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Evaluating Mosquito-Borne Disease Risk Areas in Muktsar District, India: A Decision-Making Approach Using GIS and AHP

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Abstract

Mosquito-borne diseases are those that are transmitted by the bite of an infected mosquito. Stagnant bodies of water are frequently preferred as mosquito breeding places. However, from producing eggs to the final stage, several elements contribute to its incubation, maturity, and growth to the point where it is capable of biting and transmitting diseases. The primary goal of this research is to focus on connected environmental determinants that provide optimal breeding locations and vulnerability mapping of mosquito-borne diseases using geospatial techniques and a decision-making approach. The analytical hierarchy process was combined with a geographic information system to create a map of mosquito-borne diseases in Muktsar district of Punjab state. The weights of selected variables were determined using a choice-based varied ranking method, which involved building a pair-wise comparison matrix. Initially, ten important environmental parameters were selected to determine their weight using a pair-wise comparison matrix. At the same time, the weight of each related element was employed as a geo-database to aid with overlay analysis. The consistency ratio was derived to evaluate the decision-making process and significance measurement. The consistency ratio of choice factors was found to be 0.0470, which is less than 0.1 and regarded consistent and acceptable. According to the study's findings, proximity to water bodies is a major influence, followed by moisture content, water index, availability of shade area, and the presence of vegetation in mosquito-borne disease prevalence. The current findings demonstrate the wide range of uses of satellites data and spatial techniques in epidemic diseases zonation.

Keywords: Mosquito-borne diseases; Geospatial analysis; Analytic Hierarchy Process; Public health

1 Introduction

Mosquito-borne diseases are the leading public health issues in tropical and sub-tropical regions, where climatic and environmental variables significantly impact the dynamics of dengue and malaria transmission⁽¹⁻⁴⁾. Numerous studies have

supported the factor of land use/land cover⁽⁵⁾, temperature⁽⁶⁾, moisture⁽⁷⁾, elevation⁽⁸⁾ having positive relationships with the prevalence of mosquitoes borne disease. Although the relationship is sporadic in nature, confining to particular areas having certain climatic parameters,

for instance, temperature determines the rate of mosquito growth and the adult mosquitoes' eventual survival. Malaria risk levels in a particular area are also significantly influenced by variables such as vegetation types, population density, poverty levels, and other social and economic development factors⁽⁹⁾. In addition, the higher relative humidity and temperatures in non-wooded areas result in higher rates of malaria infection than in forested areas that is linked to the emergence of mosquito-borne diseases⁽¹⁰⁾.

Mosquito-borne diseases are more prevalent in developing countries, which increases pressure on healthcare resources⁽¹¹⁾ in many resource-lacking countries. According to WHO estimates, every year, 50-100 million populations are affected by dengue disease, and 2.5 billion people (40% of the global population) are at risk of dengue infection⁽¹²⁾. Approximately 2.5 million cases from Southeast Asia are reported annually, of which 76 percent⁽¹³⁾ are from India alone. Many researchers have reported the presence of mosquito-borne diseases such as dengue, malaria, and chikungunya⁽¹⁴⁻¹⁶⁾ in many parts of Punjab. However, literature related to integrating the prevalence of mosquito-borne disease and environmental factors using geospatial analysis is found missing in the study area.

Research on MBD's has new prospects attributable to the growing availability of long-term satellite records and very-high resolution satellite data⁽¹⁷⁾. The use of geospatial environmental data to study the risk of diseases, including those transmitted by mosquitoes, has greatly expanded in recent decades^(18,19). Continuous environmental condition monitoring over wide areas is made possible by satellite imagery. Because there are so many sensors available, we can measure a variety of environmental factors that affect malaria receptivity, such as weather conditions like temperature, humidity, and precipitation as well as topographical characteristics like vegetation, surface water, land use, and terrain⁽¹⁷⁾. High-resolution sensor data, such as from Landsat (30 m spatial resolution), has been used to evaluate how land use, land cover, and water affect the geographical patterns of mosquito borne diseases⁽²⁰⁾. Therefore, remote sensing is a helpful technique for researching how environmental factors affect diseases like dengue and malaria that are spread by mosquitoes⁽²¹⁻²⁵⁾.

Geospatial analysis used in the study of mosquito-borne diseases⁽²⁶⁻³³⁾ is available in many works of literature, where the high temporal and spatial resolution data for estimating different parameters (e.g., temperature, rainfall, soil moisture, and land cover) are analyzed for mosquito-borne risk areas^(30,34,35). Dataset reliability and accuracy related to mosquito-borne diseases play an important role in disease control and management, which helps predict vulnerability and project risk mapping^(36,37). A correlation between Anopheles larva density and tree canopy growth using Landsat TM imagery was established in California⁽³⁸⁾ to identify mosquito-producing areas. A decision-making tool

with the help of the AHP (Analytical Hierarchy Process) technique is also used for malaria risk mapping⁽³⁹⁾ that helps in the identification of hotspot areas for mosquito-borne disease by integration of various thematic layers⁽⁴⁰⁾ related to geographic, socioeconomic, and epidemic factors.

In light of the discussion, the present paper analyzes various environmental parameters: Land Use Land Cover (LULC), Normalized Difference Vegetation Index (NDVI), Land Surface Temperature (LST), Normalized Difference Moisture Index (NDMI), Normalized Difference Water Index (NDWI), Proportion of vegetation, Land elevation, Slope Analysis, Aspect Analysis, Proximity to water bodies that are observed as potential drivers for identifying mosquito-borne disease risk areas in Muktsar district, Punjab. Furthermore, applying the analytical hierarchy process (AHP), the hotspot zones for the mosquito-borne disease are prepared to show areas vulnerable to the disease⁽⁴¹⁾.

2 Study Area

Muktsar district of Punjab is situated in the southwestern part of Punjab state between 30° 69' to 29° 87' North latitude and 74°21' to 74°86' East longitudes (Figure 1).

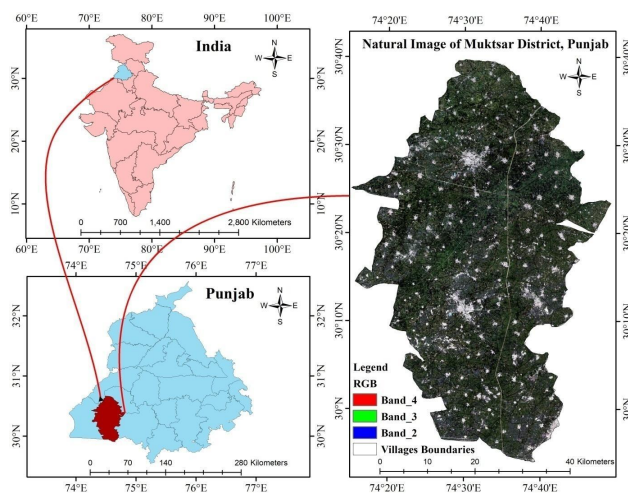


Fig. 1. Location map of the study area [Source: Prepared by Author]

The region forms a part of the Satluj River sub-Basin and the Indus Basin's alluvial plains with an average elevation of 200 Above MSL. Waterlogging is a significant feature of the district, where the southern and northwestern parts are significantly affected⁽⁴²⁾. The region features a dry sub-humid climate with grassland vegetation, reflecting the annual mean temperature between 25°C to 26°C⁽⁴³⁾; the highest mean monthly temperature is 45°C in June, and the lowest is 2°C recorded in January month. The annual rainfall of the district is 430.7 mm, where July and August are the rainiest months. According to the Census Report 2011⁽⁴⁴⁾,

the district's population is 9,01,896 persons, with a density of 348/km² and four health blocks: Chakk Shere Wala, Doda, Alamwala, and Lambi.

The district is known for the high prevalence of dengue and malaria incidences. A study conducted by Lata et al. (2017)⁽¹⁵⁾ based on clinical reports, laboratory tests, and interaction with patients shows that there was a single registered dengue case in January 2011 that jumped to 399 by December 2011 and exponentially grew to 1047 cases by 2015⁽¹⁶⁾. Due to the continuously increasing temporal dynamics of dengue fever and associated potential environmental risk factors, the study aims to fill the research gap by utilizing satellite data in the Muktsar district of Punjab.

3 Data Collection

The satellite data includes Landsat 8 OLI, SRTM Global Digital Elevation Model (DEM), and spatial point data related to mosquito-borne diseases (Table 1). Landsat data with a 30-meter spatial resolution retrieved from the Earth Explorer portal of the United States Geological Survey (USGS) are analyzed. Landsat 8 data were downloaded and analyzed for preparing Land Use/Land Cover (LULC), Normalized Difference Water Index (NDWI), Normalized Difference Vegetation Index (NDVI), Normalized Difference Moisture Index (NDMI), Land Surface Temperature (LST), Proportion of Vegetation (PV). SRTM global Digital Elevation Model (DEM) data with 30 m resolution are downloaded from <https://earthdata.nasa.gov> and are analyzed for slope and aspect maps. Water bodies are considered necessary as they provide a breeding ground for mosquitoes, so the location and extent of various water bodies, such as ponds, canals, lakes, etc., are extracted from the satellite images to perform proximity analysis.

4 Methodology

The study includes 10 (ten) deciding variables that are selected based on the relative weights for the development of mosquitoes and the transmission of diseases. The variables include land use and land cover (LULC), Normalized difference vegetation index (NDVI), land surface temperature (LST), Normalized difference moisture index (NDMI), Normalized difference water index (NDWI), Proportion of vegetation (PV), land elevation, slope, aspect and proximity to water bodies (PWBs).

The Landsat 8 dataset's Band 4 (NIR, 30 m) and Band 3 (Red, 30 m) is used for the analysis, and NDVI is determined using the formula below-

$$NDVI = (NIR - RED) / (NIR + RED)$$

The Landsat 8 NIR (30 m) and SWIR (30 m) Bands suitable for calculating the normalized differential moisture index

(NDMI) (Figure 5). Consequently, we used the following equation to determine the moisture content-

$$NDMI = \frac{NIR - SWIR}{NIR + SWIR}$$

NIR stands for near-infrared light (Band 4), whereas SWIR stands for short-wave infrared (Band 5), having 30 m spatial resolution for Landsat 8 data.

Band 2 and Band 4 of Landsat 8, having 30 m resolution, were used (Figure 6). Band 2 distinguishes between muddy and clear water and reasonably well penetrates clean water, and Band 4 is regarded favorably for identifying and assessing vegetation and mapping the biomass content. We calculated the NDWI using the formula below-

$$NDWI = \frac{GREEN - NIR}{GREEN + NIR}$$

Green is Band 2 (30 m), and NIR is Band 4 (30 m).

The land surface temperature derived from band 10 of Landsat 8 TIRS data has the highest accuracy. So, band 10, the thermal band of the Landsat 8 dataset, was used to determine the land surface temperature (LST) of the Muktsar district of Punjab (Figure 4).

The adopted scale of importance ranges from 1 to 9 (Table 2) for assigning risk values to 47 sub-factors on a scale from 1 to 5, where 5 denotes very high, and 1 denotes very low sensitive zones of mosquito-borne disease. Table 4 lists 47 sub-factors ranging from 1 (equally important towards MBDs outbreak) to 9 (very important towards MBDs breakout) based on the importance level. The calculated risk value shows the contribution of the sub-factor for MBDs.

A multi-criteria decision approach - Analytical Hierarchy Process (AHP) with various supporting factors is used to identify and map mosquito-borne disease vulnerability areas. The procedure helps to structure the decision criteria into a hierarchy of alternatives that are individually analyzed based on a pairwise comparison matrix (PCM) to compare individual criteria for establishing the weight to calculate the performance score or importance. PCM is a relative ranking-based matrix table that determines the weight value of each alternative according to a chosen criterion. The compliments and divides of the same alternatives in the matrix represent the importance rank of all options^(45,46). PCM provides the relative weights of each criterion to the others. The weightage for each alternative is calculated once the comparison rank is fitted to assess the consistency for inclusion in the choice. AHP provides a consistency ratio (CR) comparing the matrix's consistency index (CI) to calculate a measure of PCM consistency. The ratio is constructed so that a value of more than 0.1 is considered inconsistent for judgments, and a value of 0 is regarded as being fully consistent⁽⁴⁷⁾. The value zero or values very near to zero (i.e., 0.02 or 0.05) are very acceptable. Using CI and RI, consistency ratio (CR) was derived, with CI



Table 1. Types of data, source, and purpose considered for mosquito-borne diseases analysis

Dataset	Data type	Spatial resolution	Source & date of acquisition	Purpose
Landsat 8	Raster	Bands 4 and 5 (30 m), thermal bands 10 and 11 (30 m), Bands 5, 6, and 4 (30 m).	USGS-earth Explorer, 27-09-2017.	Land surface temperature, proportions of Vegetation, Land use land cover, normalized difference vegetation index, normalized difference moisture index, and normalized difference water index.
Shuttle Radar Topography Mission (SRTM) Global DEM	Raster	SRTM 1 Arc with 30 m spatial resolution	https://earthdata.nasa.gov, 2017	Land elevation, slope, and aspect map
Water bodies	Vector; converted to raster	Resized at 30 m	Extracted from Landsat 8 satellite imageries. 2017	Proximate analysis
Boundaries map	Vector	Resized at 30 m	https://bhuvan-app1.nrsc.gov.in/state/PB, 2022	Delineation of village boundaries

being calculated using the following equation-

$$CR = CR/RI$$

$$CI = (\lambda_{max} - n)/(n - 1)$$

Here, "RI" stands for "Random Index," "CI" for "Consistency Index," and " λ_{max} " for "Average of $\sum w_1...w_n$." If the value of RI falls between the range of 0 to 0.09, the matrix will be deemed reasonably consistent, and the decision-making process utilizing AHP may proceed. RI depends on the number of elements being compared (i.e., the number of alternatives in PCM).

Table 2. Numeric scale to establish pairwise comparison matrix adopted from Saaty. [Source: Saaty T.L., 2001 (47)]

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

Table 3. Numeric value of the random index (RI) to measure consistency [Source: Saaty T.L., 1990 (45)]

N	2	3	4	5	6	7	8	9	10	11	12
RI	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.53

5 Results and Discussion

I) Land use land cover

Mosquito-borne diseases positively correlate with water bodies and low-lying areas as they provide suitable platforms for breeding and transmission⁽⁴⁸⁾ of mosquito populations such as dengue and malaria. The change in land use types also provides shelter to the mosquito population's potential for mosquito-borne disease transmission⁽⁴⁹⁾ from one location to a new site. The land use / land cover map of Muktsar districts 30 m spatial resolution of Landsat 8 data classified into five land use/land cover classes based on the supervised classification in the GIS environment (Figure 2).

II) Normalized difference vegetation index (NDVI)

Several researchers have underlined the normalized difference vegetation index (NDVI) in the study of diseases spread by mosquitoes because mosquito-borne infections were shown to be more prevalent in areas with low terrain and forest cover⁽⁴⁸⁾. It is possible to describe the habitat suitability for various mosquito species using vegetation indices, particularly those based on the normalized difference vegetation index⁽⁵⁰⁻⁵²⁾. Greenery is associated with more precipitation, resulting in a suitable environment⁽⁵¹⁾ for mosquito habitats.

The relationship between normalized differential vegetation index⁽⁵³⁾ and mosquito⁽⁵⁴⁾ population is positively associated. Numerous remote-sensing satellites have bands in the



red (R) and near-infrared (NIR) to calculate the normalized difference between vegetation index (NDVI), and most crucially, the NIR to red wavelength ratio is connected with absorbed photo-synthetically active light (APAR). The NDVI determines the vegetation index (VI) of the Muktsar district (Figure 3) employed to measure the amount of greenery. The near-infrared leaf scattering and the red chlorophyll absorption of the green leaf are normalized by NDVI. Red and near-infrared bands are, therefore, necessary.

Values -0.1 and 0.143 generally correspond to settlements; low yet positive values ranging between 0.144 to 0.264 reflect shrub and grassland, and high positive values, ranging between 0.387 to 0.507, depict dense vegetation.

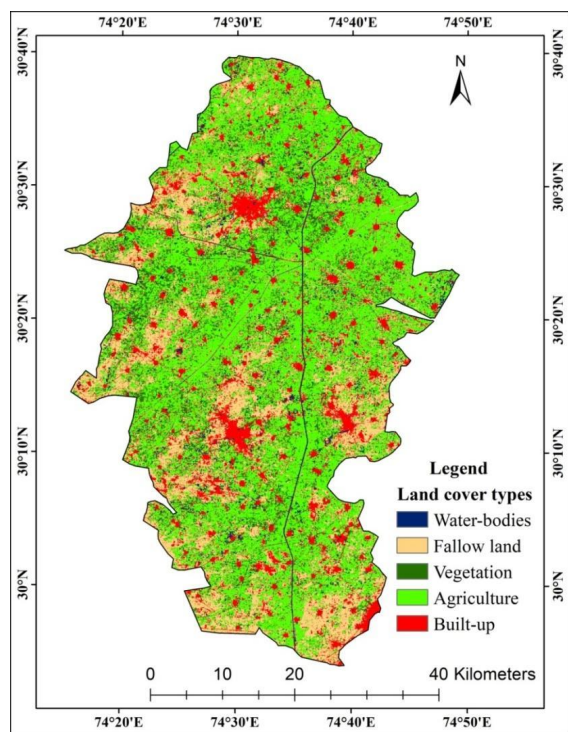


Fig. 2. Land Use/Land Cover (2017) map of Muktsar district, Punjab [Source: Prepared by Author]

III) Land surface temperature

The growth of mosquito larvae is usually greatly influenced by the surface temperature. The mosquito’s feeding behavior is influenced by the air temperature and the land surface, as the land surface temperature impacts the vectors’ ability to survive⁽⁵⁵⁾ and complete the life cycle. Extreme temperatures (too high above 40°C or too low temperature below 5°C) are not conducive for mosquitoes to survive, and so, in temperatures between 15°C to 32°C⁽⁵⁶⁾, mosquitoes can be found suitable.

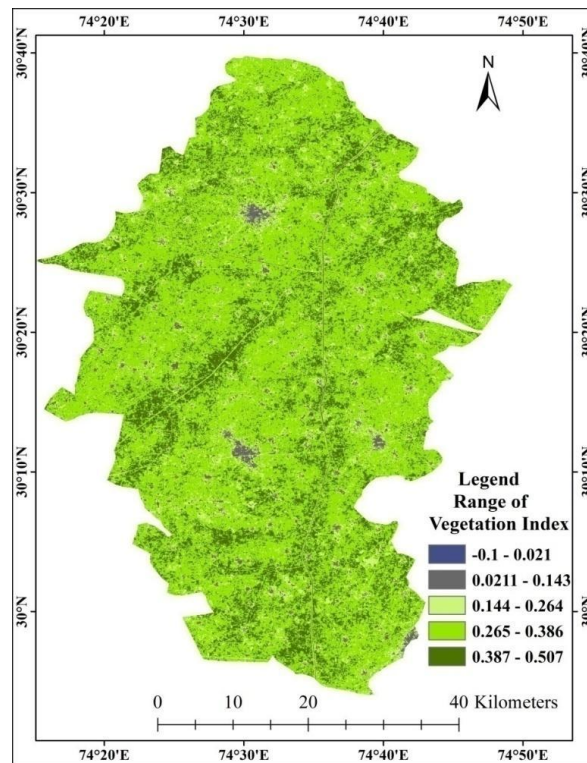


Fig. 3. Normalized Difference Vegetation Index (2017) of Muktsar district, Punjab [Source: Prepared by Author]

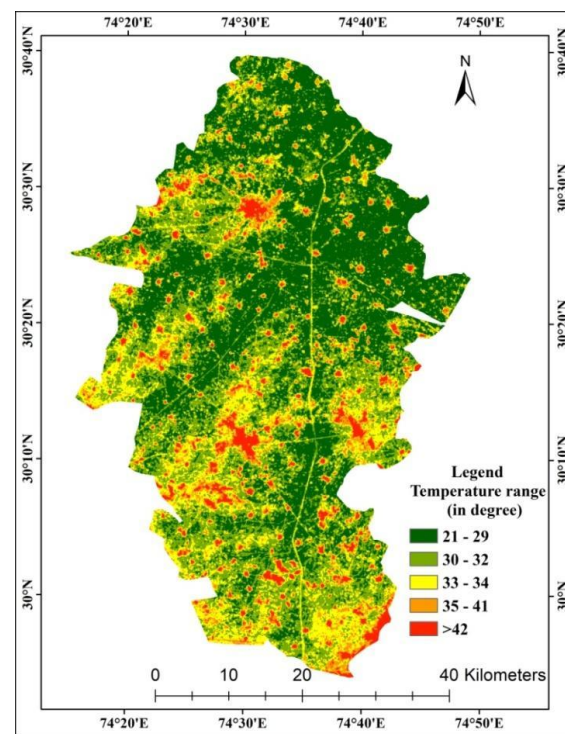


Fig. 4. Land Surface Temperature (September 2017) of Muktsar district, Punjab [Source: Prepared by Author]

IV) Normalized Difference Moisture Index

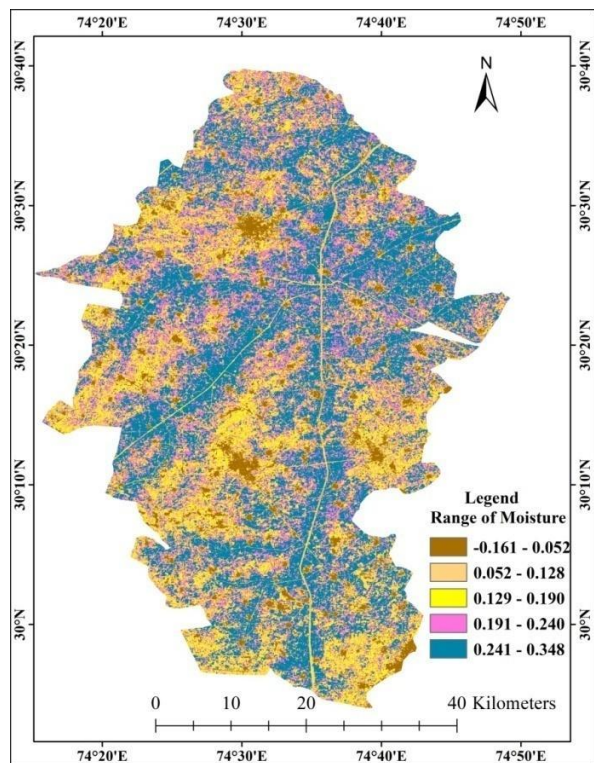


Fig. 5. Normalized Difference Moisture Index (2017) of Muktsar district, Punjab [Source: Prepared by Author]

The internal structure of the leaf influences the reflectance in the NIR band, and the SWIR band reflects changes in the water content of the vegetation. NIR is useful for classifying vegetation, and SWIR is useful for assessing the moisture content of soil and vegetation. A darker location highlights an area with more water content in SWIR. The normalized differential moisture index ranges from - 1 to 1, with - 1 denoting extremely low/deficient moisture levels and 1 (one) denoting extremely high moisture levels.

V) Normalized Difference Water Index

Spatiotemporal fluctuations of water bodies can accumulate diseases related to vectors borne⁽⁵⁷⁾ and diffuse to nearby areas. Based on the reflectance bands, the normalized difference water index (NDWI) for identifying open water bodies^(58,59).

Normalized difference water index values over zero or below zero indicate built-up areas, while high positive values indicate the presence of water bodies (Figure 6).

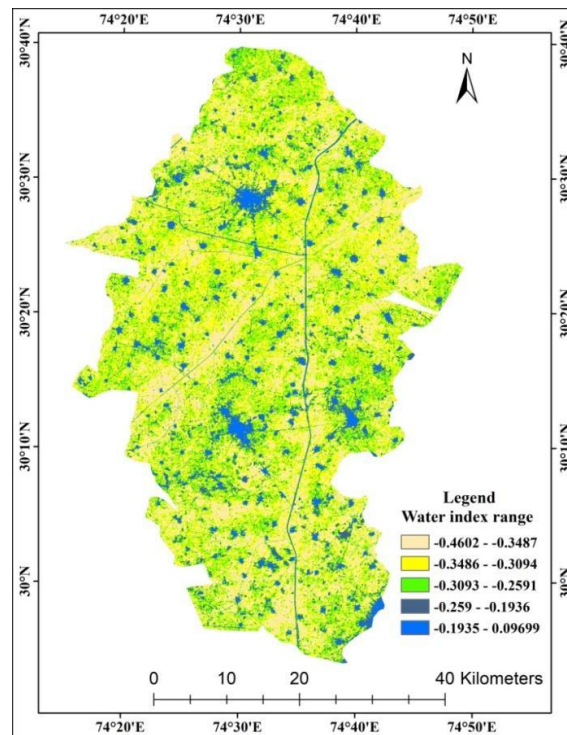


Fig. 6. Normalized difference water index (2017) of Muktsar district, Punjab [Source: Prepared by Author]

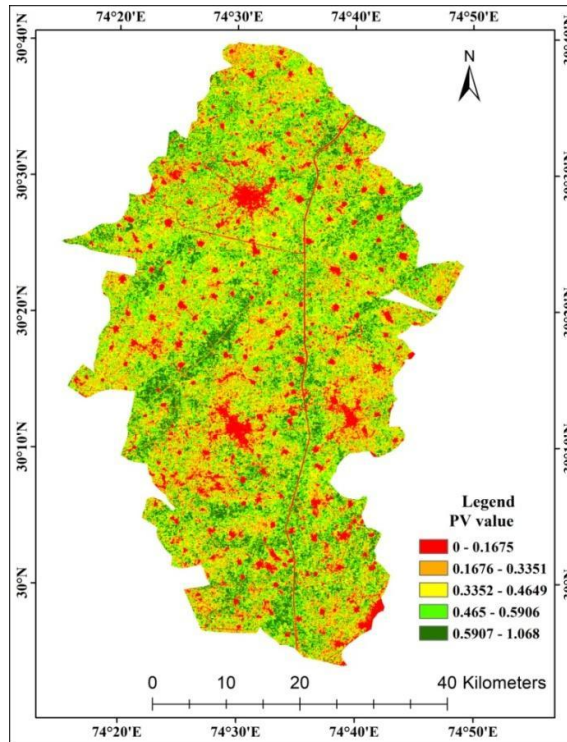


Fig. 7. Proportion of Vegetation (2017) in Muktsar district, Punjab [Source: Prepared by Author]

VI) Proportion of vegetation

The decomposed leaves from the vegetation form litter can produce high moisture content. They may provide an ideal habitat for mosquitoes⁽³⁹⁾ breeding, larval growth, and pupal development. Using the Landsat 8 dataset, the percentage of vegetation or PV value is determined (Figure 7). We used the following equation for the identical Landsat 8 NIR and RED Bands picture-

$$PV = ((NDVI - NDVI_{min}) / (NDVI_{max} - NDVI_{min}))^2$$

The normalized difference vegetation index's minimum and maximum values are denoted by NDVimin and NDVimax, respectively. PV ranges from 0 to 1 and has a positive value, where 0 or near 0 indicates an area not covered by vegetation. A value of 1 or close to 1 denotes an area heavily covered by vegetation.

VII) Land elevation

Mosquito-borne diseases are typically related to low-lying areas, wetlands, and water bodies, such as channels, streamlets, and lakes⁽⁵⁵⁾, as it forms suitable breeding grounds for mosquito. The Muktsar district is elevated towards the eastern side and gradually lower towards the western regions, ranging from the lowest point (175 m) to the highest point (240 m). Topography influences the breeding habitats for malaria risk and vulnerability⁽⁸⁾; thus, we considered the study of land elevation for determining the dengue risk zone⁽²⁶⁾.

VIII) Slope Analysis

The slope of an area also determines mosquito larval habitats^(8,39,60) as water stagnant are a feature of less slope area. The locations with slopes of 0-1 depict water bodies and other flat lands. These regions have very gentle slopes and are suitable for mosquito behavior. Less than 1 to more than 17-degree variations exist in the district slope.

IX) Aspect Analysis

Low air temperature and high moisture in shadowed locations⁽³⁹⁾ are crucial in transmitting mosquito-borne diseases⁽⁸⁾. The global digital elevation model SRTM 1 arc's 30 m resolution DEM reveals that the shadow areas in the northern-eastern to south-west directions do not receive direct sunshine and have excessive moisture content and a relatively high proportion of plants compared to other aspects.

X) Proximity to water bodies

Female Anopheles mosquitoes (the primary vector of malaria) can fly to 2 km, and Aedes mosquitoes (the primary vector of dengue virus) that reproduce in fresh stagnant water⁽⁶¹⁾ can soar to 100–200 m, maximum 300–500 m which

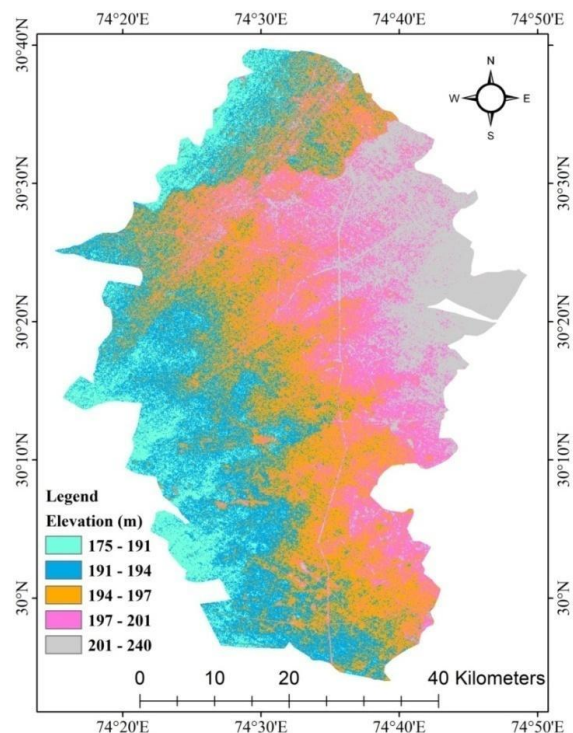


Fig. 8. Land Elevation of Muktsar district, Punjab [Source: Prepared by Author]

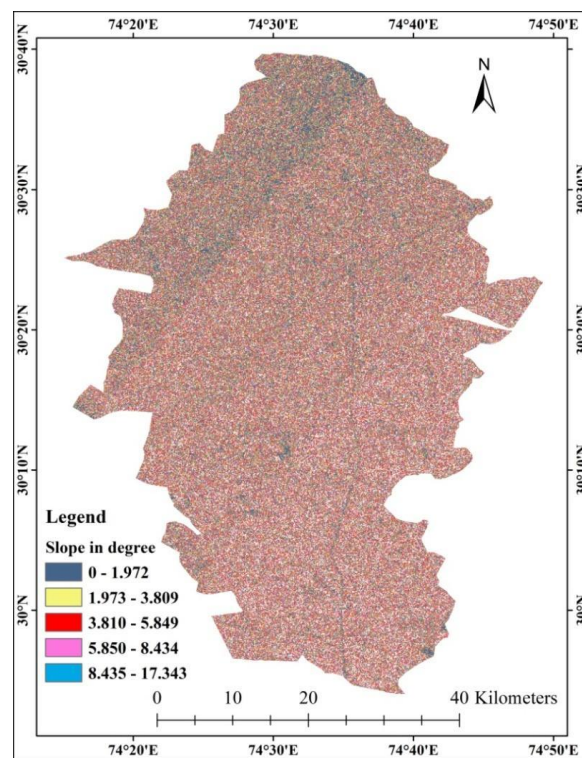


Fig. 9. Slope Analysis of Muktsar District, Punjab [Source: Prepared by Author]

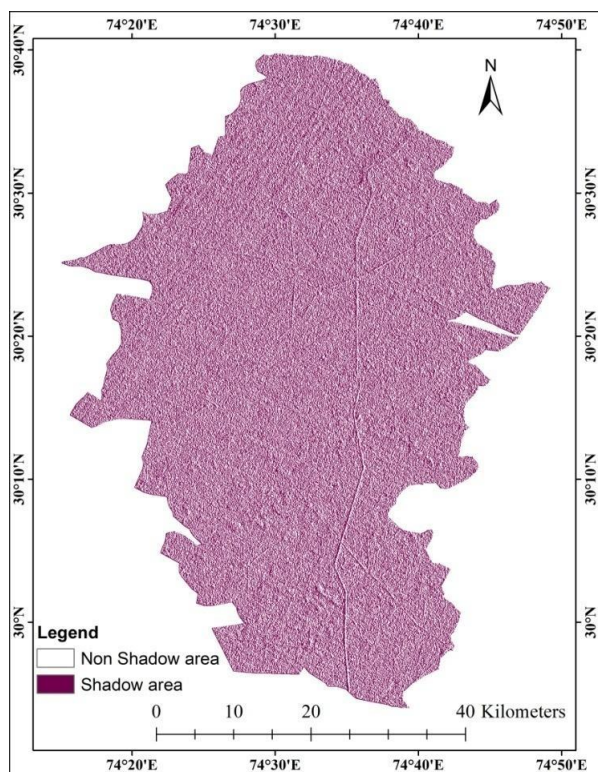


Fig. 10. Aspect Analysis of Muktsar district [Source: Prepared by author]

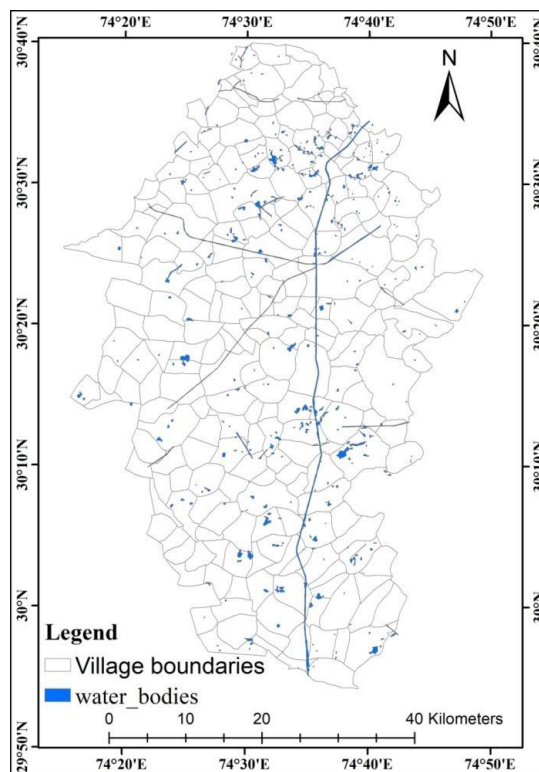


Fig. 11. Locations of water bodies (2017) in Muktsar district, Punjab [Source: Prepared by Author]

increases risk in urban areas due to the presence of wastewater points⁽⁵⁵⁾. Mosquito-borne illnesses like dengue are more common in places close to water bodies and areas with standing water⁽⁶²⁾. So, the risk zones for mosquito-borne disease are identified by considering the presence of water bodies. Accordingly, for proximate analysis, we identified the water bodies (small to large ponds, canals, and lakes) in the study area (Figures 11 and 12).

The Consistency Index (CI) and Consistency Ratio (CR):

The Consistency Index (CI) and Consistency Ratio (CR) are considered to assess the outcome, decision-making error, and empirical bias during the process of assigning ranks. The summary of the weights of all 10 factors, along with CI and CR is given in Table 4. If the CI/index ratio for the resulting random matrix is found to be (0.1), the decision-making process and rank selection may be viewed as inconsistent⁽⁴⁷⁾. The consistency ratio of all the factors is found 0.0470. The outcome demonstrates that the estimated consistency ratio value is consistently smaller than 0.1 for all of the chosen parameters. Therefore, when a pairwise comparison matrix was created, it may be assumed that the rank selection was always an appropriate decision.

The moisture index, water index, and distance from water bodies have been providing the most significant risk of mosquito-borne diseases because these ranges of values have

always been considered for offering suitable sites for mosquito breeding and growth, according to weightage calculated from pairwise comparison as shown in Table 4. A percentage of vegetation with a value of 0.387–0.507 and a vegetation index of 0.5907–1.068 is regarded as areas with a high risk of mosquito-borne diseases. Low land or land with no elevation was also discovered to be a significant risk factor for MBD outbreaks.

Comparison matrix of the chosen 10 parameters is built together with weightage to overlay (Table 4). Each component is not equally significant and does not provide an equally favorable environment for breeding. To decide to assign a risk rank to each element, prior studies and the environmental factors affecting the growth of *Aedes* and *Anopheles* were taken into account. The outcome indicates that, of all the chosen causal factors, proximity to water bodies carries the highest risk (0.2297 weight value). This indicates that proximity to water bodies is more at fault than other chosen factors for the development of mosquito-borne disease. With weights of 0.1593 and 0.1394, respectively, the next most important components are NDMI and NDWI. Since mosquitoes always need a comfortable temperature to thrive, land surface temperature (LST) has a substantial weight value of 0.1146. In accordance, the prevalence of mosquito-borne diseases in Muktsar district is significantly influenced by

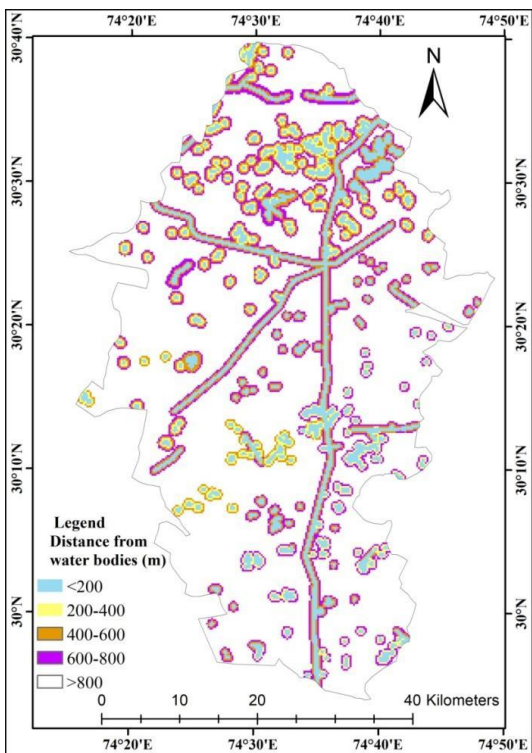


Fig. 12. Proximity to water bodies in Muktsar district, Punjab [Source: Prepared by Author]

LULC, NDVI, vegetation proportion, land elevation, slope degree, and aspect, with weights of 0.0689, 0.401, 0.0435, and 0.0522, respectively. The consistency ratio was determined to be 0.0470, which is accepted for the comparison matrix.

A weighted overlay of the selected parameters is employed using the GIS tool to extract the mosquito-borne disease susceptible zones (Figure 13). The outcome demonstrates that there are only a few very high and very low vulnerable zones and that the majority of places fall into the intermediate MBD vulnerable zones. The northern portions of Muktsar, which cover Chak Shere Wala health block and areas along with Sirhind Feeder and Rajasthan Feeder canals covering Alamwala and Lambi health blocks, fall under a very high-risk zone for mosquito-borne diseases (areas shown (Figure 13) in circles).

Mosquitoes’ maturation times are influenced directly and indirectly by a comfortable temperature and humidity^(6,63). Various types of land cover, including waterlogged areas, water bodies, agricultural land that has become stagnant, and densely populated areas, have been identified as sensitive locations for mosquito-borne diseases⁽⁵⁾. Numerous mosquito-endemic sites might have similar studies done using the same methods. Similar studies would aid researchers in selecting various local environmental, climatologically, and socioeconomic aspects as decision-making cri-

teria.

Southeast and central parts have a very low incidence of MBDs, and some areas have no cases of these diseases, but the northeastern and southwestern areas have moderate to high susceptibility to MBDs. Therefore, several regions with a very high and high prevalence of these diseases were plotted to blend with the MBDs’ final result (Figure 13). The outcome demonstrates that these reported areas are more uniform with the final layer and frequently merged with very high to high zones as derived from spatial analysis of multi-criteria based choice factors.

The susceptibility of areas and reported MBD’s cases are positively correlated with each other’s as shown in Figure 14.

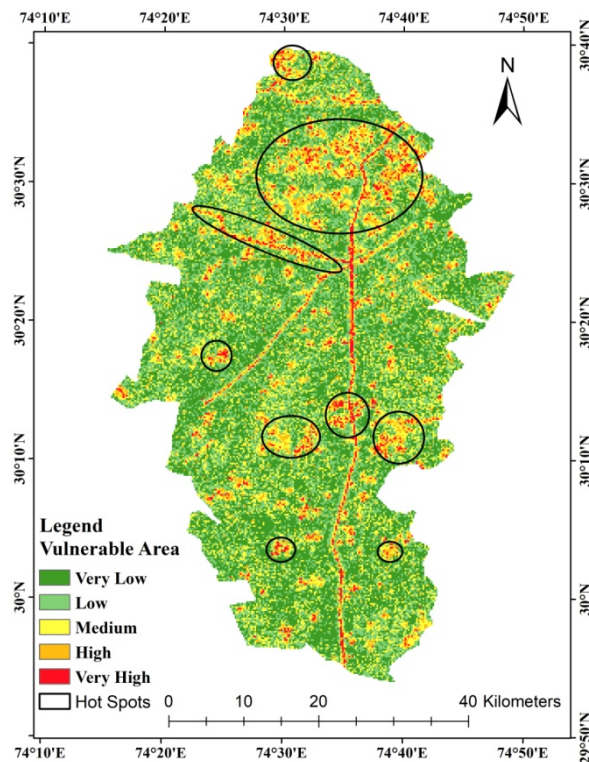


Fig. 13. AHP based identification of MBDs hotspot zones [Source: Prepared by Author]

Estimation of Population at Risk of MBDs

To estimate the population at risk of mosquito-borne diseases in the Muktsar district, the study multiplied the derived mosquito-borne disease risk map raster and the district population density for the year 2011, using zonal statistics in ArcGIS environment to determine the population vulnerable to mosquito-borne disease in the district. The computation is also done at the health block level to get a clear distribution of the mosquito-borne disease risk.

Table 4. Weight value of each MBDs causative factor for final overlay [Source: Prepared by Author]

	LULC	NDVI	LST	NDWI	NDMI	PV	LE	SL	AS	PWBs	PCM based weight	Ax	λ_{max}	Weight (%)
LULC	1	1	1/3	1/4	1/4	1	2	2	2	1/4	0.6630	0.6630	10.5296	6.2969
NDVI	1	1	1/2	1/3	1/3	1	2	2	2	1/3	0.7262	0.7262	10.5322	6.8951
LST	3	2	1	1/2	1	2	3	3	1	1/3	1.2306	1.2306	10.7349	11.4641
NDWI	4	3	2	1	1	1	2	3	3	1/3	1.5229	1.5229	10.9191	13.9471
NDMI	4	3	1	1	1	2	4	4	4	1/2	1.7086	1.7086	10.7214	15.9365
PV	1	1	1/2	1	1/2	1	2	3	3	1/3	0.9444	0.9444	10.6290	8.8856
LE	1/2	1/2	1/3	1/2	1/4	1/2	1	1/2	1/2	1/3	0.4224	0.4224	10.5205	4.0154
SL	1/2	1/2	1/3	1/3	1/4	1/3	2	1	1	0.25	0.4525	0.4525	10.4020	4.3504
AS	1/2	1/2	1	1/3	1/4	1/3	2	1	1	1/3	0.5484	0.5484	10.4890	5.2292
PWBs	4	3	3	3	2	3	3	4	3	1	2.4875	2.4875	10.8250	22.9790

CI = 0.0700, CR = 0.0470

CR value 0.1 or <0.1 is considered for acceptance

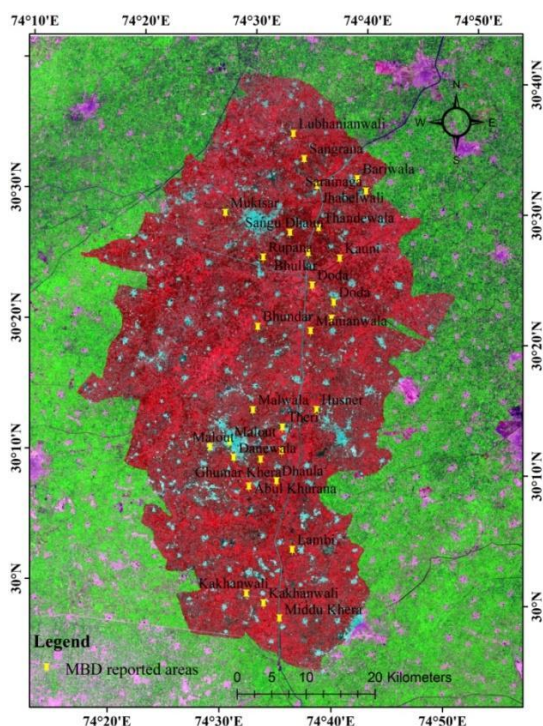


Fig. 14. Accuracy of risk zonation of Mosquito-borne diseases in Muktsar district of Punjab [Source: Prepared by Author]

The results show that over 60 percent (451100) of people in the district are actually at high risk of mosquito-borne disease infections, as illustrated in Table 5 and Figure 15. From the results, Chak Shere Wala and Alamwala health blocks have the highest number of population categorized as being at high risk of mosquito-borne disease at approximately 186464 (72 percent) and 113249 (66 percent) persons followed by Doda and Lambi health blocks with estimates of 89907 (49 percent)

Table 5. Estimate of MBD’s risk population at the health block level [Source: Prepared by Author]

Health Block	Low	Moderate	High
Alamwala	31399 (18%)	28161 (16%)	113249 (66%)
ChakShereWala	30653 (12%)	41403 (16%)	186464 (72%)
Doda	27032 (14%)	67802 (37%)	89907 (49%)
Lambi	34208 (27%)	32506 (25%)	61480 (48%)

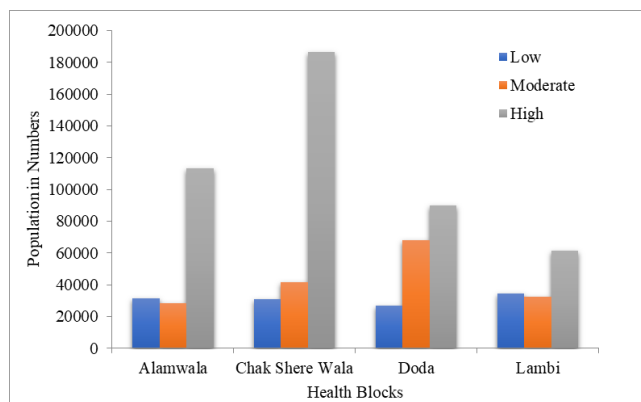


Fig. 15. Population at risk of mosquito-borne diseases (at health block level) [Source: Prepared by Author]

and 61480 (48 percent) persons. When looking towards the population having a moderate risk of mosquito-borne diseases, it is 67802 (37 percent) in Doda, 32506 (25 percent) in Lambi, 41403 (16 percent) in Chak Shere Wala, and 28161 (16 percent) in Alamwala health block. Apart from this, Chak



Shere Wala has 30653 (12 percent) people, followed by Doda Health Block, which has a 27032 (14 percent) population characterized by low risk of mosquito-borne diseases.

Conclusion

The present research investigation emphasizes the potential of a geographic information system and the use of an analytic hierarchy approach in finding mosquito-borne disease-susceptible areas. The current study found that multiple variables and environmental determinants have a significant influence on mosquito-borne diseases. These factors are all interconnected and play a significant impact in the occurrence of mosquito-borne diseases, either through direct or indirect means. For example, surface temperature, moisture content, water index, and vegetation index are all interconnected, and any one of these parameters out of balance may affect mosquito reproduction. As a result, appropriate ranges of all selected parameters were assessed and designated as high-vulnerability zones for mosquito-borne diseases. The use of satellite data and the integration of many interconnected aspects in GIS aids in the identification of areas that require further surveillance and management activities to prevent disease transmission. To minimize the effects of MBDs, it is necessary to destroy either the mosquito parasite or the human host. Detecting and destroying suitable breeding places is seen as the most effective way for attaining this goal. As a result, current research efforts on some of the linked and interconnected determinants that contribute to mosquito growth have been analyzed and GIS-based spatial analysis was used to determine mosquito-borne diseases susceptibility zones. The findings reveal various MBD-prone sites in Muktsar district. The findings also show that closeness to water bodies, the presence of moisture in the soil, a high water index, and congested developed areas all increase the risk of mosquito-borne disease transmission. On the basis of zonal statistics, it has been found that more than 60 percent of the population is under risk of mosquitoes borne diseases.

Author's contribution

AS contributed in methods used, GIS work, and writing, LTSG contributed conceptualization, methodology, framework of the paper and writing.

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