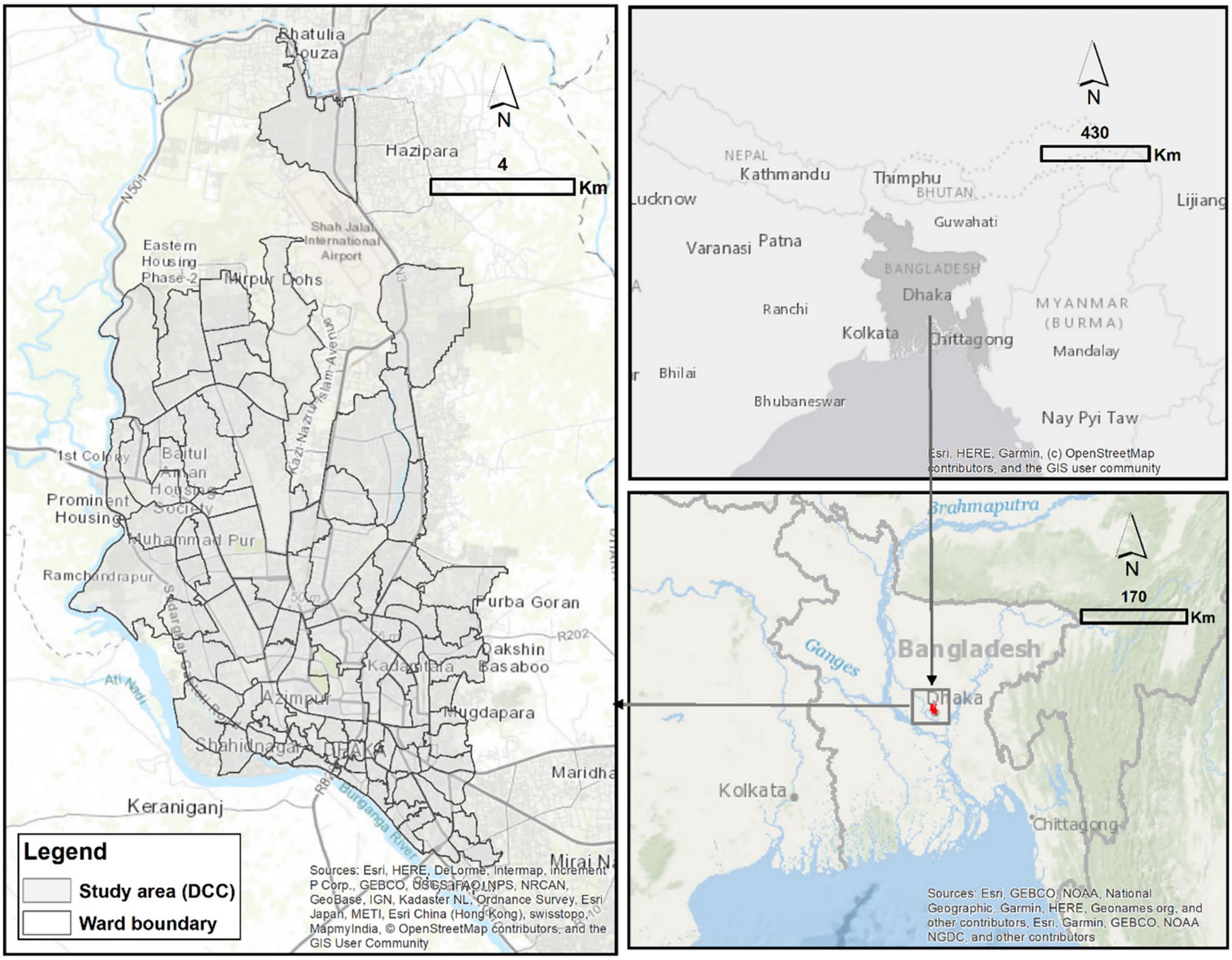

Fig. 1 Study area, Dhaka city of Bangladesh

influence on suitable breeding environments and dengue transmission. The criteria and mapping methodologies are elaborated upon in subsequent sections.

2.4.1 Factors for environmental susceptibility mapping

Environmental susceptibility is closely interlinked to the physical and environmental conditions surrounding a given area. To operationalize this construct, this study has selected eight key indicators, including land use land cover (LULC), normalized difference moisture index (NDMI), normalized difference vegetation index (NDVI), and land surface temperature (LST), alongside variables such as distance to waterlogged areas, elevation, rainfall, and humidity.

2.4.1.1 Land use land cover (LULC) LULC was used to investigate the entire land of Dhaka city, which is used for diverse purposes such as vegetation cover, waterbodies, barren land, and built-up areas. The incidence of vector-borne diseases such as dengue, malaria, and chikungunya in tropical regions is mostly associated to low-lying areas and bodies of water, and is caused by rapid changes in the landscape [34]. Shifts in natural land use, including impoundments, dams, and irrigation trigger dengue transmission by creating an ideal setting for vector reproduction [35]. Dengue-carrying mosquitoes are generated in urban environment due to inappropriate land use, and they spread to nearby rural areas [36]. It was essential to produce an LULC map to classify the different land uses and identify areas susceptible to dengue disease. The Sentinel 2, 10 m resolution satellite image was used to produce the Land use land cover map of study area using a supervised classification approach. Thus, the LULC classification categorized Dhaka into five land use categories: waterbody, bare land, vegetation cover, roads, and built-up area (Fig. 3a).

2.4.1.2 Normalized difference vegetation index (NDVI) The Normalized Difference Vegetation Index (NDVI) was used

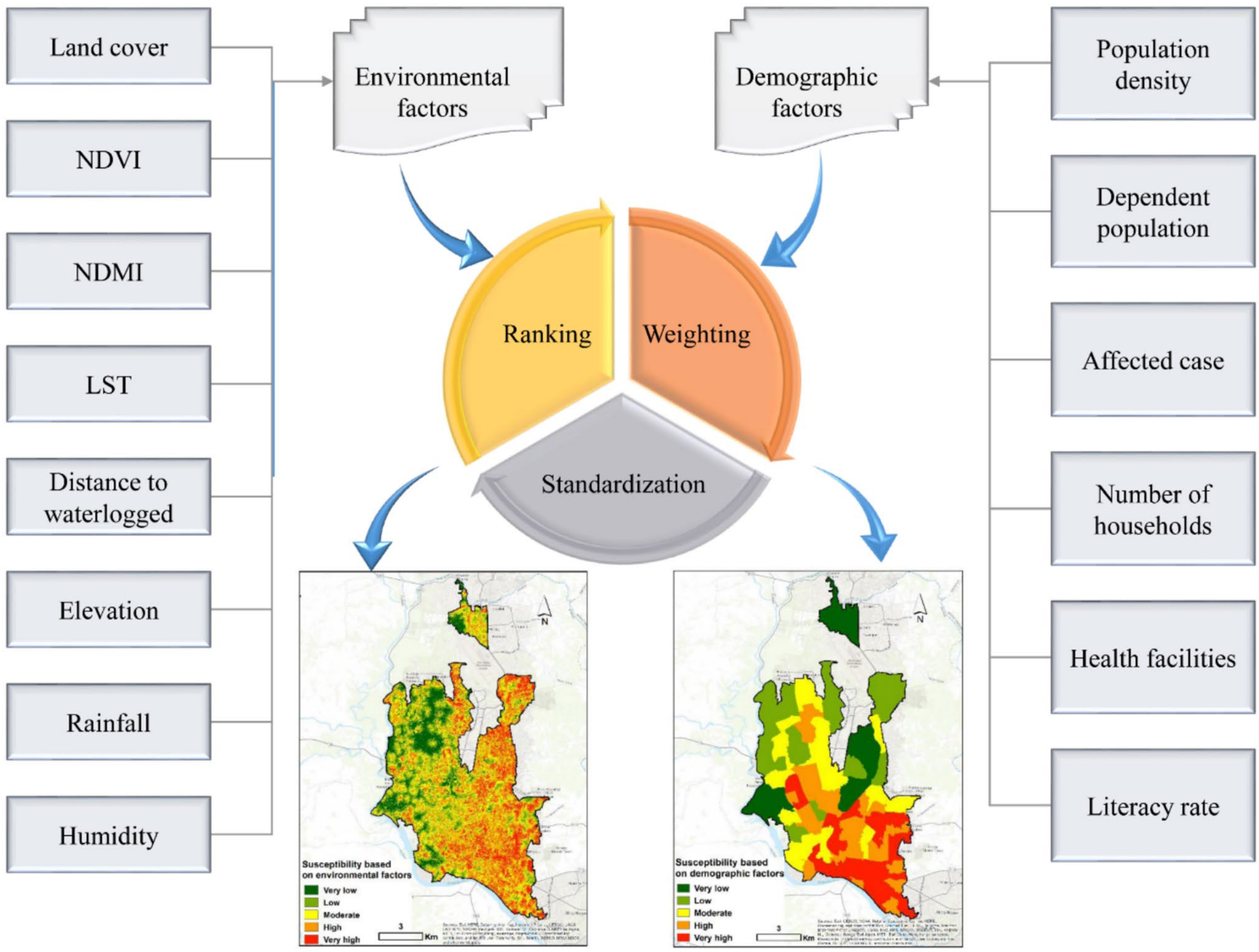

Fig. 2 The methodological flowchart illustrating the susceptibility assessment approach adopted in this study

Table 1 Data type and sources used for susceptibility analysis of Dengue diseases

Data type	Source	Period	Mapping output
Sentinel-2 (10 m resolution)	Copernicus Open Access Hub	March, 2021	Land cover, NDVI, NDMI, Distance to waterlogged
Landsat-8 (30 m resolution)	United States Geological Survey (USGS) Earth explorer	March, 2021	LST
Digital Elevation Model (DEM) at 20 m spatial resolution	Survey of Bangladesh (SOB)	2014	Elevation
Rainfall and humidity	Bangladesh Meteorological Department (BMD)	1980–2021	Rainfall, humidity
Population data	Bangladesh Bureau of Statistics (BBS)	Population Census 2011	Population density, dependent population, household numbers, literacy rate
Number of dengue affected case	Directorate General of Health Services (DGHS)	2014–2021	Affected case
Number of hospitals	Directorate General of Health Services (DGHS)	Up to 2021	Health facilities

to calculate vegetation greenness in order to understand vegetation density and assess changes in plant health. The largest concentration of vector-borne illnesses was found in areas with low land and limited forest cover, according to

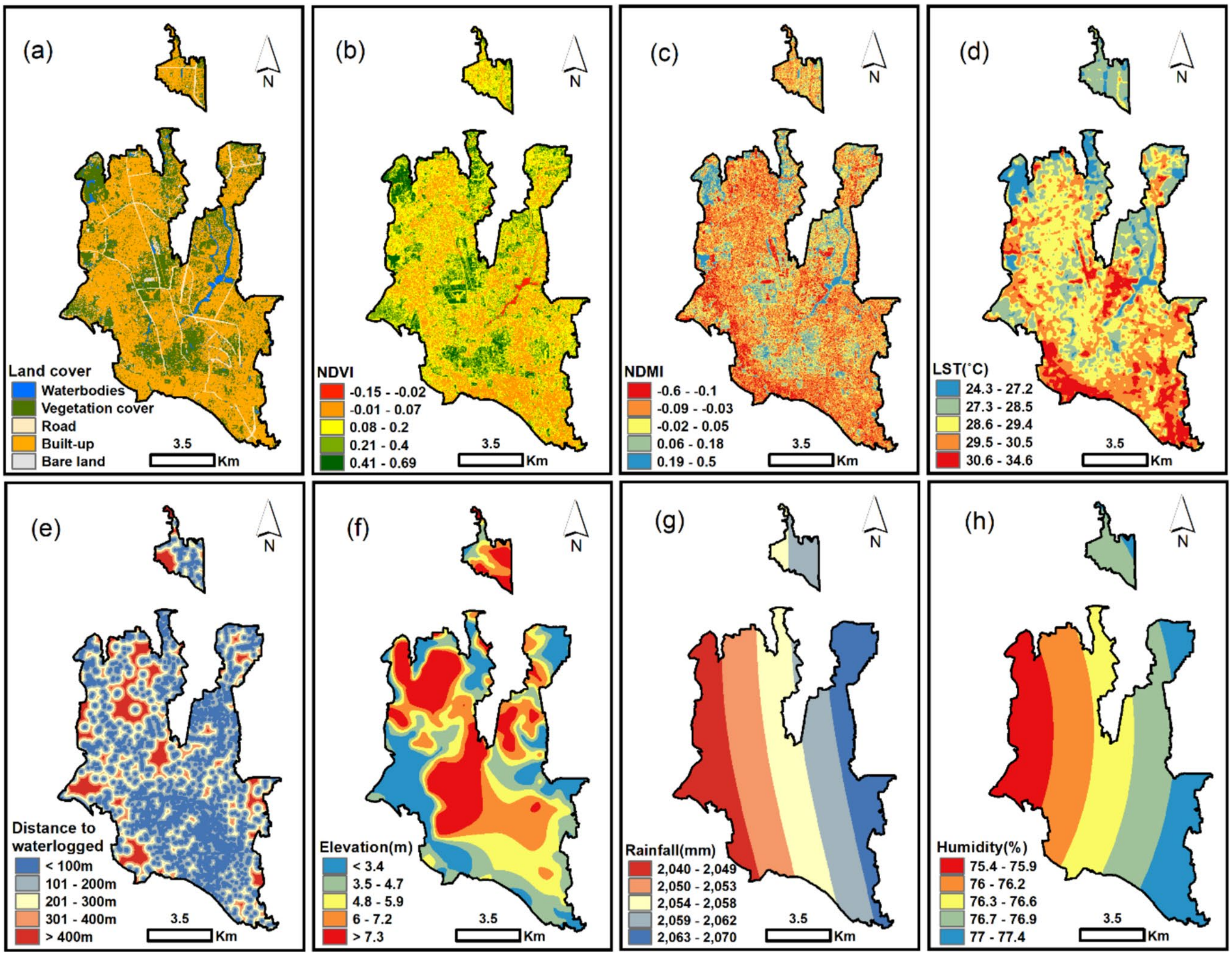

Fig. 3 Environmental susceptibility mapping factor layers: **a** Land cover, **b** NDVI, **c** NDMI **d** LST, **e** Distance to waterlogged, **f** Elevation, **g** Rainfall, and **h** Humidity

Sheela et al. [34]. NDVI and Dengue transition were shown to be inversely connected, as forest cover loss was associated with increased risk of DF [16, 37]. The ratio between the red and near-infrared (NIR) bands in the Sentinel-2, 10-m resolution image was used to calculate the NDVI and extract the vegetation index (Fig. 3b). NDVI was quantified using the following formula:

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}} \tag{1}$$

2.4.1.3 Normalized difference moisture index (NDMI) The normalized Difference Moisture Index (NDMI) influences dengue outbreaks, with areas exhibiting high NDMI having a higher chance of dengue outbreaks [16, 37]. To quantify vegetation moisture content, the NDMI was carried out. The ratio between the NIR and SWIR values of the Sentinel-2 (10 m resolution) image was used for its calculation (Fig. 3c). It is a reliable indicator of water stress in plants and can identify water stress at an early stage, before the issue becomes unmanageable. The short-wave infrared (SWIR) spectral band is highly sensitive for detecting mesophyll structure of leaves and the water content available in vegetation; while the near-infrared (NIR) band is responsible for deriving the dry matter content in the interior of the leaf. NDMI was calculated following this equation:

$$\mathrm{NDMI} = \frac{\mathrm{NIR} - \mathrm{SWIR}}{\mathrm{NIR} + \mathrm{SWIR}} \tag{2}$$

The NDMI scale runs from -1 to $+1$, where the lowest values (in red) correlate to low water content in the vegetation and the highest ones (in blue) to high water content.

2.4.1.4 Land surface temperature (LST) The growth of mosquito larvae and the feeding habits of mosquitoes are significantly influenced by air and ground temperature [38], with research identifying that mosquitoes' life expectancy is very low at extreme temperatures and optimal when the surface temperature is between 28 and 32 degrees Celsius [12, 37]. Temperature and humidity provide suitable conditions for the genetic development and maturation of the Dengue Virus (DENV) inside mosquitoes [12, 38].

Geometrically corrected Landsat-8, 30-m resolution images were used to obtain LST (Fig. 3d). To derive LST, the following methods and equations were used:

i. Radiance conversion from DN values:

Thermal Infrared Digital Numbers can be converted to top-of-atmosphere (TOA) spectral radiance by applying the radiance rescaling factor.

Top of Atmosphere (TOA) spectral Radiance:

$$L\lambda = ML * Qcal + AL \tag{3}$$

where: $L\lambda$ = TOA spectral radiance (Watts/(m^2 * sr * μm)), ML = Radiance multiplicative Band (No.), AL = Radiance Add Band (No.), Qcal = Quantized and calibrated standard product pixel values (DN).

ii. Top of Atmosphere (TOA) Brightness Temperature:

Spectral radiance data can be transformed into top-of-atmosphere brightness temperature by utilizing the thermal constant values provided in the metadata file.

$$BT = K2/\ln(K1/L\lambda + 1) - 272.15 \tag{4}$$

where: BT = Top of atmosphere brightness temperature (°C), $L\lambda$ = TOA spectral radiance (Watts/(m^2 * sr * μm)), K1 = K1 Constant Band (No.), K2 = K2 Constant Band (No.).

iii. Land Surface Emissivity (LSE):

Land surface emissivity (LSE) represents the mean emissivity of a surface element on Earth, derived from NDVI values

$$E = 0.004 * PV + 0.986 \tag{5}$$

where: E = Land Surface Emissivity, PV = Proportion of Vegetation.

iv. Land Surface Temperature (LST):

The radiative temperature known as the land surface temperature (LST) is determined by measuring the brightness temperature at the top of the atmosphere, the wavelength of the radiance emitted, and the land surface emissivity.

$$LST = (BT/1) + W * (BT/14380) * \ln(E) \tag{6}$$

where: BT = Top of atmosphere brightness temperature (°C), W = Wavelength of emitted radiance, E = Land Surface Emissivity.

2.4.1.5 Distance to waterlogged The presence of water bodies is considered the most significant factor in dengue outbreaks [8]. This is due to the fact that these types of bodies of water offer female Aedes mosquitoes—who like reproducing in fresh, stagnant water—the perfect breeding habitat. Only 100–200 m is the restricted flight range of these insects. Residential locations near waterlogged regions, as defined by a 200-m buffer zone, are therefore more likely to transmit dengue than those farther away. It has been shown that residing in flooded regions increases the danger of spreading dengue [39]. Dengue transmission is more likely in areas with waterlogged or poor drainage systems [40]. Following a study performed in Saudi Arabia by Khormi and Kumar [41], the risk of dengue transmission decreased with increasing distance from locations submerged in water. Waterlogged areas were extracted from the Sentinel 2, 10 resolution images using supervised classification techniques. The distance to waterlogged raster layer was calculated using the Euclidean distance approach (Fig. 3e). The shortest straight-line distance between each cell and the closest source point is calculated using the Euclidean distance functions. In addition to identifying cell allocation, this function can also be employed to estimate the distance and direction to the closest source.

2.4.1.6 Elevation Elevation is an essential factor that influences the dengue outbreak. There is a correlation between elevation and dengue transmission, with lower-elevation locations (such as coastal plains) experiencing higher transmission rates than higher-elevation areas [42]. We used the 2014 DEM at a 20 m spatial resolution to obtain land elevation. The 2014 DEM data were acquired from SOB (Fig. 3f).

2.4.1.7 Rainfall The propagation of the dengue virus is significantly aided by rainfall [2]. Aedes mosquitoes, the main vector for dengue infection, can thrive in stagnant water that accumulates in various places, including flower pots, tire waste bins, and blocked drainage systems by rainfall. Several studies stated that rainfall and the incidence of dengue fever are positively correlated [43]. Heavy rainfall can lead to the accumulation of standing water, providing an ideal breeding ground for Aedes mosquitoes, the primary vector for dengue transmission [44]. Dengue cases increase with increasing rainfall intensity, while declining rainfall causes a gradual decrease [45]. In this study, we used the daily precipitation data (1950—2021) acquired from BMD for mapping precipitation intensity. Firstly, we made kriging interpolation with the average annual precipitation data from all weather stations in Bangladesh, and then we clipped the study area (Fig. 3g).

2.4.1.8 Humidity It is commonly known that humidity contributes to the transmission of the dengue virus and that it plays a major role in its spread. High humidity enhances the survival and reproduction of mosquitoes, thereby increasing the overall risk of dengue transmission [1]. Relative humidity exhibits a strong correlation with dengue transmission;

higher humidity provides an ideal environment for mosquito breeding, while lower humidity reduces mosquito transmission [45]. In this research, we used the daily humidity data (1950—2021) acquired from BMD for mapping humidity (Fig. 3h).

2.4.2 Factors for demographic susceptibility mapping

The assessment and zonation of vector-borne diseases are closely related to demographic factors such as population density, household characteristics, and education level. This is because humans are known to have a high potential for transmitting such diseases. This study identified six causative indicators as demographic parameters: population density, dependent population, affected case, number of households, health facilities, and literacy rate.

2.4.2.1 Population density Densely inhabited areas are more prone to a range of environmental problems, such as poor sanitation, inadequate sewage systems, and localized waste dumping, which are suspected to have a substantial influence on the development of dengue [15]. Cities with large population densities and unfavorable environmental conditions, like Dhaka city Corporation, may foster breeding conditions for Aedes mosquitoes that raise the risk of dengue transmission. The population data were collected from the BBS. In a GIS platform, the area of each ward of the Dhaka city was digitized and calculated. The population density was then determined using the ratio of total people to total area in km^2 using a field calculator. The spatial distribution of an element's density is depicted by a choropleth, which is a quantitative area map. For this study, the choropleth technique was employed to generate the population density map (Fig. 4a).

2.4.2.2 Dependent population Dependent groups, including children, the elderly, people with disabilities, and those with long-term health concerns, may be more vulnerable to dengue outbreaks for a variety of reasons, including a low immune system, substandard living conditions, and limited access to medical care, among others. The risk of developing severe dengue sickness has been found to be higher in children and elderly people, who are often members of dependent communities [46]. Mortality rates in these age categories range from 1–20%. (WHO, 2021). The dependent population layer was created using word based data from the Bangladesh Bureau of Statistics in a GIS platform (Fig. 4b).

2.4.2.3 Affected case Affected cases have a strong association with dengue transmission, indicating that areas with a greater dengue outbreak are likely to face a greater number of dengue cases [9]. In areas where dengue is endemic, individuals are more likely to be exposed to the virus, resulting in a rise in the number of infections. It is impossible for the dengue virus to transfer directly from one person to another, but Aedes mosquitos transmit it from someone infected and previously suffering from Dengue Fever [9]. An increase in dengue cases implies a more significant presence of infected individuals, which supports the Aedes mosquitoes in acquiring the Dengue virus, often heightening the susceptibility of the surroundings to Dengue infection. The dengue-affected case spatial layer was prepared using dengue case data from 2014 to 2021 (Fig. 4c). These data were collected from DGHS.

2.4.2.4 Number of households For a number of reasons, there is a correlation between higher household densities and a higher risk of dengue transmission [47]. Firstly, crowded living situations might serve as perfect breeding grounds for Aedes mosquitoes, which are the virus carriers. Small water containers, such as flower pots, used tires, and open water containers, can be found in and around residences where these mosquitoes prefer to nest. These sorts of breeding sites are usually crowded, with many of people gathered in small areas. This might lead to a rise in mosquito populations and the risk of dengue transmission. Building types, household density, and the surrounding built environment have all contributed significantly to our understanding of the epidemiology and possible dangers of dengue fever [48]. High population density, seemingly, the results of a higher concentration of households, shows close proximity as the greatest vulnerability to dengue diseases [21]. The household spatial layer was prepared using word-based number of household data in an ArcGIS environment (Fig. 4d). These data were collected from BBS.

2.4.2.5 Health facilities Healthcare facilities are crucial for preventing and managing dengue outbreaks. They can contribute to reducing the impact of dengue fever and enhancing patient outcomes by facilitating access to healthcare, identifying and treating cases, and participating in surveillance and reporting efforts. Patients who receive timely and appropriate care for their symptoms are less likely to experience severe forms of the disease and are more likely to recover quickly [49]. Early and appropriate treatment of dengue fever can significantly reduce the risk of death. The locations of several health facilities were collected from DGHS, and a spatial layer was created using ArcGIS (Fig. 4e).

2.4.2.6 Literacy rate Those who are literate may know more knowledgeable of dengue fever's symptoms, transmission, and prevention [50]. They can use this information to take the right actions to safeguard their communities and themselves against the disease. Additionally, literate people are more likely to have access to information about government

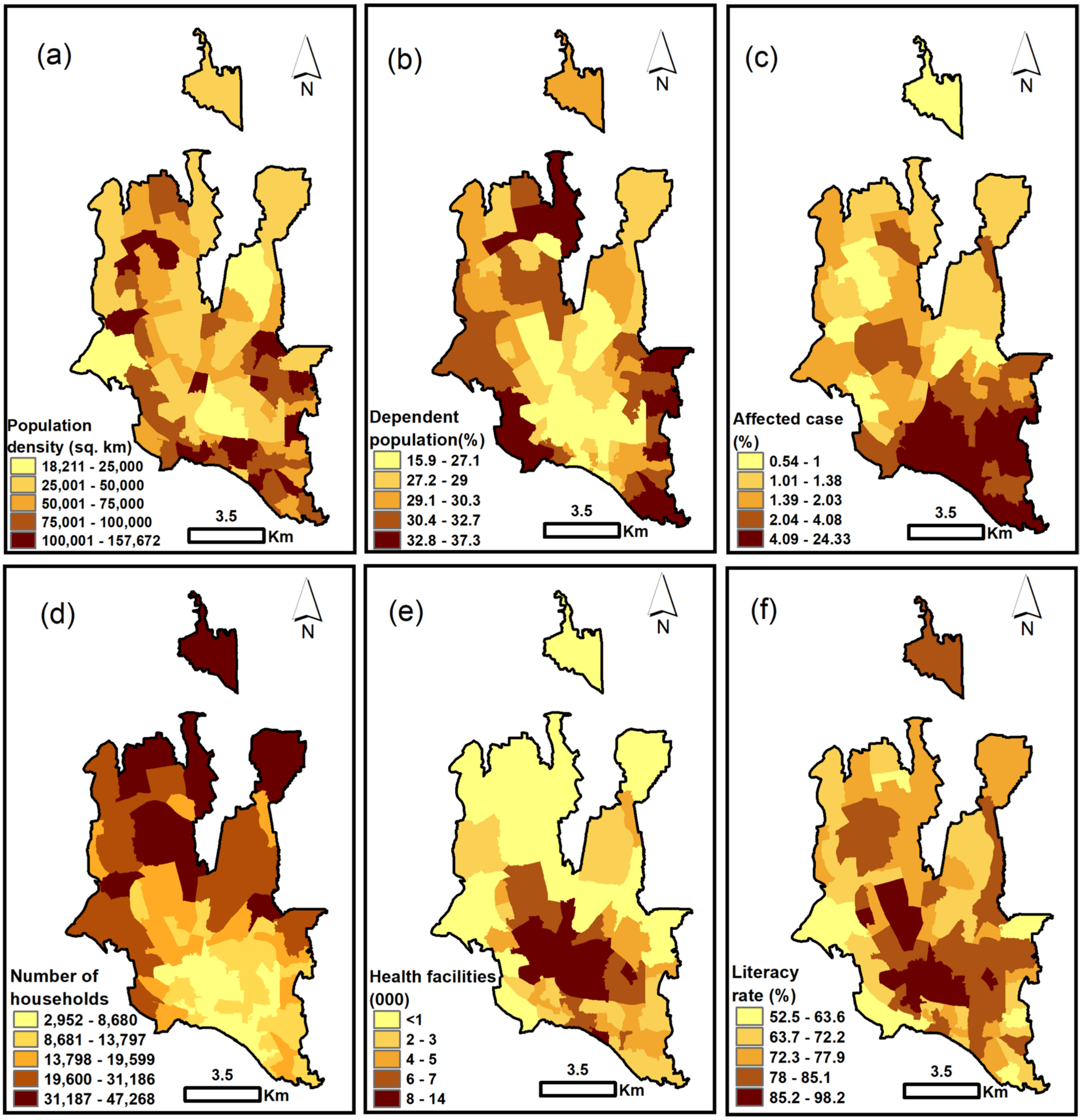

Fig. 4 Demographic susceptibility mapping factor layers: **a** Population density, **b** Dependent population, **c** Affected case **d** Number of households, **e** Health facilities, and **f** Literacy rate

programs, public health campaigns, and scientific studies on dengue fever that can assist them in making well-informed choices about how to prevent and treat the illness. On the other hand, low literacy rates can aid in the spread of dengue disease since they can result in inadequate sanitation and hygiene practices. Those who lack literacy may also have less access to medical care and other services, which might result in diseases being treated too slowly or not at all. The literacy layer was created using word-based data from BBS in a GIS platform (Fig. 4f).

2.5 Alternative ranking and normalization of criteria layers

Alternative ranking and normalized criteria layers are used to evaluate multiple criteria and rank them based on all the alternatives. Alternatives were ranked according to the contribution of susceptibility and AHP criteria. The susceptibility levels (1–5) were determined by ranking the mapped options of each spatial criterion layer (Table 2). Extremely low and extremely high vulnerabilities are indicated by ranks 1 and 5, respectively. All spatial layers were transformed to a 30 m pixel raster in order to allow the raster-based weighted overlay procedure and to aid in the multi-criteria decision-making process utilizing the AHP. The ranking values of each geographic criterion layer's options were then normalized to create a common scale ranging from 0 to 1. Equation (7) for the linear scale transformation was used to obtain normalized values.

$$p = x - \min/\max - \min) \tag{7}$$

where, p denotes the standardized score, min and max denote the minimum and maximum values of each dataset, and x denotes the cell value.

2.6 Weighting the criteria using AHP

This study evaluated the physical and social susceptibility factors using the AHP technique. Pairwise comparison matrices were created using qualitative feedback from five experts and a user, and these matrices were then utilized to weight the criteria. Experts were chosen at the national level based on their individual research expertise and extensive knowledge. The users and specialists were from government, academic, and research organizations. Physical and social susceptibilities added up to one.

The consistency ratio (CR) was computed in order to evaluate the consistency of comparisons in the pairwise comparison matrix. When the value is at or below 0.1, the CR is deemed appropriate [33]. Otherwise, a new weight computation and evaluation of the given qualitative decision are necessary.

The following equation was used to compute the CR:

$$\mathrm{CR} = \text{Consistency Index}/\text{Random Index} \tag{8}$$

where random index (RI) signifies the randomly produced average consistency index and consistency index (CI) is defined as follows:

$$\mathrm{CI} = (\max - \mathrm{n})/(\mathrm{n} - 1) \tag{9}$$

where, max is the biggest eigenvalue of the matrix and n is the order of the matrix.

Table 3 shows the criterion weights and comparison CR values derived from the pairwise comparison matrices.

2.7 Susceptibility assessment

This study used the weighted overly technique to generate susceptibility indices based on environmental and demographic factors. In this process, weights derived through AHP for each criterion of demographic and environmental were employed with their respective thematic layers for identifying the susceptible areas to dengue diseases in Dhaka city. The procedure generated susceptibility indices based on demographic and environmental factors with the values in the common scale 0 to 1. The produced indices values were then categorized into five levels named very low, low, moderate, high and very high for creating dengue susceptibility maps in terms of demographic and environmental factors.

Table 2 Ranking of factors alternatives following the contribution to dengue diseases susceptibility

Susceptibility	Factors	Ranking (Based on susceptibility)				
		Very Low (1)	Low (2)	Moderate (3)	High (4)	Very High (5)
Environmental factors	Land cover	Road	Bare land	Vegetation cover	Waterbodies	Built-up
	NDVI	0.41–0.69	0.21–0.4	0.08–0.2	−0.01–0.07	−0.15–0.02
	NDMI	−0.6 to −0.1	−0.09 to −0.03	−0.02–0.05	0.06–0.18	0.19–0.5
	LST (°)	24.3–27.2	27.3–28.5	28.6–29.4	29.5–30.5	30.6–34.6
	Distance to waterlogged	> 400 m	301–400 m	201–300 m	101–200 m	< 100 m
	Elevation	> 7.3	6–7.2	4.8–5.9	3.5–4.5	< 3.4
	Rainfall (mm)	2040–2049	2050–2053	2054–2058	2059–2062	2063–2070
	Humidity (%)	75.4–75.9	76–76.2	76.3–76.6	76.7–76.9	77–77.4
Demographic factors	Population density (sq. km)	18,211–25,000	25,001–50000	500,001–75000	75,001–100000	100,001–157672
	Dependent population (%)	15.9–27.1	27.2–29	29.1–30.3	30.4–32.7	32.8–37.3
	Affected case (%)	0.54–1	1–1.38	1.39–2.03	2.04–4.08	4.09–24.33
	Number of households	2952–8680	8681–13,797	13,798–19,599	19,600–31186	31,187–47,268
	Health facilities (000)	8–14	6–7	4–5	2–3	< 1
	Literacy rate (%)	85.2–98.2	78–85.1	72.3–77.9	63.7–72.2	52.5–63.6

Table 3 Criteria weights and consistence ratios calculated from the pairwise comparison matrices

Susceptibility	Factor	Weight
Environmental susceptibility	Land cover	0.04
	NDVI	0.15
	NDMI	0.21
	LST	0.15
	Distance to waterlogged	0.24
	Elevation	0.07
	Rainfall	0.07
	Humidity	0.06
Consistency ratio: 0.01		
Demographic susceptibility	Population density	0.27
	Dependent population	0.13
	Affected case	0.25
	Number of households	0.09
	Health facilities	0.19
	Literacy rate	0.06
Consistency ratio: 0.03		

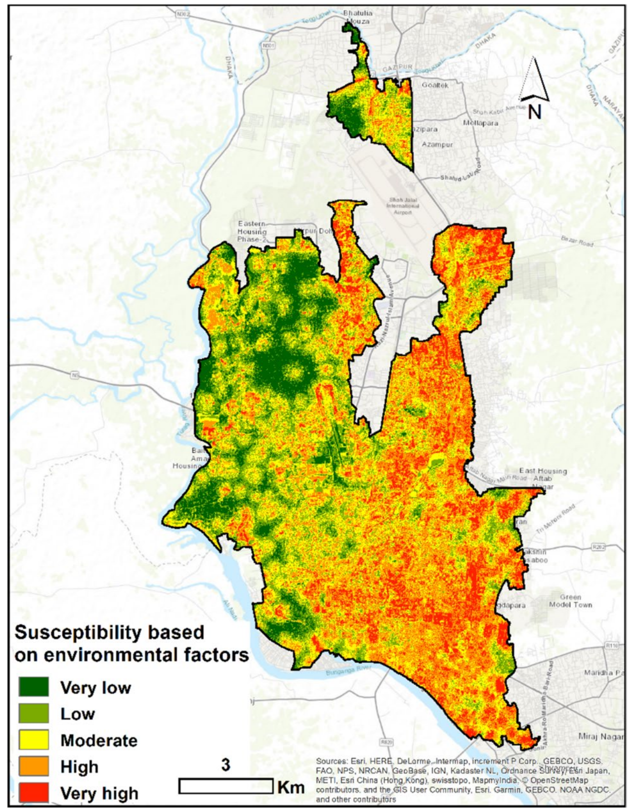

Fig. 5 Map of environmental susceptibility to dengue of the study area

2.8 Validation

The technique of mapping spatial susceptibility is not supported by any established validation mechanism. Nevertheless, a qualitative validation approach was employed to assess the spatial susceptibility maps. A field visit was undertaken in the last month of 2021 in order to evaluate the precision of our susceptibility maps produced by software. During the field tour, over 60 people—locals, experts, and policymakers—were interviewed in-depth regarding the validity of the geographical maps of Dengue illness susceptibility that had been developed. Through personal observation, the genuine vulnerability to Dengue sickness was confirmed by visiting certain vulnerable regions that were identified from the produced maps.

3 Results and discussion

3.1 Susceptibility based on environmental factors

Figure 5 illustrates the spatial variation in dengue susceptibility across Dhaka city Corporation, highlighting its relationship with environmental and physiographic characteristics. The map categorizes dengue susceptibility into five levels, each represented by distinct colors: very low (blue), low (light green), moderate (yellow), high (reddish-yellow), and very high (red). Susceptibility varied spatially, with higher vulnerability observed in eastern zones compared to western areas. The eastern region is predominantly covered by areas of high to very high susceptibility, while the western region is largely dominated by low to very low susceptibility.

In terms of administrative division, the southern part of Dhaka South City Corporation (DSCC) shows higher dengue susceptibility than the northern part of Dhaka North City Corporation (DNCC). Several areas within DSCC exhibit a significant concentration of higher susceptibility, including Dania, Postogola, Sadarghat, Mirhazirbagh, Bangshal, Ganderia, Wari, Tikatuli, Shahbagh, Kamalapur, Saidabad, Nuton Bazar, Khilgaon, Meradia, Southern Basabo, and Dhalpur. Meanwhile, Ward 3 in the western DSCC, encompassing Kamrangirchar, Baghalpur, and Borhanpur, shows lower susceptibility. Moderate susceptibility is sparse and scattered, represented by yellow on the map.

Similarly, the western side of DNCC exhibits low susceptibility, but with a notable difference: the eastern part of DNCC is dominated by higher susceptibility. Ward 9, as well as parts of Wards 8 and 10 (including Bashundhara Residential Area, Kurmitola, Bhatara, Gulshan, Banani, Nakhalpara, Old Airport, Rampura, Vasantek, and Badda), show high to very high susceptibility. In contrast, areas such as Basila, Mohammadpur, Shyamoli, Agargaon, Diabari, Mirpur-1, Ahmednagar, Pirerbagh, Shewrapara, Pallabi, and Mirpur DOHS in the western DNCC exhibit predominantly low to

Table 4 Area coverage of susceptibility mapping (based on environmental and demographic factors) classes and share of the events according to the defined classes

Susceptibility	Susceptibility based of environmental factors		Susceptibility based of demographic factors	
	Area(km^2)	Area (%)	Area (km^2)	Area (%)
Very low	12.0	9.8	18.9	15.4
Low	25.0	20.4	30.0	24.5
Moderate	33.8	27.6	27.2	22.3
High	35.8	29.3	24.1	19.7
Very high	15.7	12.8	22.2	18.1

very low susceptibility. Moderate susceptibility is minimal and scattered across the region.

Overall, the eastern part of Dhaka city exhibits higher susceptibility to dengue due to environmental conditions, while the western part is relatively less prone. Among the two city corporations, DSCC stands out for its significant prevalence of high susceptibility, whereas DNCC is more associated with low susceptibility.

The analysis identified significant geographic heterogeneity in dengue susceptibility. As shown in Table 4, the study area is primarily characterized by high-to-very-high susceptibility, covering 42.1% of the total land area. Low-to-very-low susceptibility covers 30.2%, while moderate susceptibility accounts for 27.6%. Notably, Southern and eastern regions exhibited the highest susceptibility levels, whereas the western and northwestern regions show predominantly low susceptibility due to environmental factors.

3.2 Susceptibility based on demographic factors.

Figure 6 illustrates dengue susceptibility across Dhaka City Corporation (DCC), with a focus on its demographic characteristics. The map categorizes susceptibility into five levels, each represented by a distinct color: very low (blue), low (light green), moderate (yellow), high (reddish-yellow), and very high (red). The map clearly indicates that dengue fever is more prevalent in Dhaka South City Corporation (DSCC) compared to Dhaka North City Corporation (DNCC), where lower susceptibility levels are more common. In DSCC, areas with high susceptibility are overwhelmingly dominant, covering 100% of regions such as Dania, Dholaipar, Mir Hazirbag, Mugdapara, Kadamtala, Maddhya Basabo, Khilgaon, Malibagh, Railway Officers Colony, AGB Colony, T&T Colony, Paribagh, Dhaka University, Shahidnagar, Sadarghat, Babu Bazar, Begum Bazar, Bangshal, Malitola, Nawabpur, Tikatuli, Gopibag, Dayaganj, Narinda, Farashganj, and Faridabad. Conversely, Ward 3 in the western part of Dhaka South City Corporation (DSCC), encompassing areas such as Northern Kamrangirchar, Shankar, Burhanpur,

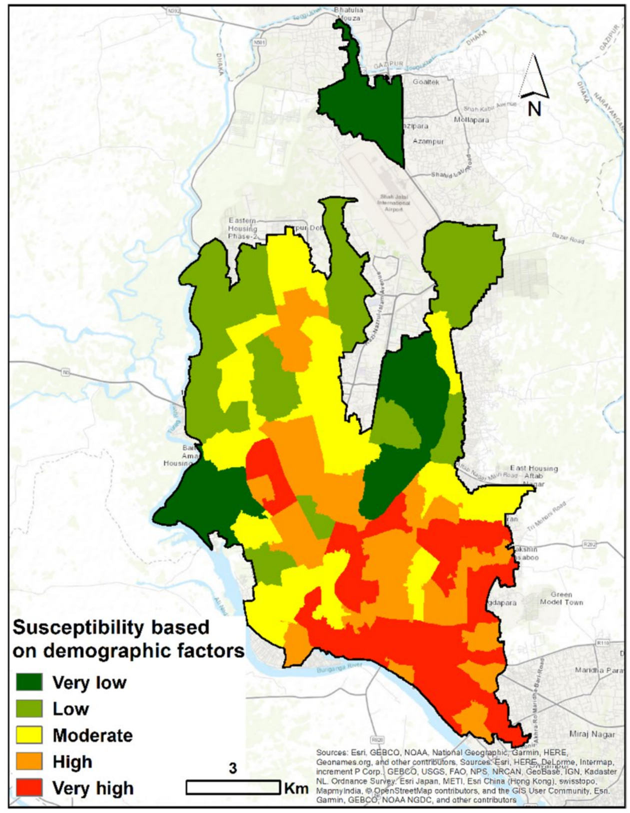

Fig. 6 Map of demographic susceptibility to dengue of the study area

Bhagalpur, Katabon, Pilkhana, Azimpur, Purana Platan, and Shantinagar, exhibits moderate susceptibility. Only two wards in the western areas (Baddanagar, Hazaribagh, Jhigatola, Kalabagan, Shukrabad) exhibit low susceptibility, marked by light green on the map.

In contrast, Dhaka North City Corporation (DNCC) predominantly exhibits low dengue susceptibility. The eastern and western borders of DNCC show reduced susceptibility, while central areas display moderate susceptibility. Notably, regions such as Tejgaon Industrial Area, Mohakhali, Banani, Gulshan, Badda, Vatara, Kuril, Kurmitola, and Bashundhara Residential Area, along with western parts including North Basila, Dhaka Uddan, Bangladesh National Zoo, Botanical Garden, Agargaon, and Vashantek, are characterized by low susceptibility. Moderate susceptibility is more widespread, encompassing areas like Ibrahimpur, Old Airport, Kafrul, Shaheenbagh, West Nakhalpara, Pallabi, Mirpur DOHS, Adabar, Middle Paikpara, Mirpur 1, 2, and 14, as well as Rampura and Baridhara. However, certain locations such as Tejkunipara, Farmgate, Chandrima Uddan, Agargaon, Mirpur 10, and Palash Nagar are identified as higher-risk zones.

Overall, the southern part of Dhaka, particularly DSCC, exhibits a higher susceptibility to dengue fever, while the northern part, represented by DNCC, shows relatively lower vulnerability. DSCC stands out for its high prevalence of dengue susceptibility, whereas DNCC benefits from a more even distribution of low to moderate susceptibility.

According to the analysis in Table 4, low to very-low susceptibility is the dominant category, covering approximately 40% of the total land area. High to very-high susceptibility accounts for 37.8%, while moderate susceptibility covers 22.3%. It is also evident that the southern and southeastern parts of Dhaka, particularly lower-middle regions, exhibit the highest susceptibility. In contrast, the northern regions, especially upper-middle areas, demonstrate lower susceptibility, with most of these areas falling into the low to very-low category, followed by moderate susceptibility in the majority of northern Dhaka.

3.3 Validation

We adopted a qualitative approach based on household responses regarding susceptibility, including in-depth personal observations and opinions of local people, experts, and policymakers, to validate the spatial distribution of dengue disease susceptibility assessed from the weight of AHP based on environmental and Demographic factors in Dhaka City Corporation (Table 5). The chosen qualitative methodology was able to deliver accurate data for analyzing the outcomes of our spatial susceptibility assessment. Out of 80 respondents, 54 (67.5%) were highly satisfied with the results, 16 (20%) were satisfied, and 10 (12.5%) expressed dissatisfaction. Additionally, the susceptibility map revealed that the southern and eastern regions fall within high-to-very-high susceptibility zones in terms of environmental and demographic factors. In contrast, the western and northern parts of Dhaka are largely characterized by low-to-extremely-low susceptibility, while the central and southern areas are predominantly in moderate to high-to-very-high susceptibility zones. Field observations by the authors further supported these findings.

4 Conclusion

This study employed geospatial techniques and a Multi-Criteria Decision-Making (MCDM) approach to analyze dengue susceptibility across Dhaka city. By categorizing 14 key factors into environmental and demographic groups and applying the Analytical Hierarchy Process (AHP), the study generated spatial maps to identify highly vulnerable areas. The findings revealed that the southern and southeastern parts of Dhaka, particularly within the South City Corporation, exhibit the highest susceptibility to dengue. In contrast, the northern and northwestern areas under the North City Corporation showed relatively lower risk. Among the analyzed variables, proximity to waterlogged areas and population density were identified as the most influential contributors to dengue vulnerability.

Validation through field surveys reinforced the model's reliability, with 67% of respondents expressing high satisfaction with the classification results. Although the study was focused on Dhaka, the geospatial MCDM framework developed here offers a scalable and transferable methodology that can be applied to other dengue-endemic urban areas, particularly in low- and middle-income countries facing similar environmental and socio-demographic challenges. Additionally, the model can be adapted for other vector-borne diseases such as malaria or chikungunya by modifying the selected criteria.

Despite its contributions, the study faced certain limitations. The reliance on older demographic data from the 2011 census may not fully reflect current urban dynamics, and the unavailability of recent high-resolution datasets for all indicators may have influenced the accuracy of the susceptibility assessment. Moreover, logistical constraints limited the extent of field validation. Nonetheless, the results provide critical insights for public health officials and urban planners to implement targeted interventions—such as improving drainage systems, regulating informal settlements, and optimizing healthcare resource allocation.

Looking ahead, future research should consider integrating long-term climatological data to account for seasonal variations in dengue transmission. Incorporating updated and more detailed socio-economic indicators—such as income level, employment, and housing quality—will help capture local disparities in disease vulnerability. In addition, machine learning approaches like Random Forest or Support Vector Machines can enhance model precision and reduce the subjectivity of traditional weighting methods. Real-time epidemiological data integration could also further improve the timeliness and accuracy of dengue risk assessments.

Table 5 A brief summary of feedback of various categories people on social and infrastructural vulnerability to tropical cyclones results during the field visit

Category of people	Total number of respondents	Highly satisfied	Satisfied	Not satisfied
General people	65	44	14	8
Policymakers	10	5	3	2
Experts	05	5	5	0
Total	80(100%)	54(67.5%)	16(20%)	10(12.5%)

In conclusion, this study not only advances the use of geospatial intelligence for public health planning in Dhaka but also provides a flexible framework for broader application. By embedding susceptibility mapping into urban governance strategies, cities can take a proactive approach to mitigate vector-borne disease risks and build long-term urban resilience.

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Data availability Data sets generated during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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