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GIS Based Modified DRASTIC-LU Index and Comparative Land Use/Land Cover Change to Evaluate Groundwater Vulnerability in Parbatipur, Dinajpur, Bangladesh

Md. Emdadul Haque

Department of Disaster Science and Management, Begum Rokeya University, Rangpur, Bangladesh
Email: e_haque27@brur.ac.bd

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Abstract

Groundwater vulnerability assessment is a very important topic nowadays which is also very challenging for sustainable environment and integrated water resource management. This study attempts to evaluate the current state of groundwater vulnerability, assess the level and measure the impact of land use/land cover on groundwater vulnerability of Parbatipur upazila of Dinajpur district, Bangladesh. GIS-based DRASTIC is used for assessing the groundwater vulnerability and Modified DRASTIC-LU is used to add the land use/land cover parameter because of the high impact of land use/land cover changes in this region. Unsupervised classification is also used to show the comparative land use/land cover of the 18 years. The DRASTIC Index shows 37% of the Parbatipur area belongs to the highly vulnerable zone while 27% is in the moderate and the rest of the 36% belongs to low vulnerable areas. Modified DRASTIC-LU results show the most alarming results that 48% area of Parbatipur belongs to a very highly vulnerable zone while 33% area belongs to a moderate groundwater vulnerability zone and 19% area has high groundwater vulnerability. The exploration of coal mining influences the groundwater resources here at Parbatipur and the result of the Comparative LU/LC shows that the human settlements of the study area have an increasing trend from 2004 to 2021. In the last 18 years, it increased as much as 2339 ha while the water body and vegetation cover are declining. A progressive vulnerability of groundwater is possibly due to a lack of water replenishment and/or over-exploitation of groundwater resources and underground coal mining along with the geographical disadvantage that accelerates the process of groundwater vulnerability in this area.

Keywords

DRASTIC, Modified DRASTIC-LU, Groundwater Vulnerability, Land Use/Land Cover, Coal Mining, Rating, Weighting

1. Introduction

The northwestern part of Bangladesh is gifted with lots of underground coal resources and sedimentary rocks. Open pit or underground coal mine projects and as a result, the change in the water table as well as the storage of water in Parbatipur upazila and its relative areas of Dinajpur district is a much discussed and important issue nowadays (Howladar et al., 2012). In eight of Bangladesh's northern districts, underground water levels have been progressively dropping, raising concerns about the possibility of desertification. It is very challenging for nearly half of the population in Parbatipur to survive there without enough groundwater to drink, irrigate, and perform other household tasks due to diminishing groundwater supplies, which have rendered nearly half of the tube wells used to access water inoperative during the dry season (International Accountability Project). Noted that despite the fact that there is a shortage of water, the Barapukuria underground coalmine contributes to the depletion of the water supplies that are now used by people for domestic and agricultural purposes. Most critically, very few residents of these areas are aware of the effects of both open-pit and underground coal mining (Fardushe & Hoque, 2014).

In 1985, the Geological Survey of Bangladesh discovered high-quality coal in Barapukuria, Parbatipur, Dinajpur and Barapukuria Coal Mine Company Limited was established in August 1998 and started production in 2005 by underground coal mining method. Immediately after a mining activity begins, dust and radiation are produced, which has an effect on the immediate environment. Long-term mining activities are allegedly to blame for the elimination of rivers, lakes, and forests (Deonandan & Dougherty, 2016). Rural families were still affected by coal mining both favourably and unfavourably (Hota & Behera, 2016). A million gallons of wastewater from a mining operation that was ongoing were dumped nearby, where they contaminated aquaculture water and agricultural field soil (Singh, 1988). The quality of groundwater is also degrading, according to some studies, as a result of some dangerous metallic elements that are present at higher than acceptable levels. The hydrology of the aquifer is pretty much completely influenced by excessive water abstraction in the area, according to the analysis of groundwater abstraction and water levels.

Significant coal mining is growing every year, and the agricultural sector is where it has the biggest influence (Baruah & Dutta, 2009). Without a question, things are great. Consequently, there is an urgent need to take action right away to lessen this impact. In terms of the environment, coal mining is a significant activity that alters the habitat and has a number of negative effects, including soil erosion, acid mine drainage, and increased sediment load as a result of abandoned and unreclaimed mined lands (Park et al., 1987).

In addition, there is a significant quantity of solid waste piled up in the form of enormous overburden dumps, forest and agricultural areas are destroyed and degraded, and mine effluents are discharged into local water bodies, among other related issues that have a negative influence on the environment. Therefore, ongoing monitoring of these lands is necessary for their efficient reclamation and management. The Barapukuria coal mining region has experienced significant landscape alteration as a result of several anthropogenic activities. Since 2005, underground mining has been a significant activity, changing the landscape significantly by turning native agricultural land and the soils they are associated with into heavily disturbed mine.

Land cover and land use (LULC) changes have many definitions, although they are commonly used in the same context. The natural properties of the earth's surface, such as the distribution of plants, water, soil, and other land components, are referred to as land cover (Rawat & Kumar, 2015). Land use, on the other hand, emphasises the economic factors while taking into account the human component of land usage. The main elements affecting land use and land cover in an area are physical and socioeconomic factors. Changes in land use and cover, primarily brought on by human activity, are crucial in fundamentally altering the climate (Jensen, 2005).

Since LULC changes are linked to local, regional, and global climate conditions, the carbon cycle, biodiversity stability, clean water, agriculture, and food security, they play a significant role in spatiotemporal environmental stability (Abebe et al., 2022). The process of environmental change must thus be understood, as well as the issue that must be fixed, if living standards are to be raised in a sustainable manner (Anderson et al., 2001). Monitoring the ongoing pattern of land use/land cover through time is essential for maintaining sustainable development.

Therefore, this study aims to find out the realities of groundwater vulnerabilities in Parbatipur, Dinajpur and those areas with static land use conditions and assess the vulnerability of groundwater due to underground coal mining activities and land use/ land cover changes as well as to show comparative LULC for the last 18 years.

2. Materials and Methods

2.1. Study Area

There is just one active mining site in Bangladesh, and that is the Barapukuria coalfield which is established in August 1998 and started its production in 2005. The field is situated in Parbatipur, an Upazila of Bangladesh's Dinajpur District's Rangpur Division (**Figure 1**). The coordinates of Parbatipur are 25˚39'12''N and 88˚54'56''E. Its overall area is 395.1 km^2, and there are 53,146 houses there. The upazilas of Saidpur to the north, Phulbari to the south, Badarganj to the east, and Chirir Bandar to the west border the area. Barapukuria coal mine is situated in the

Dinajpur District of Northwest Bangladesh, approximately 350 kilometers from Dhaka and 10 kilometers from the Indian border, between the latitudes of 25˚17' and 25˚32' north and the longitudes of 88˚44' and 89˚01' east. The area is 30 meters above sea level, relatively flat, and made up of an alluvial plain with slightly raised terraces created by the drainage of the sub-Himalayan-river systems (the Ganges/Padma and Jamuna rivers) during prehistoric times.

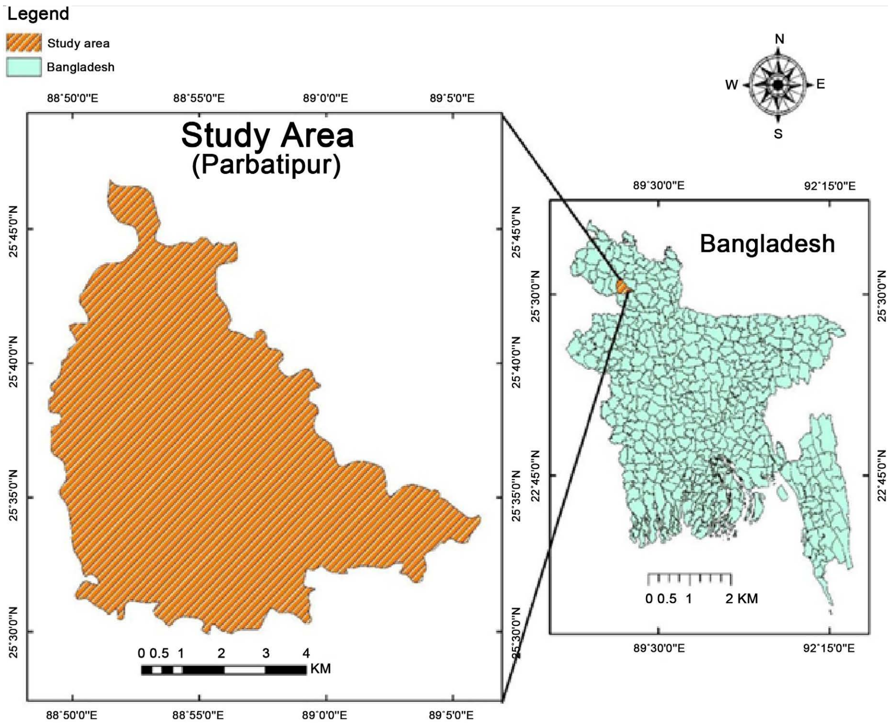


Figure 1. Study area.

2.2. Geology and Climatic Situation

The Himalayan Foredeep to the north, the Shillong Shield/Platform to the east, and the Indian Peninsular Shield to the west define the Parbatipur region in Bangladesh's Dinajpur Shield (Desikachar, 1974; Khan, 1991). The Gondwana coal basins, which include Barapukuria, Phulbari, Khalaspir, and Dighipara, are mostly located within the Bangladesh portion of the Garo-Rajmahal gap, also known as the 'Rangpur Saddle.' The coal either sub-crop and extends into the Barapukuria basin or is terminated beneath the overlaying Tertiary sediments on the northern boundary of the Phulbari basin. From west to east, the basin and strata deepen, with coal depths peaking in the basin's centre (Gupta & Gupta, 2014).

The study area is situated at a height of 37 meters above sea level. The climate in this region is warm and temperate. In this part of the country, the summers are much rainier than the winters. The wet season is hot, humid, and gloomy, while the dry season is warm and mostly clear. This climate is known as Cwa (humid temperate climate with dry winter) by Köppen and Geiger. From March 20 to June 22, the hot season lasts 3 months, with an average daily high temperature of over

91˚F. The average annual rainfall is 2498 millimetres (98.3 inches). From December 5 to February 6, the cooler season lasts for 2.0 months, with daily high temperatures below 77˚F. January 13 is the coldest day of the year, with an average low of 51˚F and a high of 72˚F (Weather Spark) (Table 1).

Table 1. Climatic data of the study area (2020).

Month	Mean Monthly Temperature (˚C)	Mean Monthly Rainfall (mm)	Evaporation (mm)	Evapotranspiration (mm)
January	18	6	51	66.3
February	21	9	70	91
March	26	12	124	161.2
April	29	128	122	158.6
May	29	327	110	143
June	30	343	121	157.3
July	30	859	123	159.9
August	30	140	155	201.5
September	30	287	98	127.4
October	29	187	103	133.9
November	24	42	79	102.7
December	19	1	47	61.1

Evapotranspiration = Evaporation × Crop Coefficient, Source: BMD, BRRI (Bangladesh Rice Research Institute).

2.3. Data Collection

At first, I collect and examine current data, records, maps, and images from a variety of organizations and institutions. Collecting literary, hydrogeological, and climatic data (Precipitation, Aquifer, Hydraulic Conductivity, Vadose zone, Water table, Soil media and so on) and examining and verifying the accuracy of the data. All of the data was provided by the Bangladesh Water Development Board (BWDB), Dinajpur; the Institute of Water Modeling (IWM), and the Barind Multipurpose Development Authority (BMDA), Asia Energy Corporation (Bangladesh) Pty Limited. The satellite DEM data is collected from Environmental Systems Research Institute Inc. (ESRI) and USGS (United States Geological Survey).

2.4. Field Experiment

Field experiments are primarily used to collect geological and geographical data from the Barapukuria Coal Mine area (aquifer recharge, hydraulic conductivity, Soil media, water table, Topography, recharge-discharge, borehole and so on). The following are some of the results of the field tests:

1) Pumping test: Used for collecting data like boundary conditions.

2) Water level monitoring: Used for collecting data on observation and pumping wells.

2.5. Data Processing and Analysis

The collected data and field test data are manually analyzed and interpreted, as well as by computers using various tools. All of the data and maps were analyzed and interpreted using the software mentioned below.

1) Arc GIS 10.5 is used for the preparation of different location maps (Study area map, Different groundwater parameter maps).

2) Spatial distribution tool (Arc GIS 10.5) has been used for the preparation of Groundwater depth maps.

3) Rainfall and groundwater levels are plotted in Excel.

4) Water table data prepared by Excel.

5) DRASTIC and Modified DRASTIC-LU mapping my ARC GIS 10.5.

6) Comparative LULC change assessment is done by Arc GIS 10.5.

2.6. Methods to Assessing the Vulnerability of Groundwater Using the DRASTIC Model

Since 1970, several researchers have created various aquifer vulnerability mapping techniques. However, DRASTIC has been the method that porous aquifers have most often used to map aquifer vulnerability (Aller et al., 1987). Because mine leaching into groundwater and the intersection of the aquifer by topsoil removal owing to open pit mining are the major causes of pollution in this study, the aquifer vulnerability in the basin was determined using the DRASTIC approach.

The grades and weights assigned to the seven characteristics were used to create a DRASTIC technique. They are hydraulic conductivity (C), aquifer media (A), soil media (S), topography (T), impact of the vadose zone (I), depth of groundwater (D), and net recharge (R). Based on functional curves, each parameter is separated into ranges and given various ratings on a scale from 1 (least vulnerability possibility) to 10 (highest vulnerability potential) (**Table 2**).

This grade is based on DRASTIC weighting elements that range from 1 (least significant) to 5 (most significant) and groundwater pollution due to coal mining activities. In this study, the alluvium regions were weighed using contamination weight, while the other basin areas were weighed using DRASTIC weight. The DRASTIC Vulnerability Index (DVI), as determined by the linear additive combination of the aforementioned parameters with the ratings and weights, is calculated as follows [17]:

$$DVI = D_rD_w + R_rR_w + A_rA_w + S_rS_w + T_rT_w + I_rI_w + C_rC_w \quad (1)$$

where,

D_r	Rating for the depth of the water table
D_w	Weight assigned to the depth ofthe water table
R_r	Rating for the aquifer recharge
R_w	Weight for the aquifer recharge
A_r	Rating assigned to aquifer media

Continued

A_w	Weight assigned to aquifer media
S_r	Rating for the soil media
S_w	Weight for the soil media
T_r	Rating for topography (slope)
T_w	Weight assigned to topography
I_r	Rating assigned to impact of vadose zone
I_w	Weight assigned to impact of vadose zone
C_r	Rating for rates of hydraulic conductivity
C_w	Weight given to hydraulic conductivity

Only the characteristics of the study area's properties were used to generate the rating ranges. Each DRASTIC parameter is divided into a number of classes by the range component, or important media kinds that may have an impact on the potential for contamination (Ehteshami et al., 1991). The rating scale may vary depending on the subject area. To estimate the parameter rating ranges, it is necessary to have a solid understanding of the geology and hydrogeology of the research region.

Table 2. Datasets used for DRASTIC and modified DRASTIC-LU model.

SL No.	DRASTIC Parameter	Dataset Source	No. of Samples/Wells	Observation Period	Spatial Coverage	Method of Preparation/ Interpolation
1	Depth to Water Table (D)	Field data (Piezometers) + BWDB	8 wells (6 piezometers + 2 BWDB wells)	Jan-Dec 2020 (monthly)	~25 km² study area	IDW interpolation (ArcGIS 10.5)
2	Net Recharge (R)	BMD rainfall data + BRRI crop coefficient	Meteorological dataset	Jan-Dec 2020	Entire study area	Water balance method + IDW
3	Aquifer Media (A)	BMDA & BWDB borehole logs	12 boreholes	Static dataset	Study area	Lithological classification + GIS mapping
4	Soil Media (S)	BMDA soil maps + field sampling	10 samples	2020	Entire study area	Vector classification → raster conversion
5	Topography (T)	DEM (USGS & ESRI, 30 m resolution)	Raster dataset	Not time-dependent	Entire study area	Slope analysis using Spatial Analyst
6	Vadose Zone Impact (I)	Borehole lithological logs	12 boreholes	Static dataset	Study area	Lithological interpretation + IDW

Continued

7	Hydraulic Conductivity (C)IDW interpolation	Pumping test data	5 wells	2020	Study area	IDW interpolation
8	Land Use/Land Cover (LU/LC)	Landsat 8 satellite imagery	Raster dataset (30 m resolution)	2020	Entire study area	Supervised classification (ArcGIS 10.5)

The integration of climatic, hydrogeological, and land use data establishes a strong foundation for assessing groundwater vulnerability. Utilizing both primary field observations and dependable secondary data sources enhances the accuracy and spatial reliability of the dataset. The application of GIS-based methods, including IDW interpolation and spatial analysis techniques, further improves the precision of the generated thematic maps. In addition, incorporating Land Use/Land Cover into the Modified DRASTIC-LU model increases the sensitivity of the assessment by accounting for human-induced impacts. Overall, the data and methodological approach employed in this study are well-structured, consistent, and appropriate for effectively evaluating groundwater vulnerability in the Barapukuria Coal Mine region.

2.7. Methods to Assessing the Vulnerability of Groundwater Using Modified DRASTIC-LU Model

Using the reclass function in the spatial analyst tool in ArcGIS, the DRASTIC-LU/LC characteristics (depth to water table, net recharge, aquifer media, soil media, topography, impact of vadose zone, hydraulic conductivity, and land use/land cover pattern) were reclassified. The vulnerability index map was then created using the weighted overlay function in ArcGIS using the empirical approach, Equation (3), that has previously been used by other researchers (Kumar & Pramod Krishna, 2020; Plain et al., 2014).

$$\begin{aligned}\text{DRASTIC-LU/LC index} = {} & (D_r \times D_w) + (R_r \times R_w) + (A_r \times A_w) \\ & + (S_r \times S_w) + (T_r \times T_w) + (I_r \times I_w) \\ & + (C_r \times C_w) + (LU/LC_r \times LU/LC_w)\end{aligned} \quad (2)$$

Where (Table 3):

LU/LC_r = Rating given to Land Use/Land Cover.

LU/LC_w = Weighting given to Land Use/Land Cover.

Table 3. Range of vulnerability related to DRASTIC index (Malakootian & Nozari, 2020).

SL No.	DRASTIC Index Score	Vulnerability
1	23 - 46	Very low
2	47 - 92	Low

Continued

3	93 - 136	Moderate
4	137 - 184	High
5	>184	Very high

2.8. Data Acquisition of LULC

Landsat-4 Thematic Mapper data from the year 2005 is used for the categorization of land use and land cover, whereas Landsat-8, OLI data is utilized for the year 2021. The Landsat-4 and Landsat-8 sensors have a sweep of 185 km and a spectral resolution of 30 m, respectively. The same reference systems, UTM (zone 45) North and WGS 84 datum, were used to project all of the data. The research region is covered by Landsat's Worldwide Reference System's route 146 and row 022. With the use of images from Sentinel-2A and Google Earth, the ground truth data were established. These facts were used to classify the photos and evaluate the classification's accuracy.

Different digital image processing techniques were used to investigate land use/landcover changes and generate LULC maps of the research region for the three-year time periods of 2005 and 2021 using multi-dated TM Landsat data sets of the Parbatipur area.

2.9. Mapping and Accuracy Assessment

First, picture pre-processing and enhancement were applied to all three data sets. Using the Arc Gis 10.8 application software, the photos were corrected geometrically, radiometrically, and atmospherically. In Landsat-4 TM visible to shortwave infrared (bands 1 to 5 and 7) and in Landsat-8, OLI with pixel size 30 m, all bands of the picture were used for layer stacking. The area of interest (AOI) for each image was then created by overlaying a shapefile of the research region, and a subset was obtained.

The LULC maps, on the other hand, were created after editing and finalization for the years 2005 and 2021. The rate of the classes in Km^2 was extracted, and the rates were split according to each individual year after measuring the percentage change for each year against each LULC type. Using Arc GIS software and unsupervised classification techniques, six primary LULC classes were implemented. In order to get higher accuracy results and reduce misclassification, post-classified pictures were cleaned. Due to the low spatial resolution of the Landsat data sets, mixed pixels are a frequent issue when identifying the pictures.

2.10. Change Detection

Several approaches are used to monitor and analyze changes to the earth's surface. The post-classification method has established itself as the most often used strategy in change detection analysis. Comparing separately created categorized images is necessary. This method's methodology is based on the independent correction of the categorized pictures, the creation of thematic maps, and the comparison of related labels to pinpoint regions of change (Mishra, 2017). In this instance, a post-classification approach was used to carry out a LULC change detection investigation for the Parbatipur area.

The image came from the United States Geological Survey (USGS) and Environmental Systems Research Institute, Inc. (ESRI). The trend, class total, net change, class change, percent change, and rate of each LULC change between the years 2005, 2013 and 2021 were computed in addition to obtaining the dynamic changes of each class category during the study period, i.e., from 2005 to 2013. These calculations were made using the Arc GIS software and post-classification comparison method.

3. Results and Discussions

3.1. Groundwater Vulnerability Assessment and Comparative Lulc Changes Analysis

3.1.1. Assessment of Aquifer Vulnerability with DRASTIC Method

Each parameter's range in the current study produced three, four, five, or six classes. The number of range classes has no impact on the final outcome as long as the minimum and maximum rating values remain constant. For instance, the three classes of the depth of the water table parameter were assigned rating values of 9, 5, and 1, respectively, for the depths of 0 - 10, 10 - 20, and 20 - 30 m. The same characteristic was then split into six classes, with ratings of 9, 8, 7, 5, and 1 being given for depths of 0 - 5, 5 - 10, 15 - 20, 25 - 30, and 30 - 35 m, respectively. Nearly identical findings were obtained when the DVI value was computed and the vulnerability classes (high, medium, and low) were identified using the quartile classification approach. This demonstrates that in DRASTIC applications, the rating value is more significant than the range classes. The DVI may be quantified by the user using the DRASTIC method to highlight locations that are more likely than others to be affected by groundwater pollution. A higher DRASTIC score suggests increased groundwater contamination risk.

When estimating aquifer vulnerability using the DRASTIC technique, it is important to take into account the seven hydrogeological parameters (depth to water, net recharge, aquifer media, soil media, topography, inpact of vadose zone, and hydraulic conductivity). These input data came from written sources, field research, state hydrologic and meteorological operations, as well as administration of agricultural and village operations. Seven thematic maps were created utilising this input data and based on GIS to perform the aquifer vulnerability analysis using DRASTIC.

1) Depth of water table (D)

This is significant because it establishes the thickness of the materials that pollutants must traverse before getting to the water table. According to Chakraborty et al., (2007), it also impacts the amount of time that pollution has to undergo chemical and biological processes including dispersion, oxidation, natural attenuation, sorption, etc. Therefore, the deeper the water table, the lower the possibility of contaminants getting there and the higher the chance that they will be attenuated. The groundwater depth map (Figure 2) was created using the information from 6 piezometers.

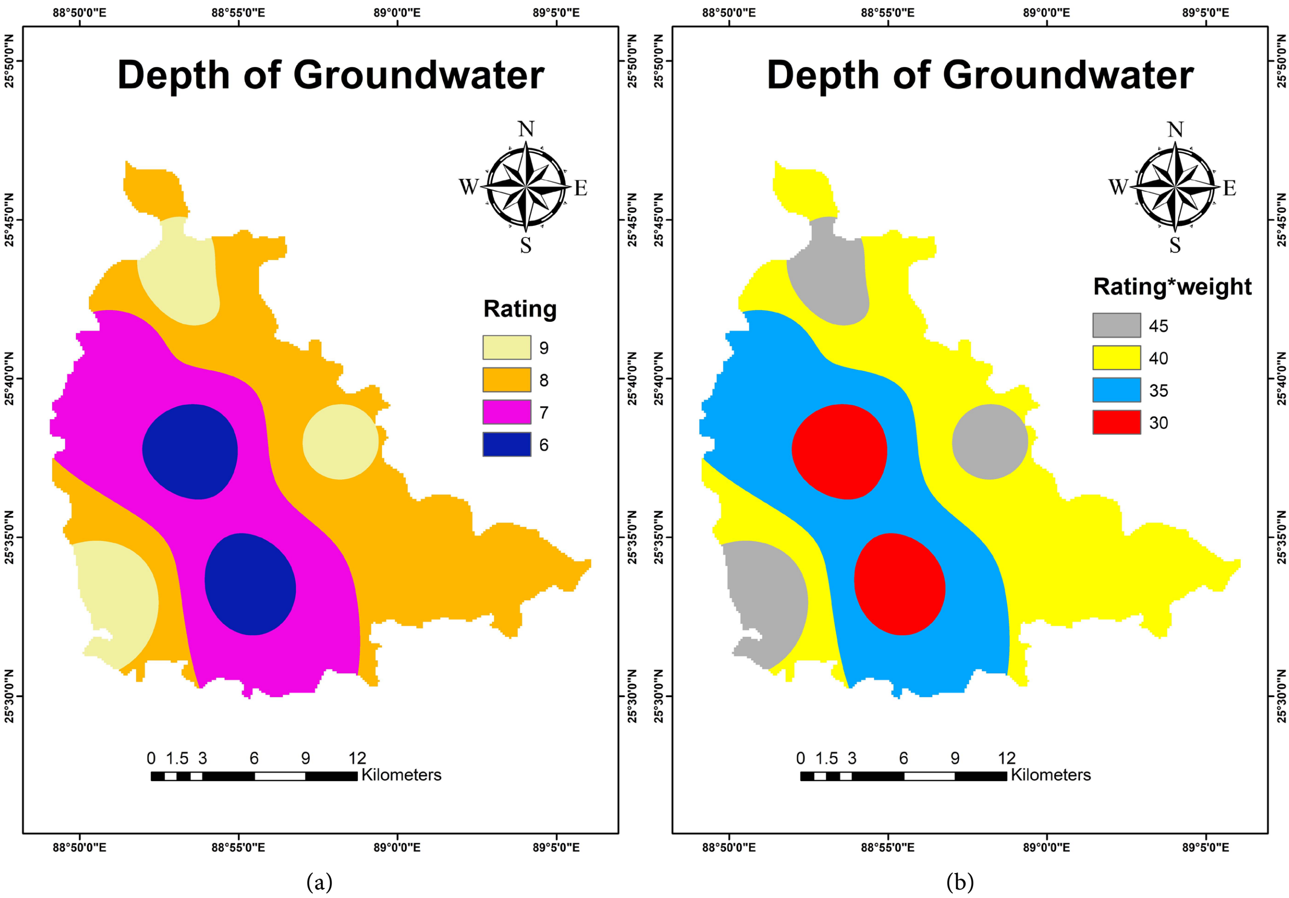


Figure 2. Depth of Water table rating and weighting.

According to the collected data, the groundwater depths vary from 3.89 to 8.21 m in the Parbatipur Upazila. The groundwater depth map of the study area is classified into six groups (0 - 1.5, 1.5 - 3, 3 - 6, 5 - 7, 7 - 10, and 10 - 20 m). The groundwater depth weight is determined as 5. The rating values of the groundwater depth classes vary from 5 to 10. The values for weight and rating are presented in Figure 2. As we can see the rating and weighting is pretty high in Kholahat, BelaiChandi and Mosthafapur region. The rating and weighting is lesser at some parts of Habra, Chandipur and Manmathpur region.

2) Net recharge (R)

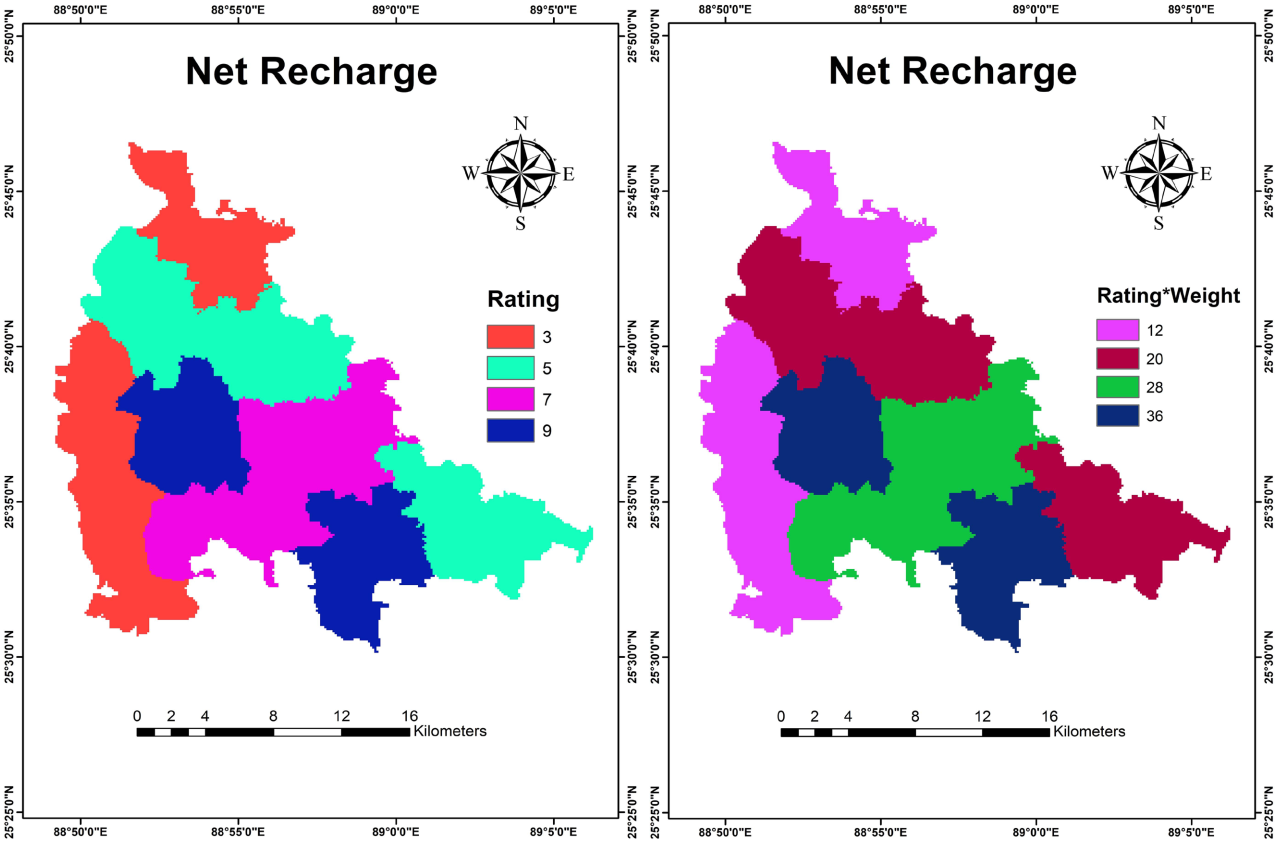
A simplified water balance method based on annual rainfall (P) and evapotranspiration data (ET) was used to calculate net recharge (R). The equation applied is $R = P - ET$. The Bangladesh Meteorological Department provided rainfall data, and standard empirical techniques and regional climate records were used to estimate evapotranspiration values. Following the conventional DRASTIC categorization scheme, the study area's computed net recharge values, which range from

263 mm to 450 mm/year, were divided into four recharging zones (250 - 300, 300 - 350, 350 - 400, and 400 - 450 mm/year).

Since greater recharge improves the movement of pollutants from the surface to the aquifer, higher recharge values were given higher ratings in order to adhere to DRASTIC principles. As a result, zones with recharge rates between 400 - 450 mm/year were rated as the most vulnerable (9), whereas zones with lower recharge rates were rated lower. Table 4 and Figure 3 illustrate the net recharge ratings and weighting.

Table 4. Rating and weighting values used in DRASTIC.

Parameter	Range	Drastic		
		Rating	Weight	Total Weight (Rating * Weight)
Groundwater depth (m) D	0 - 1.5	10	5	50
	1.5 - 3	9		45
	3 - 5	8		40
	5 - 7	7		35
	7 - 10	6		30
	10 - 20	5		25
Net Recharge (mm/year) R	250 - 300	3	4	12
	300 - 350	5		20
	350 - 400	7		28
	400 - 450	9		36
Aquifer Media A	Imbedded	6	3	18
	Alluvium	4		12
	Sandy braided	5		15
	Sand	9		27
Soil media S	Gravel	9	2	18
	Sedimentation	8		16
	Sand-clay	3		6
	Clay	1		2
Topography (Slope^0) T	0 - 2	10	1	10
	2 - 6	9		9
	6 - 12	5		5
	12 - 20	3		3
	20 - 32	1		1
Impact of Vadose zone I	Gravel	9	5	45
	Silt	3		15
	Clay	1		5
Hydraulic Conductivity(m/s) C	10 - 15	4	3	12
	16 - 25	5		15
	26 - 40	7		21
	40 - 60	8		24



(a) (b)

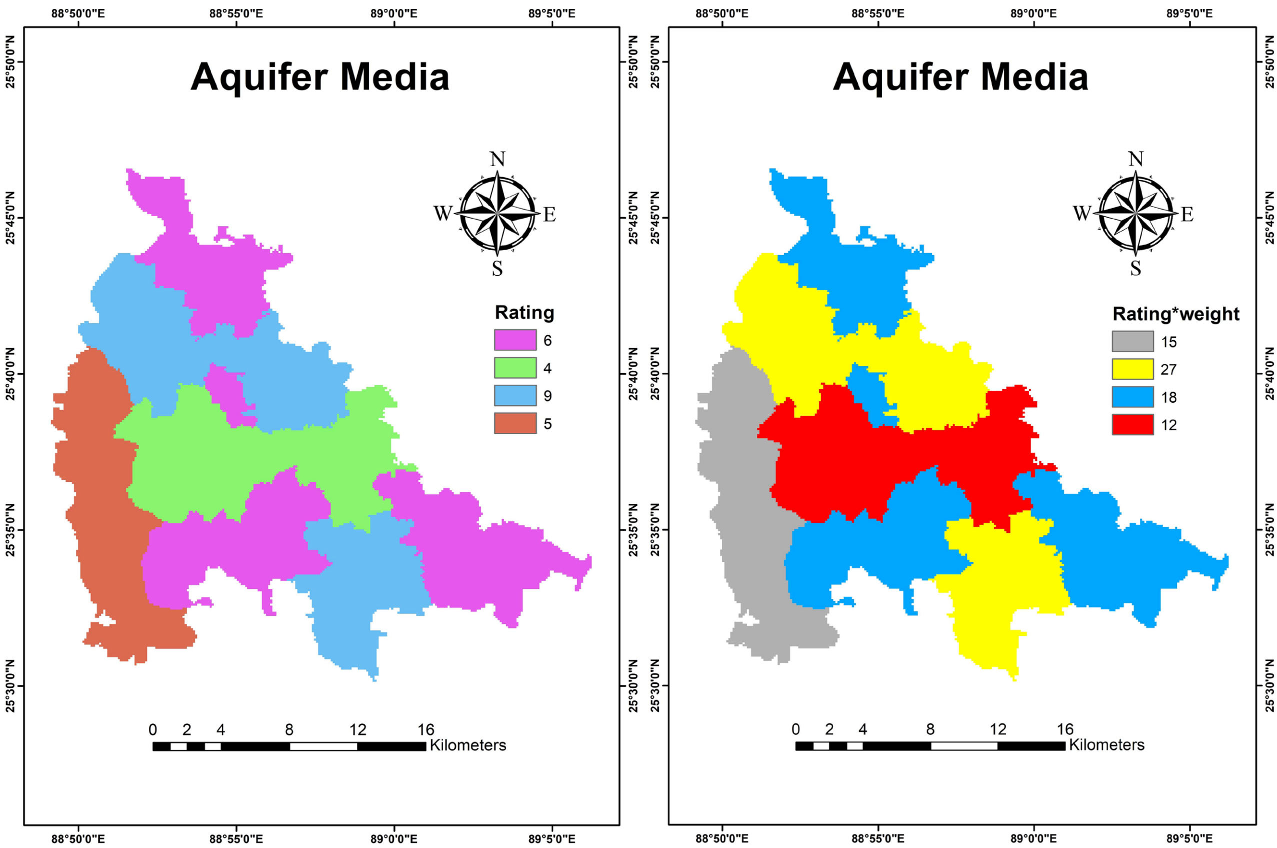
Figure 3. Net recharge rating and weighting.

As we can see from **Figure 3**, net recharges rating and weighting is higher in Hamidpur and Chandipur (Where little Jamuna River is active) region while rating and weighting rate is very low in Belaichandi and Mostafapur union. In Habra, Palashbari region the rating, weighting is also more than average and in Manmathpur, Rampur, Harirampur the rating, weighting is below average.

3) Aquifer media (A)

Groundwater flow contaminant fate and transport modeling are important components of most aquifer remediation studies [26]. Four units were identified in this study's aquifer media map based on hydrogeological and lithological features: sand, sandy braided deposits, embedded formations, and alluvium. According to DRASTIC criteria, embedded formations were given lower vulnerability ratings due to their lesser permeability, whereas highly permeable materials like sand and alluvium were given higher ratings due to their rapid contaminant movement. The grades for sandy braided deposits were moderate. The assigned ratings, ranging from 4 to 9, reflect the relative vulnerability of each unit and are presented in **Table 4** and **Figure 4**.

Figure 4 shows, the rating and weighting is highest at the Rampur, Manmathpur and Hamidpur union of Parbatipur Upazila while the rating and weighting rate is lowest at Chandipur, Palashbari Union. Belaichandi, Mostafapur, Mominpur, Habra, Hariampur and some parts of Manmathpur and Hamidpur belong to the average kinds of rating and weighting in the context of the DRASTIC index.



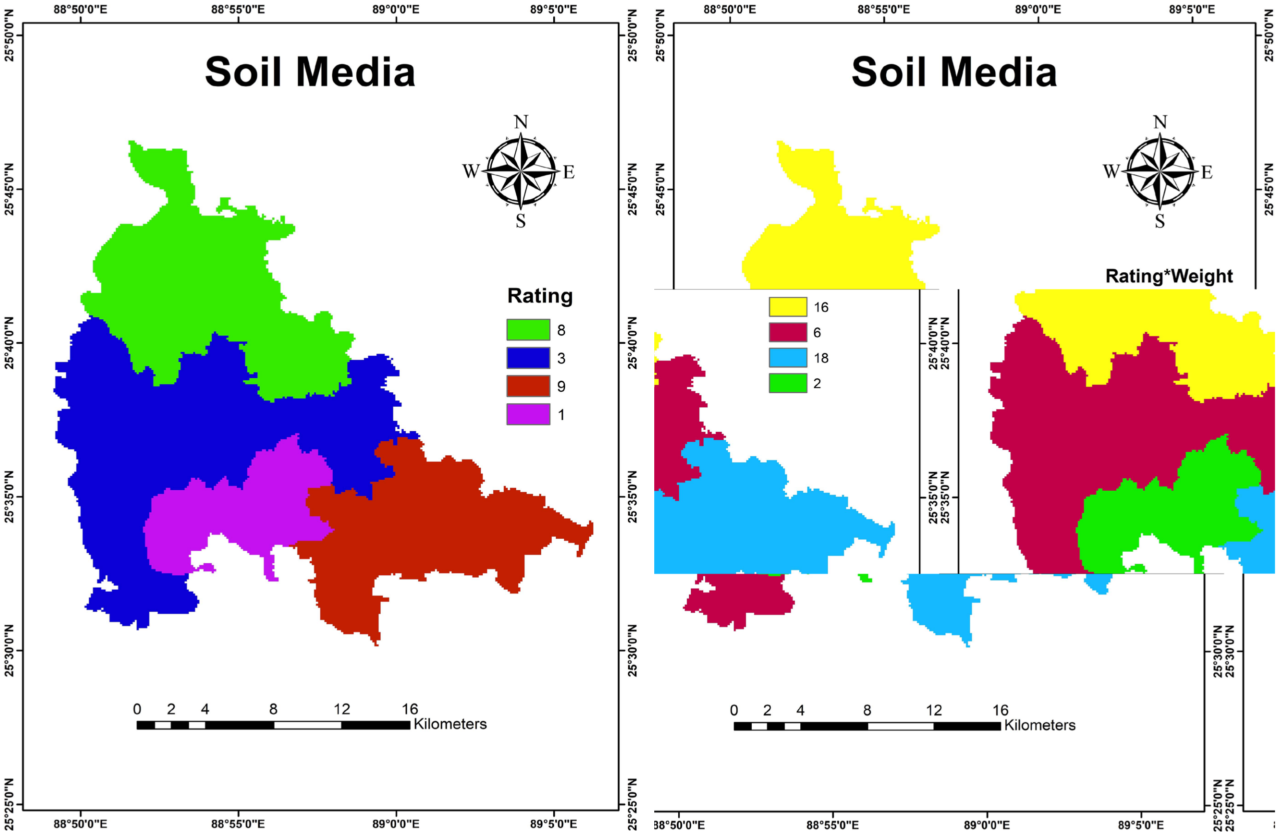
(a) (b)

Figure 4. Aquifer media rating and weighting.

4) Soil media (S)

Soil cover is a key factor in assessing aquifer vulnerability because it affects both groundwater recharge and the migration of contaminants through the vadose zone. In this study, a soil map obtained from the Barind Multipurpose Development Authority (BMDA) was digitized and analyzed using GIS techniques. Based on their physical properties, soils were classified into four categories: clay, sandy clay, gravel, and gravel-sand deposits. According to the DRASTIC model guidelines, soils with coarser textures, such as gravel and sandy materials, were given higher ratings due to their greater permeability and enhanced capacity to transmit pollutants. Conversely, clay soils received the lowest rating because their low permeability and strong adsorption properties limit the movement of contaminants. The ratings and corresponding weights for soil media are presented in Table 4 and Figure 5.

Figure 5 shows, the rating and weighting is highest at the Hrirampur and Hamidpur union. Belaichani and some parts of Manmathpur, Rampur's rating and weighting are also a bit high. The rating and weighting rate is lowest at the Habra union whileMostafapur, Mominpur, Parbatipur Sadar and some parts of Palashbari consist of average rating and weighting in the context of the DRASTIC Index.



(a) (b)

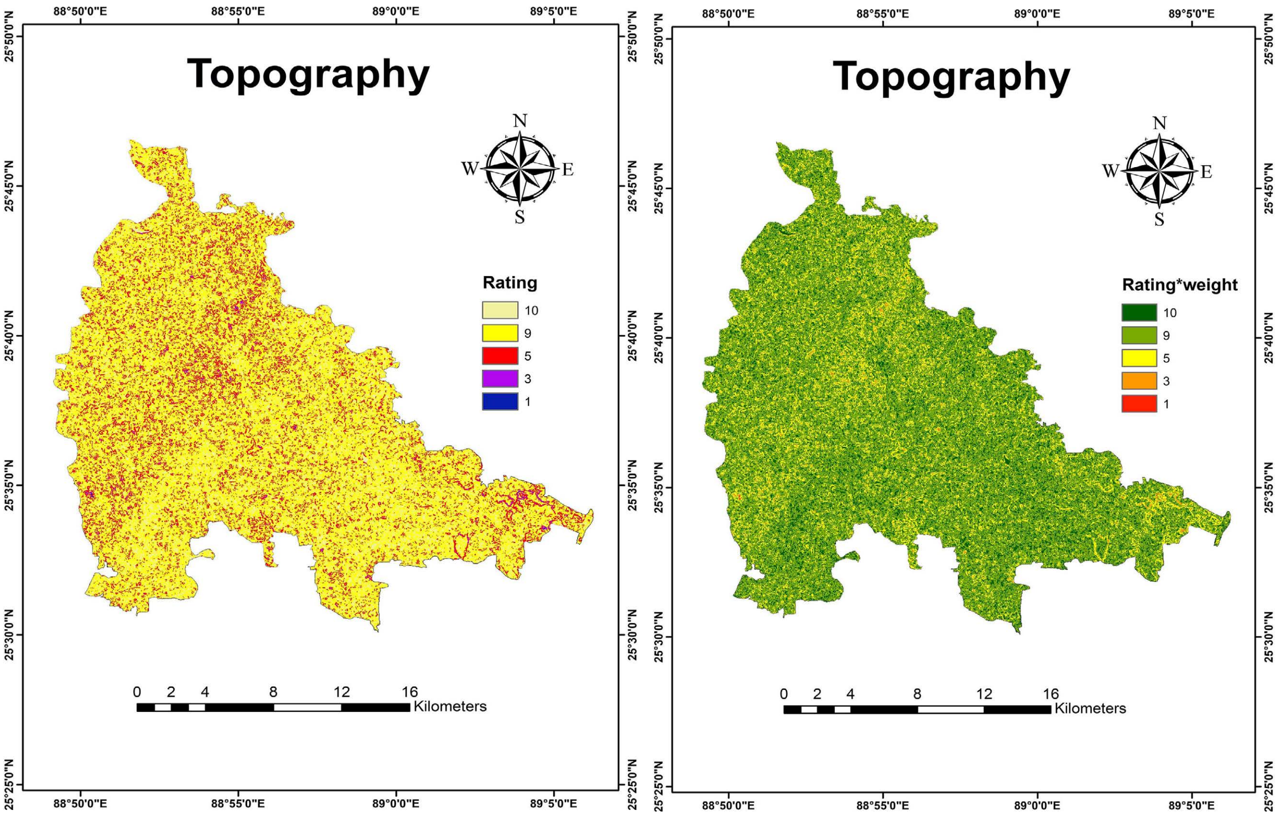
Figure 5. Soil media rating and weighting.

5) Topography (T)

The slope is a common way to represent topography. A pollutant's context of runoff and the amount of settling it may endure before permeating the soil are both determined by the slope degree, which has a significant impact. Using digitalized 1:25,000 scale topographical maps, a digital elevation model (DEM) of the research region was created. The DRASTIC technique was developed to work with five different slope classes. The topography is rated on a scale of 1 to 10, with 1 being the DRASTIC weight assigned to it. Six classes make up the total topographical class, and they fall into the following ranges: (0 - 2), (2 - 6), (6 - 12), (12 - 20), and (20 - 32). Table 4 and Figure 6 show the ratings that each class received, which ranged from 10 (>200) to 1 (0 - 20).

6) Impact of vadose zone (I)

The vadose zone, also known as the unsaturated zone, is vital in regulating the infiltration of rainfall and the transport of contaminants before they reach the groundwater table. In this study, information on the vadose zone and underlying geological formations was collected from borehole logs supplied by the Bangladesh Water Development Board. Based on their characteristics, the vadose zone materials in the study area were grouped into three categories: gravel, silt, and clay. In accordance with DRASTIC guidelines, highly permeable materials such as gravel and sand were assigned higher ratings because they allow rapid water movement and have limited capacity to filter contaminants. In contrast, clay-rich layers were given lower ratings due to their low permeability and greater ability to impede the movement of pollutants.The ratings for this parameter range from 1 to 9, with a weight of 5, as presented in Table 4 and Figure 7.



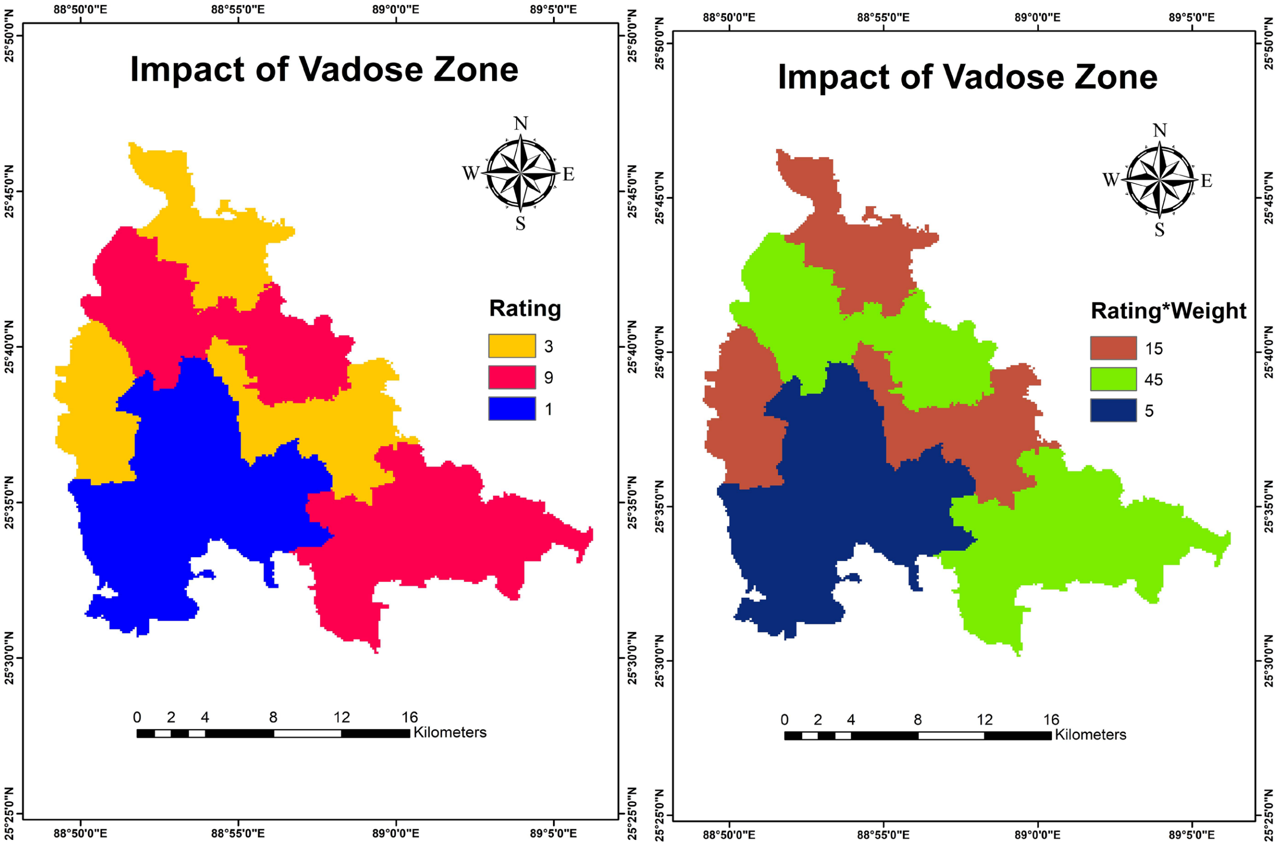
(a) (b)

Figure 6. Topography rating and weighting.

Figure 7 shows the rating and weighting are pretty high in Manmathapur and Rampur regions while the rating and weighting are pretty low in Mostafapur, Chandipur and Habra regions. Belaichandi, some parts of Manmathapur and Palashbari belongs to the average rating-weighting zone.

7) Hydraulic conductivity (C)

In this study, hydraulic conductivity data were derived from pumping test results of wells located within the study area. The originally reported values were adjusted and converted into standard units of m/day, instead of m/s, to maintain consistency with hydrogeological conventions. The observed hydraulic conductivity in the area varies from approximately 10 - 15 m/day to 40 - 60 m/day. According to DRASTIC guidelines, higher conductivity values were given higher ratings because they indicate more rapid contaminant transport and greater vulnerability, while lower conductivity values were assigned lower ratings. The corresponding ratings and weights for this parameter are presented in Table 4 and Figure 8.



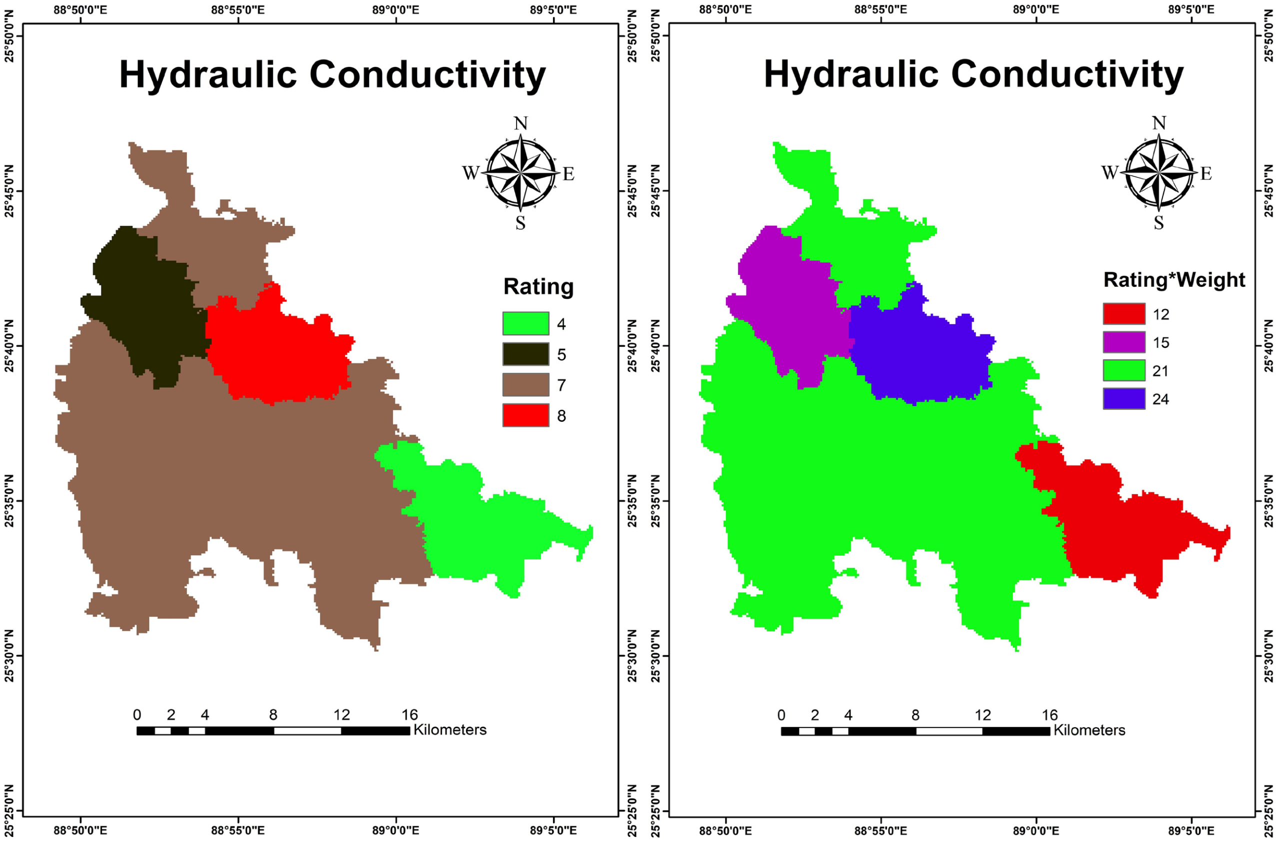
(a) (b)

Figure 7. Impact of vadose zone rating and weighting.

According to Figure 8, the rating and weighting of the Hydraulic Conductivity is the highest at Rampur Union. Harirampur Union belongs to the lowest rating and weighting area. The rest of the study area including Belaichandi, Manmathpur, Mominpur, Mostafapur, Habra, Hamidpur, Palashbari and some parts of the Parbatipur union belongs to the average rating and weighting.

3.1.2. Vulnerability of Groundwater

The DRASTIC model is frequently used to evaluate groundwater susceptibility, however, because the anthropogenic influence is not incorporated as a model parameter, this model is not ideal for a built-up area. The 'effect of anthropogenic activities' (indicated by the letter 'A' in the acronym) was included as an extra restriction to the DRASTIC model in the current study in order to overcome this limitation. The satellite interpretations were used as an additional parameter in the current investigation, and land usage in close proximity to populated areas was used to validate the technique.



(a) (b)

Figure 8. Hydraulic conductivity rating and weighting.

The DRASTIC Vulnerability Index was computed according to equation1 and is between 81 and 167. Also, a DRASTIC Vulnerability map of the study area was prepared using overlay analyses of the seven hydro-geological parameters mentioned previously. The DRASTIC risk map (Figure 9) displays three susceptibility groups, namely low, moderate, and high, based on the DRASTIC index.

According to the vulnerability index (Table 2), 37% area (Habra, Chndipur, Palahbari and some parts of Mostafapur) is highly vulnerable, 36% area (Manmathpur, Rampur, Harirampur and some parts of Mominpur and Mostafapur) lies between Low vulnerability, and rest of 27% area (Belaichandi, Hamidpur and some parts of Mominpur and Mostafapur) belongs to Moderate Vulnerability.

Barapukuria underground coal mine, which is situated in the southern part of Parbatipur upazila has a great impact on groundwater. This mining activity is one of the biggest reasons that, this part of Parbatipur belongs to the high groundwater vulnerability zone.

From Figure 10, it is clear that 37% area is highly vulnerable, 36% area lies between Low vulnerability, and rest of 27% area belongs to Moderate Vulnerable.

3.1.3. Modified DRASTIC-LU

Under the reclass function of the spatial analyst tool in ArcGIS, the DRASTIC-LU/LC characteristics (depth to water table, net recharge, aquifer media, soil

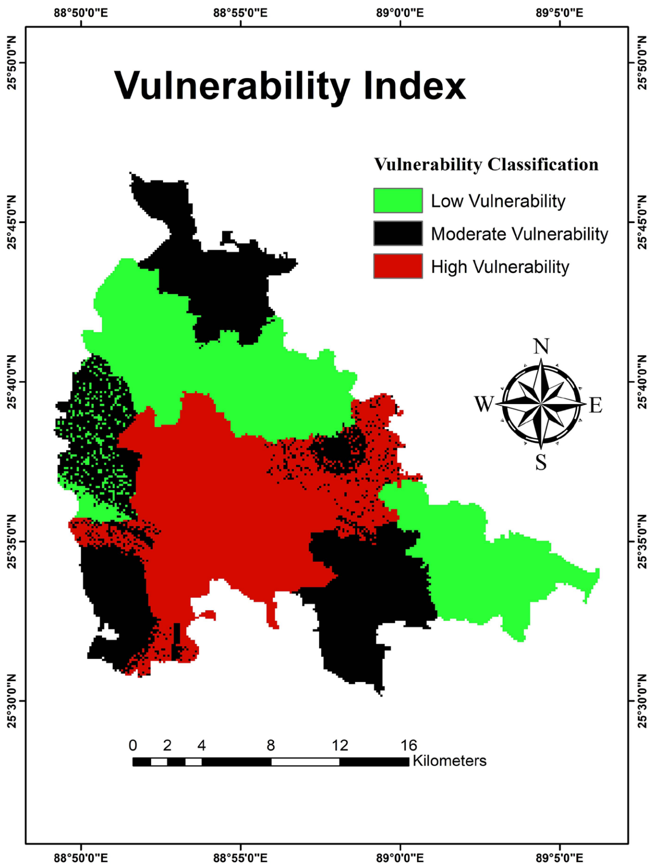


Figure 9. Groundwater vulnerability index map.

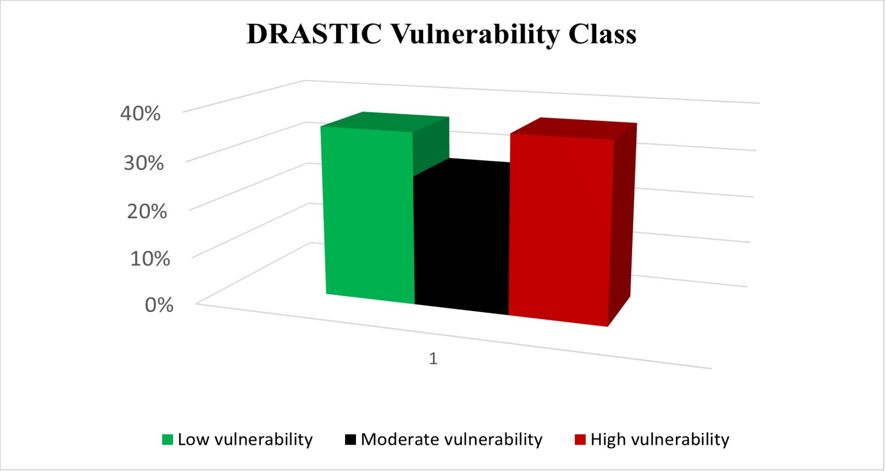


Figure 10. Vulnerability area classification.

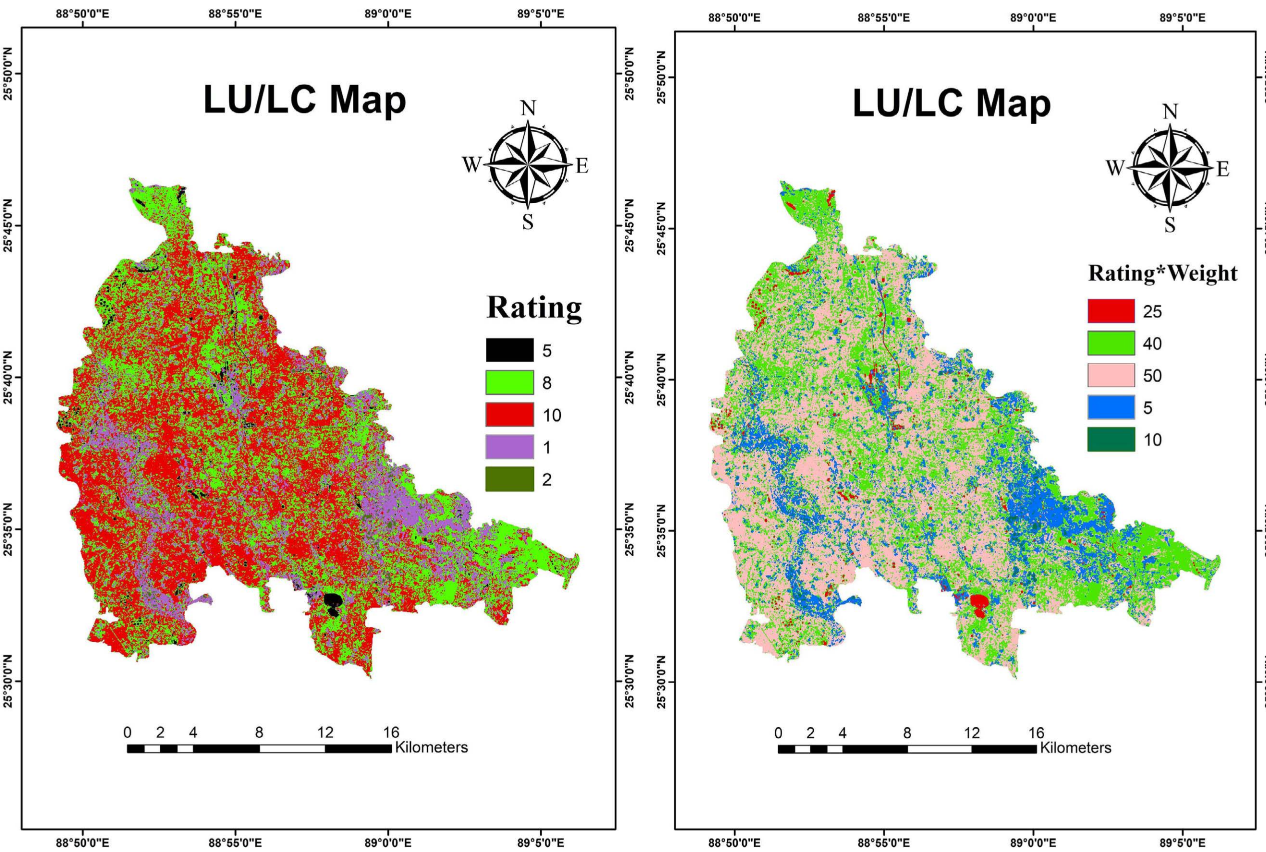
media, topography, impact of vadose zone, hydraulic conductivity, and land use/land cover pattern) were reclassified. To begin with, the intrinsic vulnerability was examined using the DRASTIC model. To map the precise vulnerability of groundwater, the DRASTIC model (DRASTIC-LU) with the addition of a land-use element was put forward (Table 5).

Table 5. Rating and weighting values used in modified DRASTIC-LU.

Parameter	Range	Drastic		
		Rating	Weight	Total Weight (Rating * Weight)
Groundwater depth (m) D	0 - 1.5	10	5	50
	1.5 - 3	9		45
	3 - 5	8		40
	5 - 7	7		35
	7 - 10	6		30
	10 - 20	5		25
Net Recharge (mm/year) R	250 - 300	3	4	12
	300 - 350	5		20
	350 - 400	7		28
	400 - 450	9		36
Aquifer Media A	Imbedded	6	3	18
	Alluvium	4		12
	Sandy braided	5		15
	Sand	9		27
Soil media S	Gravel	9	2	18
	Sedimentation	8		16
	Sand - clay	3		6
	Clay	1		2
Topography (Slope^0) T	0 - 2	10	1	10
	2 - 6	9		9
	6 - 12	5		5
	12 - 20	3		3
	20 - 32	1		1
Impact of Vadose zone I	Gravel	9	5	45
	Silt	3		15
	Clay	1		5
Hydraulic Conductivity (m/s) C	10 - 15	4	3	12
	16 - 25	5		15
	26 - 40	7		21
	40 - 60	8		24
Land Use/Land Cover	Water Body	5	5	25
	Vegetation	8		40
	Settlements	10		50
	Bare land	1		5
	Forest	2		10

1) Land use/Land cover

The LU/LC map in this study includes five classes: water bodies, vegetation (including agricultural land), settlements, bare land, and forest. Landsat imagery from the United States Geological Survey was used to generate LU/LC maps for 2004, 2013, and 2021. A consistent supervised Maximum Likelihood Classification (MLC) approach was applied across all time periods to ensure comparability and avoid classification bias. Training samples were derived from Google Earth imagery, field observations, and topographic references. In the DRASTIC-LU model, LU/LC was assigned a rating range of 2 - 10 with a weight of 5, reflecting its influence on groundwater vulnerability.



(a) (b)

Figure 11. Land use/land cover rating and weighting.

The rating and weighting of the LU/LC map show, approximately 46% of the region is designated as a settlement area on the LU/LC map (Figure 11), Vegetation (including agricultural land) covered almost 35% area, Bare land covered roughly 15% of total area and the rest of two shares 4% area approximately. This suggests, there are lots of anthropogenic activities and due to this activity, the area is vulnerable to groundwater.

2) Modified DRASTIC-LU/LC index map

Based on the possible groundwater vulnerability, each of the eight factors was given a weight and rating. The Analytical Hierarchy Process (AHP) was used to help determine which parameter has a greater impact on groundwater vulnerability than the other (Kumar & Pramod Krishna, 2020). The Analytical Hierarchy Process (AHP) was utilized to evaluate the relative significance of each parameter, with expert knowledge playing an essential role in selecting criteria and refining their weights. The groundwater vulnerability index was subsequently produced using the weighted overlay tool in ArcGIS, combined with an empirical equation (Equation (2)) commonly used in related studies. To enhance the accuracy of the assessment, a hybrid weighting method was adopted by combining conventional DRASTIC weights with those derived from AHP. Initially, intrinsic vulnerability was assessed using the standard DRASTIC model, after which the modified DRASTIC-LU model incorporated Land Use/Land Cover (LU/LC) to better account for human impacts. Pairwise comparison matrices were constructed based on expert judgment and literature review, and their consistency was tested using the Consistency Ratio (CR < 0.1) (Mkumbo, 2022), confirming acceptable reliability. This integrated framework retains the core structure of the DRASTIC model while improving parameter weighting, thereby providing a more comprehensive and realistic assessment of groundwater vulnerability.

Modified DRASTIC-LU index (**Figure 12** and **Figure 13**) shows that, according to the DRASTIC vulnerability class, 48% (Belaichandi, Chandipur, Habra, Mostafapur and Hamidpur union) of the total Parbatipur area has very high groundwater vulnerability. 33% area belongs to a moderate groundwater vulnerability zone

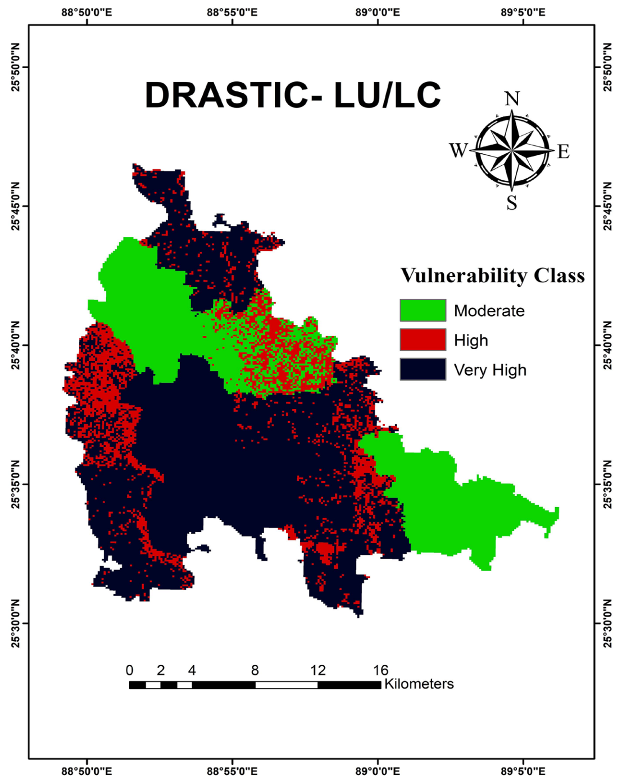


Figure 12. Modified DRASTIC-LU vulnerability index map.

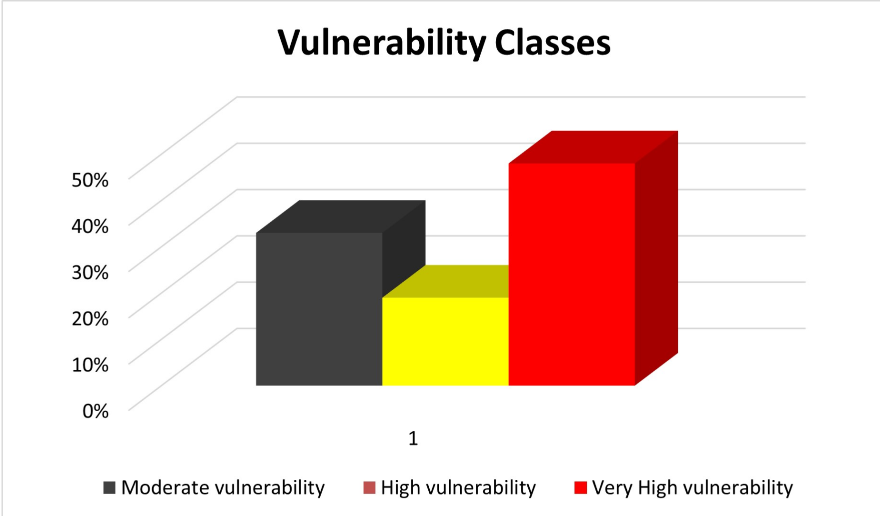


Figure 13. Modified DRASTIC-Lu vulnerability area classification.

and 19% (Mominpur and Rampur union) area has high groundwater vulnerability. After adding the eighth parameter land use/ land cover, the DRASTIC vulnerability index changes significantly. 48% area become very high in vulnerability index. Before adding this parameter, the vulnerability index shares only low, moderate and high vulnerability zone between the study areas. The DRASTIC-LU/LC map can be identified by Low, moderate, and high vulnerability zones (Mkumbo et al., 2022), with corresponding areas of 29.2 km^2 (10.65%), 120.4 km^2 (43.9%), and 124.4 km^2 (45.40%). So, we can say that land use/land cover has a very healthy impact to increase the vulnerability rate for the region (**Table 6**).

Table 6. Modified DRASTIC-LU index-based area calculation.

Vulnerability Class	Area (In Percentage)	Area (In Hector)
Moderate	33%	13,034 ha
High	19%	7504 ha
Very high	48%	18,959 ha

3.1.4. DRASTIC Index vs. Modified DRASTIC-LU Index

Figure 14, indicate the comparison between normal DRASTIC and Modified DRASTIC-LU, the degree of change in the various land use and land cover categories throughout the eighteen-year period from 2004 to 2021and their vulnerabilities categories.

3.1.5. Comparative LULC for the Last 20 Years

In the research region, five key land use and land cover types were identified: water body, vegetation, forest cover, settlements, bare land, and forest. **Figure 15** shows the maps of the study area's land use and land cover for three different time periods. **Table 7** displays the spatial distribution and area statistics of five land use/land cover groups. Table 7 also displays percentages of the area occupied by each land use and land cover category.

Table 8 shows the degree of change in the various land use and land cover categories throughout the eighteen-year period from 2004 to 2021. Table 9 and Table 10 display the rate of change for each land cover type during an eight-year period.

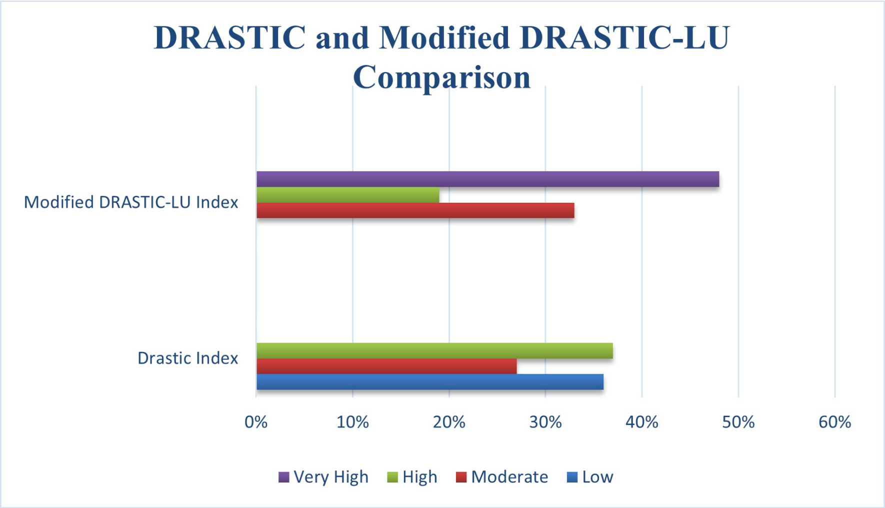
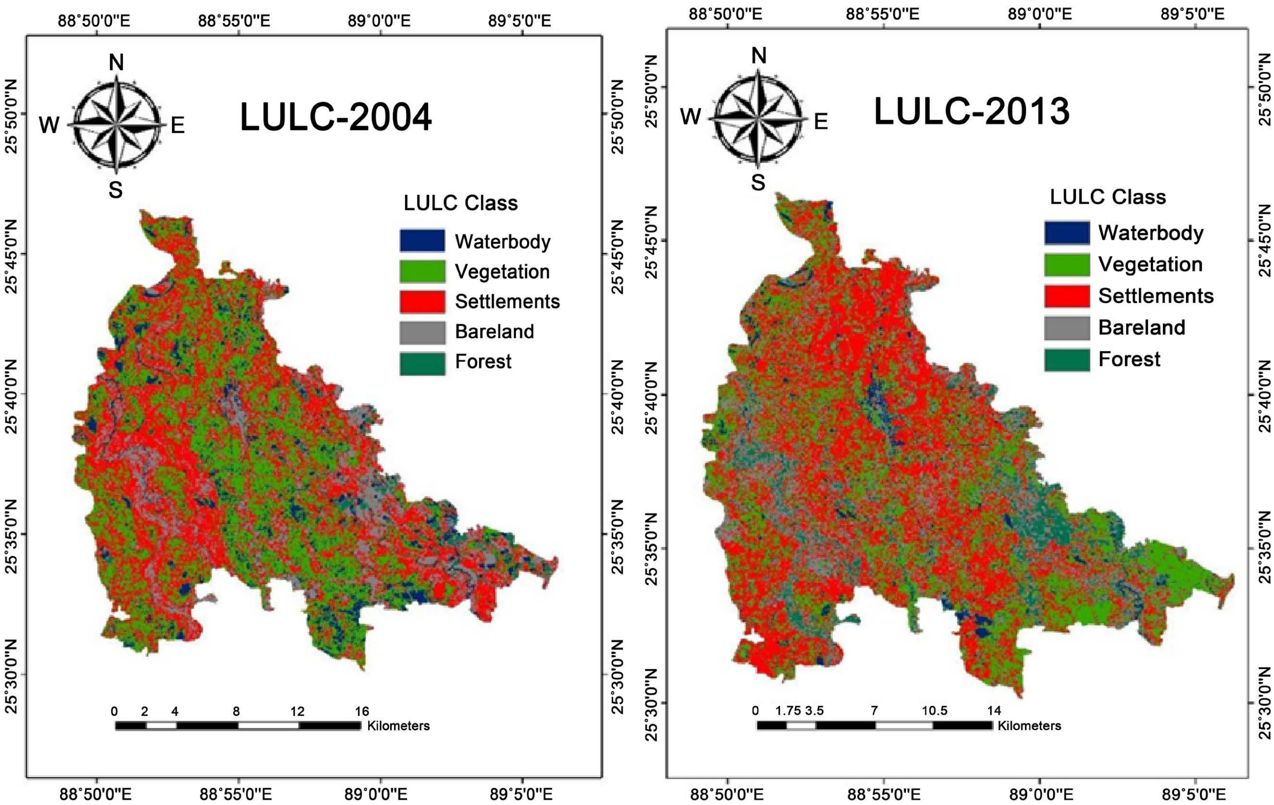


Figure 14. DRASTIC and modified DRASTIC-LU comparison (In percentage).



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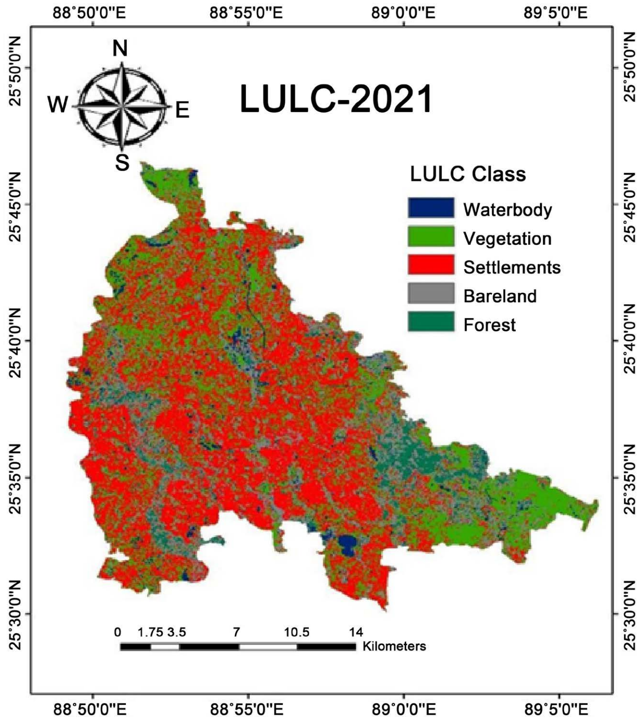

(c)

Figure 15. LULC of different time period.

Table 7. Areal distribution of LULC classes in Hector.

LULC Classes	2004 (Ha)	2013 (Ha)	2021 (Ha)
Waterbody	3711	1765	1541
Vegetation	14,255	11,882	12,005
Settlements	14,608	15,562	16,947
Bareland	7014	7761	7014
Forest	1990	2524	1990

Table 8. Vulnerability comparison between DRASTIC and modified DRASTIC-LU index (In percentage and hector).

Vulnerability	Low	Moderate	High	Very High
Drastic Index	36%	27%	37%	0%
	14,219 ha	10,664 ha	18,959 ha	0 ha
Modified DRASTIC-LU Index	0%	33%	19%	48%
	0 ha	13,034 ha	7504 ha	18,959 ha

Table 9. Areal distribution of LULC classes in percentage.

LULC Classes	2004 (%)	2013 (%)	2021 (%)
Waterbody	9.39	4.46	3.90
Vegetation	36.09	30.08	30.39

Continued

Settlements	36.98	39.40	42.90
Bareland	16.15	19.65	17.75
Forest	1.37	6.39	5

Table 10. Net change in areal extent (percentage) of land cover.

LULC Classes	(2004-2013) (%)	(2013-2021) (%)	Net Change (%)
Waterbody	−4.93	−0.56	−5.49
Vegetation	−6.01	0.39	5.7
Settlements	2.42	3.5	5.92
Bareland	3.5	−1.87	1.6
Forest	5.02	−1.39	3.63

The water body of the study area shows decreasing trend from 2004 to 2021. Covering an area of 3711 Ha in the year 2004, 1765 Ha in 2013 and 1541 Ha in the year 2021 (**Table 8**). The total decrease of 2170 Ha in 18 years. The total amount of vegetation was 14255 Ha in 2004. In 2013 it was 11882 Ha and in 2021, it is 12005 Ha which also shows a decreasing trend. The net decrease is 2250 Ha.

The development of rural and urban communities into agricultural land was discovered to be the reason for the rise in built-up areas. The Human settlements of the study area show an increasing trend from 2004 to 2021. In 2004, settlements covered an area of 14608 Ha, in 2013 it was 15562 Ha and in 2021 it turns into 16947 Ha. In the last 18 years, it increased as much as 2339 Ha.

The land cover category of barren land increased from 1990 Ha to 2524 Ha between the years 2004 to 2013. In 2021 it stays at the same amount as in 2004 after decreasing by 747 Ha. That means after 18 years the net change is 0.

The net change of forest land is also 0. In 2004, total forest of Parbatipur Upazila was 1990 Ha. In 2013 the forest land increased by 534 Ha and turns into 2524 Ha. In between (2013-2021) it's again decreased by 534 Ha. That means the forest land remains 1990 Ha now (**Figures 16-18**, **Table 11**).

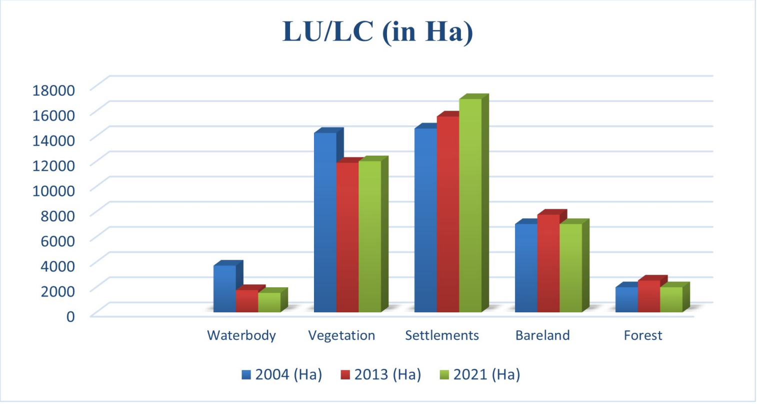

Figure 16. Areal distribution of LULC classes.

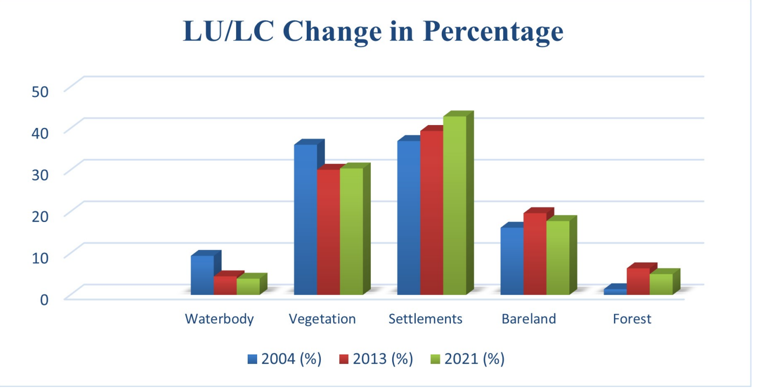

Figure 17. Areal distribution of LULC classes in percentage.

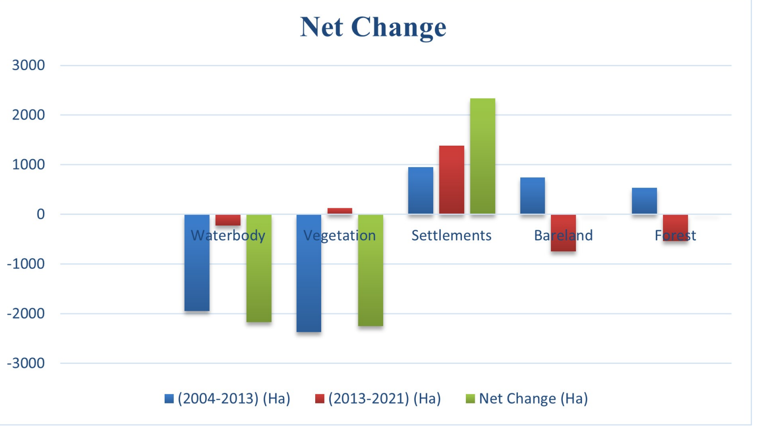

Figure 18. Net change in areal extent (Ha).

Table 11. Net change in areal extent (Ha) of land cover.

LULC Classes	(2004-2013) (Ha)	(2013-2021) (Ha)	Net Change (Ha)
Waterbody	−1946	−224	−2170
Vegetation	−2373	123	−2250
Settlements	954	1385	2339
Bareland	747	−747	0
Forest	534	−534	0

3.1.6. LULC Validation and Accuracy Assessment

To verify the reliability of the classified LULC maps, an accuracy assessment was performed using an independent validation dataset. Reference information was derived from high-resolution Google Earth imagery along with a limited number of field verification points collected from the study area. For each year (2004, 2013, and 2021), a total of 150 stratified random validation points were utilized to evaluate classification accuracy.

A confusion matrix was generated for each classified map to assess its classification performance. Based on this matrix, key accuracy indicators such as overall accuracy (OA), producer's accuracy, user's accuracy, and the Kappa coefficient were calculated.

The classification outcomes (Table 12) demonstrated a high level of consistency between the classified results and the reference data. Overall accuracy values varied from 86% to 91% over the three examined years, while the Kappa coefficient ranged between 0.82 to 0.88, reflecting strong to near-perfect agreement based on standard evaluation criteria. These validation findings indicate that the LULC classification results are dependable and appropriate for multi-temporal change detection studies.

Overall, the accuracy assessment confirms that the generated LULC maps are statistically robust and can be reliably used for temporal change analysis as well as groundwater vulnerability assessment.

Table 12. LULC classification accuracy.

Year	Overall Accuracy (%)	Kappa Coefficient
2004	86%	0.82
2013	89%	0.85
2021	91%	0.88

The above analysis shows that most people in the study area are not concerned about their groundwater condition and its future state. People already face a lack of drinking water during the summer season. Drought occurs in that part of the country quite regularly. A progressive declining trend of groundwater levels is possibly due to a lack of replenishment and/or over-exploitation of groundwater resources. Geographically the area is 30 - 35 meters above from sea surface. Underground coal mining along with this geographical disadvantage gear up the process of high groundwater vulnerability in those areas. If the quantity of vulnerability increases at the calculated rate, it will be disastrous for the people and the social environment of the study area. The LULC of these areas is changing at an alarming rate. It also shows that the agricultural environment suffers damage because of the lack of water for irrigation which may end up with food insecurity. The most alarming matter is that the people of these areas are not well aware of it and they have no training or knowledge about water resources management. No organization of Govt. or non Govt. is active to train them on how to save water and harvest rainwater for the future and how not to waste it.

The rapid transformation of LULC (land use and land cover) in urban areas is becoming a significant issue for Bangladesh's northern region. Human settlement is in a higher increasing trend while vegetation land is decreasing in quickly time which is also not good for the natural environment. Because of industrialization, which includes coal mining operations here, this fast shift is presently happening at an unprecedented rate.

Although the southern portion of Parbatipur Upazila shows relatively high groundwater vulnerability, the DRASTIC and modified DRASTIC-LU models used in this study mainly reflect intrinsic hydrogeological conditions and land use effects, rather than the direct influence of specific human activities. The Barapukuria underground coal mine may play a role in localized groundwater stress through processes such as dewatering and surface disturbance; however, this research does not incorporate direct hydrogeological or geochemical evidence (such as groundwater level decline data, water quality measurements, or spatial proximity analysis to mining areas) to quantitatively assess its impact.

As a result, coal mining should be viewed as a possible contributing factor rather than the main cause of the observed vulnerability patterns. The higher vulnerability in the southern region is more convincingly attributed to factors such as shallow groundwater depth, highly permeable aquifer materials, increased recharge rates, and expanding human activities—particularly settlement growth—as represented in the DRASTIC and DRASTIC-LU assessments.

Based on these outcomes, it is clear that effective management strategies, continuous monitoring, and the use of geospatial technologies are necessary to address emerging environmental issues. Remote sensing and GIS-based techniques offer powerful tools for tracking land use and land cover changes and forecasting future trends. Such approaches can support better decision-making and contribute to the development of sustainable measures for reducing groundwater vulnerability and managing urban expansion in the study area.

4. Conclusion

The purpose of this study is to analyze the realities of groundwater current condition, vulnerability analysis, Different groundwater parameter mapping and LULC change for the last 20 years approximately. Due to unique geographical features, and the study area is higher than any other part of Bangladesh which makes the study area more vulnerable to drought. Underground coal mining also has a big impact on the area. The geo environment such as lithology or stratigraphy will be endangered due to underground coal mining activities. From this study I have arrived at the following major conclusions:

We used the DRASTIC parameter for analyzing groundwater vulnerability in this area which is important for the validity of this method. The DRASTIC method is rigid in the assignment of ratings and weights to the model parameters. In this study, detailed hydrogeological field studies were performed to reduce the margin of error. The rating values of parameters were determined, dependent on the field and regional properties of the study area.

The DRASTIC vulnerability index shows that over one-third of the study area is facing higher groundwater vulnerability which is very alarming for the local people. The considerable groundwater vulnerability in certain places is exacerbated by underground coal mining and this geographic disadvantage. It also demonstrates the harm that a shortage of irrigation water does to the agricultural environment, which may lead to food poverty. A steady decline in groundwater levels may be caused by inadequate replenishment or excessive groundwater use.

The Modified DRASTIC-LU Vulnerability Index shows, 48% of Parbatipur Upazila belongs to a very high groundwater vulnerability zone, while 19% area belongs to a high vulnerability zone and the rest of the 33% area belongs to a moderate vulnerability zone.

Through the combination of GIS and Remote sensing methods between 2004 and 2021, the study has employed the classification approach to detect environmental change as well as land use and land cover changes in the Parbatipur Upazila of Dinajpur district. Nevertheless, a few restrictions could have an impact on the study's findings; to start, cloud cover may skew satellite data, and seasonal changes can change the number of water bodies and vegetation. Second, some of the areas in the study region were categorized as vegetation cover during the training sample because they were hidden in plant material, which can have an impact on the pixel value for prediction results.

Using maximum likelihood classification, the supervised classification has been done based on four different LULC types: water body, bare land, forests, settlements, and vegetation index. As vegetation cover dominated the research region, GIS analysis was used to map the change over several time periods, revealing an alarming pattern in the decline of thick vegetation. The water body of the study area shows a decreasing trend from 2004 to 2021. The trajectory of human population growth is outpacing the rapid decline of vegetative land, which is bad for the environment. This rapid transition is currently occurring at an unheard-of rate as a result of industrialization, which includes coal mining activities here. Due to the beginning of mining operations at the Barapukuria coal mine in this location, the built-up area's density rose in 2021 compared to 2004.

Only competent management planning and monitoring can respond to emerging problems swiftly and effectively. By using satellite images and associated data, we may predict future changes and respond appropriately to upcoming changes in urban growth. GIS (Geographic Information Systems) and remote sensing are useful but very affordable technologies for understanding the spatial and temporal dynamics of LULC. Remote sensing, which is helpful for the patterns and processes of LULC change, provides multitemporal data, whereas GIS is helpful for mapping and analyzing such patterns. The vast majority of wealthy nations have access to up-to-date and comprehensive LULC data, although Bangladesh and other developing nations frequently lack such resources. In these situations, objective evaluation of environmental changes utilizing GIS and remote sensing technologies can offer crucial information that can help policymakers execute programs more sustainably.

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Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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Appendix

Table A1. Observation wells properties.

Observation Bore	Transmissivity (m^2/d)	Storativity	Specific Yield
PM1	1033	0.0001	0.001
PM2	1411	0.017	0.1
PM3	128	8.5×10^{-5}	0.06
PM4	275	0.0018	0.29
PM5	450	0.004	0.16
PM6	754	3.70×10^{-5}	0.0014
PM7	289	8.4×10^{-5}	0.034
PM8	1207	0.03	0.1

(Source: Asia Energy Corporation (Bangladesh) Pty Limited, 2005).

Table A2. Pumping test record.

Well Name	Easting	Northing	Screen Elevation (m)	Screen ID	Time (d)	Water Level (m)
PM1/OW1	697297.8	2821781	95.5	A	0	3.32
					0.75	9.142
					0.9	9.176
					0.98	9.198
					1.06	9.218
					1.31	9.245
PM2/OW2	697305.6	2821854	95.5	A	0	3.45
					0.77	3.816
					0.98	3.865
					1.25	3.917
					1.4	3.902
					1.83	3.968
PM3/OW3	697331.2	2821746	37.5	A	0	3.598
					0.9	9.857
					1.4	9.9
					1.67	9.92
					1.93	9.96
					2.08	9.993
PM4/OW4	697618.0	2820636	46.5	A	0	2.322
					1.25	3.025
					1.33	3.06
					1.42	3.094
					1.58	3.14
					1.67	3.145

Continued

PM5/OW5	697634.8	2820567	38.5	A	0	1.59
					1.19	2.97
					1.69	3.29
					1.85	3.31
					2.02	3.34
					2.27	3.37
PM6/OW6	699218.5	2820744	57.5	A	0	3.92
					0.93	6.06
					1.09	6.06
					1.3	6.08
					1.51	6.12
					1.68	6.13
PM7/OW7	699254.7	2820707	40	A	0	4.072
					1.09	6.762
					1.34	6.785
					1.51	6.812
					1.68	6.816
					1.93	6.868
PM8/OW8	699318.5	2820700	47.5	A	0	3.99
					0.92	4.365
					1.08	4.354
					1.26	4.368
					1.51	4.412
					1.67	4.412

(Source: Asia Energy Corporation (Bangladesh) Pty Limited, 2005).

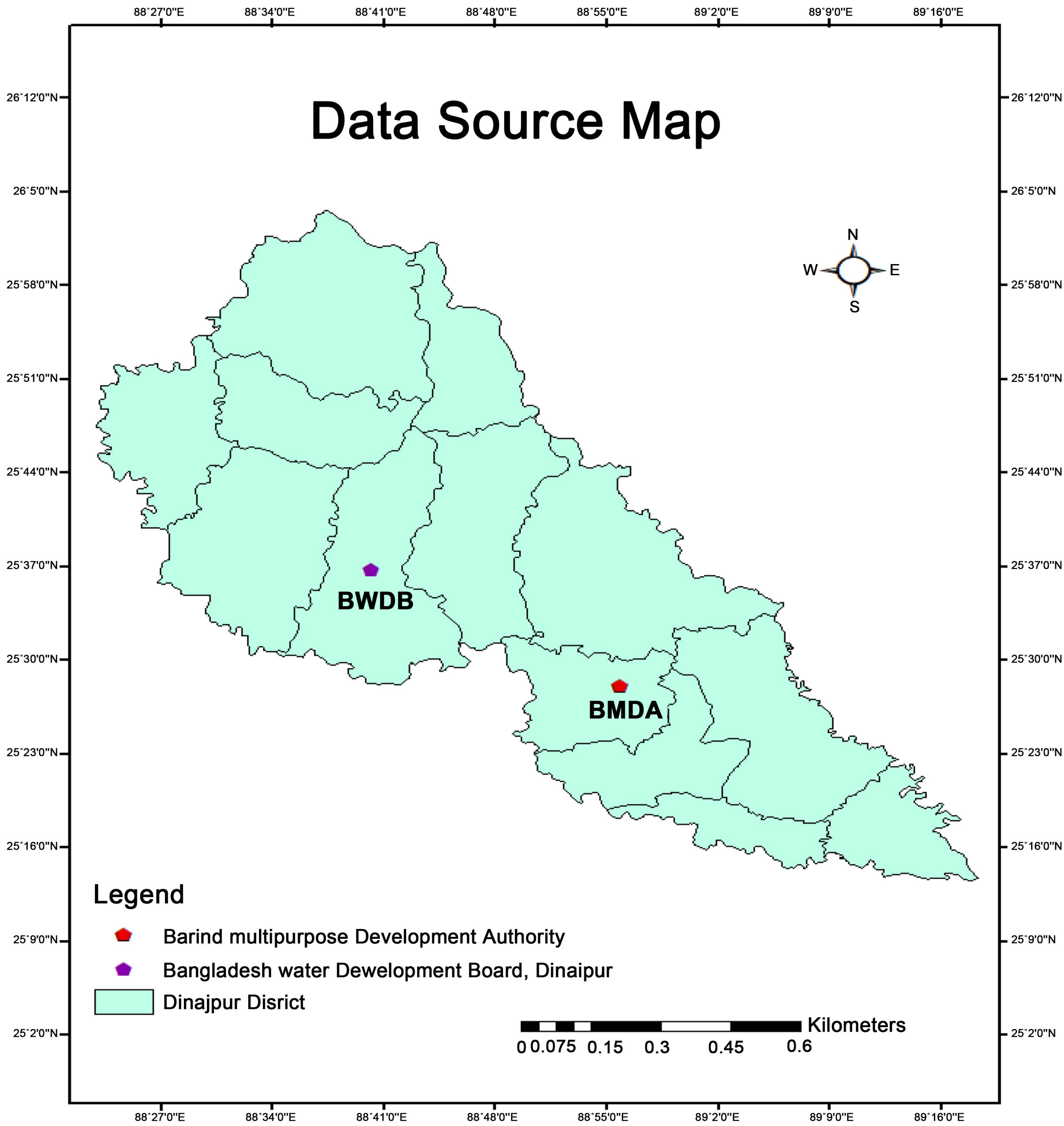

Figure A1. Data source map.