ENVIRONMENTAL VULNERABILITY ASSESSMENT IN THE SOUTH-WEST COASTAL REGION OF BANGLADESH USING PRINCIPAL COMPONENT ANALYSIS

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Being located in a low-lying coastal zone and having a unique brackish water ecosystem, the South-west region of Bangladesh is highly susceptible to environmental vulnerability. An assessment of environmental vulnerability over this large area of 24,188 km^2 is a complex process and one of the most essential parts for any coastal zone management. Since the changes in the environmental indicators are posing adverse impacts, the environment tends to be more vulnerable. This study assesses the environmental vulnerability in 40 Upazilas (lower level of the administrative unit) in the South-west region of Bangladesh. After reviewing the literature, this study incorporated 10 relevant indicators (i.e. soil type, average temperature, vegetation change, population density, population change, road density, surface salinity, Cumulative Dry Day (CDD), Cumulative Wet Day (CWD), groundwater level). Principal Component Analysis (PCA) was applied to find the weight for each indicator in IBM SPSS 20 software and the values were normalized into a unified dimension. The generated environmental vulnerability map is assorted into five vulnerability groups consisting of very low, low, medium, high, very high vulnerabilities with an interval of 0-0.05, 0.05-0.4, 0.4-0.5, 0.5-0.6, 0.6-1.0 respectively. From the spatial analysis, it has been seen that the vulnerability groups representing very low, low, medium, high, and very high contain 10%, 35%, 28%, 17%, and 10% of the Upazilas, respectively. The findings of environmental vulnerability assessment can support effective guidance for long-term environmental management in terms of coastal zone management. The development framework can be assessed at different spatial and temporal scales in the coastal zone with the availability of environmental indicator data and by applying the PCA method.

Keywords: Environmental vulnerability, Principal Component Analysis (PCA), south-west region, coastal zone, Bangladesh

INTRODUCTION

The global and regional environment is experiencing unprecedented stress and deterioration due to climate change, economic development, and human activities (Blanco et al., 2017; Chen et al., 2016; He et al., 2017; A. Li et al., 2006; Liang et al., 2017; Liang et al., 2017). Therefore, environmental vulnerability assessment has become crucial in recent years. This environmental evaluation practice was first introduced in the 1960s as a tool to access the environmental situation (He et al., 2018). Due to overestimation and underestimation of the environmental impact (Basso et al., 2000) new concept of environmental vulnerability focusing on vulnerability analysis is introduced (Wang et al., 2008; Weston, 2004).

As a new branch of environment assessment, many methods have been proposed, such as the comprehensive evaluation method (Wang et al., 2008), the fuzzy evaluation method (Adriaenssens et al., 2004; Enea and Salemi, 2001), the gray evaluation method along with the artificial neural-network evaluation method (Džeroski, 2001; Hao and Zhou, 2002; Park et al., 2004) and the landscape evaluation method (Kangas et al., 2000). The indicators used in these models are not always easy to be acquired and operated. For example, the neural-network method needs several historical data, which especially is a problem of using existing domain knowledge in the learning process (A. Li et al., 2006; M. Li et al., 2006). Moreover, the methods developed for a small spatial scale have been confronted with serious criticism when used at the regional level (DeAngelis et al., 1990; Suter, 1993), where information may be available on terrestrial and aquatic ecosystems, land-use changes, and a variety of simultaneous stressors (Tran et al., 2002). Hence, regional environmental vulnerability assessment remains a great challenge (Boughton et al., 1999; Jones et al., 1997).

According to IPCC, vulnerability is defined as a function of exposure, sensitivity, and adaptive capacity (Parry et al., 2007). Exposure refers to the system which is affected by natural disaster. As the concept of environmental vulnerability is yet to be fully expounded, the development of vulnerability indices should be conducted at smaller scales and must be context-specific (Beroya-Eitner, 2016; Schwarz et al., 2011; Sietz et al., 2011; Tubi et al., 2012). Therefore, it's a challenge to identify those indicators that can capture environmental vulnerability attribute from the diverse and often

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incommensurate data. Though many studies on vulnerability assessment of environmental services can be found, research on environmental vulnerability assessment is very few comparatively.

In recent years remote sensing (RS) and geographic information system (GIS) has become a powerful tool to assess the environment in macro or micro spatial scale (Krivtsov, 2004; MacMillan et al., 2004; Store and Jokimäki, 2003). RS and GIS have few important features such as it can generate new information by integrating the existing datasets having with the spatial referencing system (Goodchild, 1993). RS and GIS technique has become a mostly wide used tool to assess regional ecological risk (Gaudet, 1994; Xu et al., 2004), environmental degradation (Bastin et al., 1995; Holm, 2003), and landscape changes (Gobster et al., 2000; Gustafson et al., 2005), studies addressing regional environmental vulnerability evaluation are limited.

Bangladesh is a developing country and environmental problem is not only our country focus but also it is a hot topic in the world. In the last 20 years, Bangladesh has been experiencing rapid economic growth and urbanization with an average annual growth rate of 7% in the Gross Domestic Product (GDP). However, the coastal regions of Bangladesh represent more rapid economic growth than those in the other regions. Lack of synchronized development of private firms and industrial structure cause the regional disparity. The urbanization rate of the country has increased to 28.1% in 2011 from 5% in 1974 (World Bank 2012). These types of rapid economic growth and urbanization lead to severe environmental problems, such as atmospheric pollution, water contamination, waste pollution, forest deficit, water and soil loss, desertification, and accelerated extinction of biologic species. These environmental problems have adversely affected human health and economic development. This situation indicates that environmental problems may seriously restrict sustainable development and economic development achievements. Therefore, it's an urgent and indispensable task to evaluate environmental vulnerability in Bangladesh. However, little research has focused on environmental vulnerability assessment in Bangladesh at a division or specific zone level because of the construction difficulty of the environmental vulnerability assessment frame and data limits.

Integration of GIS and Multi-criteria analysis (MCA) is a useful tool to evaluate Environmental vulnerability and it helps decision-makers understand the various impacts of natural and fictitious elements on the environmental system. Under this circumstance, evaluating environmental vulnerability is necessary to make implications for environmental conservation and management.

STUDY AREA

The study area (figure 1) is situated in the south-west region of Bangladesh's coast. It is the low-lying zone of the country and has a unique brackish water ecosystem. In the west of the area, the River Hariabhanga along the India–Bangladesh border is situated. The world’s largest mangrove forest, the Sundarbans is situated in the south of this region along with the Bay of Bengal. An assessment of environmental vulnerability over this large area of 24,188 km^2 is a complex process and one of the most essential parts for any coastal zone management. This study assesses the environmental vulnerability in 40 Upazilas (lower level of the administrative unit) in the South-west region of Bangladesh.

Sundarbans has great ecological importance in shoreline stabilization, reduction of coastal erosion, sediment and nutrient retention, storm protection, flood and flow control, and water quality (Shibly and Takewaka, 2013). It protects the South-west region from natural hazards and provides the livelihood for 3 million people (Hossain et al., 2016). The freshwater flows through the coastal region from upstream to the Bay of Bengal. There is a constantly fresh and saline water interaction in the coastal region of Bangladesh. Reducing freshwater flow made the intrusion of salinity goes into the upstream. Salinity intrusion in the region occurs during the dry season (December–March). Salinity magnitude is the maximum in this South-west region (Akter et al., 2019). Due to the high salinity level, inhabitants of these regions are more dependent on groundwater. Over dependency and reduced upstream freshwater affects the groundwater level. Thus, the coast of Bangladesh is known as a zone of multiple vulnerabilities as well as opportunities. It is prone to several natural and man-made hazards, such as storm surges, erosion, high arsenic content of groundwater, waterlogging, water and soil salinity, etc. (Hussain et al., 2012).

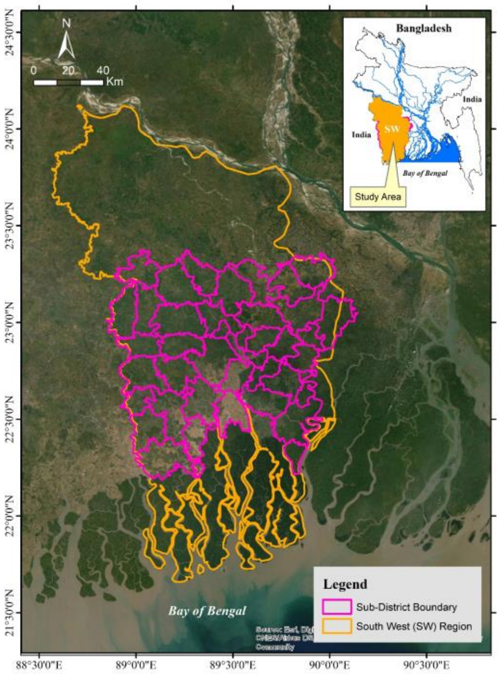

Figure 1. Study Area

METHODOLOGY

This study aimed to quantify the environmental vulnerability of the study area by assigning and aggregating weights to ten individual indicators of environmental vulnerability. Figure 2 outlines the major steps that were undertaken:

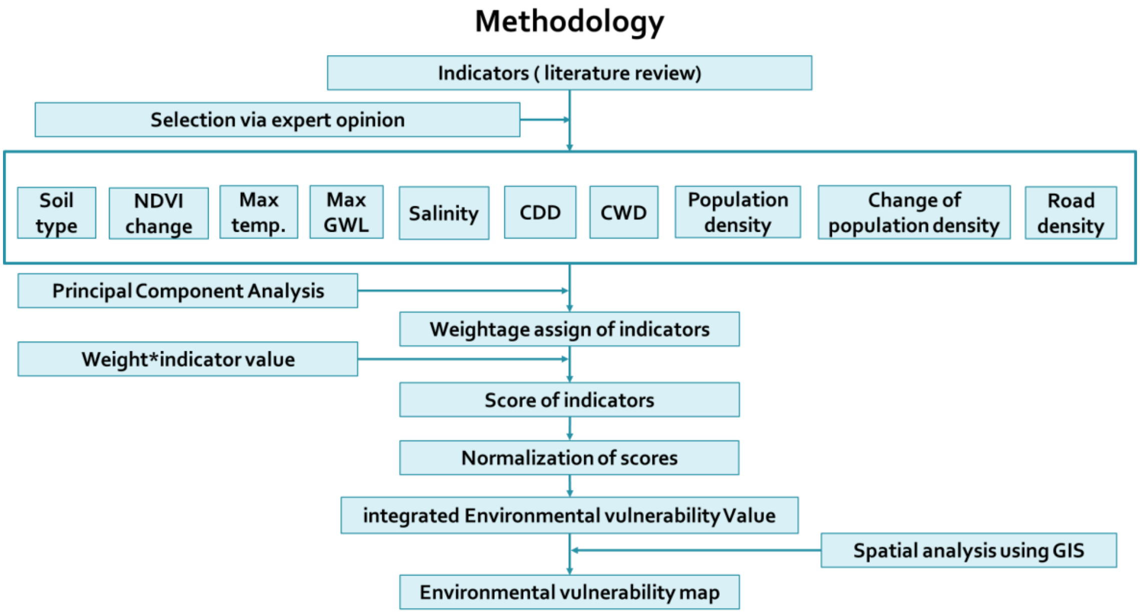

Figure 2. The methodology steps used in the study

Indicator Selection

The environment is affected by various natural and human indicators. It is important and essential to select appropriate indicators for environmental vulnerability evaluation. In order to synthetically analyze environmental vulnerability in the coastal area of Bangladesh, ten indicators were initially selected after the literature review (Table 1) and considering the geographic position, climate condition, soil type, and anthropogenic situation. It should be noted that this selection was not exhaustive and that only those salient indicators for which information is of great significance were considered.

Table 1: Indicators used in assessing environmental vulnerability in the coastal zone of Bangladesh

Indicators	Reviewed Paper
Soil type	(Ifeanyi et al., 2010; A. Li et al., 2006; Liu et al., 2017; Wang et al., 2008)
NDVI change	(Ifeanyi et al., 2010; A. Li et al., 2006; Liu et al., 2017; Rahman et al., 2014; Akter et al. 2019)
Max temperature	(A. Li et al., 2006; Liu et al., 2017)
Max Groundwater level	(Zabeo et al., 2011)
Salinity	(Zabeo et al., 2011)
Cumulative dry day (CDD)	(Zabeo et al., 2011)
Cumulative wet day (CWD)	(Zabeo et al., 2011)
Population density	(A. Li et al., 2006; Liu et al., 2017; Rahman et al., 2014; Wang et al., 2008; Akter et al., 2019)
Change of Population density	(Tran et al., 2002)
Road density	(Wang et al., 2008; Akter et al., 2019)

Data Sets and Sources

In this present study, ten indicators were selected from the literature review for vulnerability assessment (Table 2). A wide range of datasets was used to explore selected indicators. These data were collected from remote sensing data, data published in statistics and reports. The selection of data sources should be influenced by their accuracy and resolution, together with the nature of the problem to be investigated.

Table 2: Details the characteristics of datasets used in the current study.

indicators	Indicator description	Data description
Soil type	Topsoil texture	Data source: SRDI Data unit: km^2
NDVI change	Vegetation cover over the surface	Data Source: Landsat 8 and 5 Satellite data Data unit: 30m resolution
Max temperature	Monthly maximum temperature	Data Source: BMD Data unit: Daily temperature (^oC)
Max Groundwater level	Dry season Groundwater level below from the surface	Data Source: BWDB Data unit: Weekly data (m)
Salinity	Average saline intrusion level	Data Source: www.deccma.com Data unit: salinity magnitude in ppt
Cumulative dry day (CDD)	Amount of Continues dry day	Data Source: Calculated from BWDB data Data unit: Days
Cumulative wet day (CWD)	Amount of Continues wet day	Data Source: Calculated from BWDB data Data unit: Days
Population density	Population number per unit area	Data source: BBS,2011 Data unit: Number of populations per unit Upazila area (km^2)
Change of Population density	Change in population number per unit area in the specific period	Data Source: BBS,2011 Data unit: percentage of population change per unit Upazila
Road density	Coverage of road compared to the land	Data Source: BBS,2011 Data unit: percentage of road per unit Upazila

The degree of vegetation degradation is derived by comparing the Landsat 5 and 8 satellite data for November of 2011 and November of 2019. The last 30 year's climate and groundwater level data were collected from Bangladesh Metrological Department (BMD) and Bangladesh Water Development Board (BWDB). Climate extreme indices (i.e., CDD and CWD) was derived from freely available software called Rclimdex (Nowreen, Murshed, Islam, Bhaskaran, & Hasan, 2015). This software was developed by ETCCDMI (Expert Team on Climate Change Detection Monitoring and Indices) and can be downloaded from the ETCCDI website (http://etccdi.pacificclimate.org/software.shtml). Soil type and salinity coverage of the study area were obtained from the SRDI (Soil Resource Development Institute) and DECCMA (Deltas, Vulnerability, and Climate Change: Migration and Adaptation) project, respectively. Human activities such as population density, road density were collected from the Bangladesh Bureau of Statistics, 2011 (BBS, 2011)

Principal Component Analysis (PCA)

It is crucial to converting data of climate condition, land use/land cover, soil and water losses, and landform into an integrated evaluation index to evaluate the environmental condition (Munda et al., 1994). Transformation of the original variables into new and uncorrelated variables (axis), namely principal components which are linearly combined with original variables is the design principle of Principal Component Analysis (PCA). In maximum variance's direction, new axes lie along. Indices of this type can be found objectively, provided by PCA so that the data set's variation can be concisely accounted for (Wheeler et al., 2013). Information on the most distinctive parameters on which original information remains intact even after data reduction is provided by Principal components (PCs).

PCA can be expressed as:

$$Y_i = a_{i1}x_1 + a_{i2}x_2 + a_{i3}x_3 + \cdots \dots \dots \dots . + a_{im}x_m \qquad (1)$$

Where Y is the component score, a is the component loading, x is the measured value of a variable, i is the component number, and m is the total number of variables.

In Multiband spatial data, data attributes are transformed into a new multivariate attribute space whose axes rotate with respect to the original space. Axes are uncorrelated in new space. PCA gives results in the form of the multiband new spatial data set which has an equal number of bands like original data. The greatest variance will be in the first principal component, while the second will express the second most variance where the first doesn't describe it. 95 percent of the total variance is represented by the first three to four layers (PC's) in many cases, so that the principal component's remaining layer may be dropped. Conventional orthogonal functions lag behind than PCA Functions as they are developed from the data matrix as unique functions and not of predefined forms. This has particular usefulness if the nature of component patterns is unknown in advance (A. Li et al., 2006). So in this study, the PCA was used for the evaluation of environmental vulnerability. The formulae of PCA evaluation are:

$$E = r_1Y_1 + r_2Y_2 + r_3Y_3 + \cdots \dots \dots \dots + r_nY_n \qquad (2)$$

where E is the environmental synthetic evaluation index, r is the contribution ratio of the principal component, Y is the principal component, and n is the number of principal components retained, and

$$r_{i=} \frac{\lambda_i}{\sum_{i=1}^{m} \lambda i} \qquad (3)$$

Where r_i is the contribution ratio of the ith principal component and i is the eigenvalue of the ith principal component.

The obtained results from the PCA model were continuous values and were classified into different environmental vulnerability levels. The PCA model has continuous values and these values were classified into several classes to explore environmental vulnerability levels. This classification is the most important thinks to evaluate vulnerability so it should be objective and logical. The natural breaks classification (NBC) is a graphical tool and it can explore the statistical distribution of the classes and clusters in the attribute space. Because the classes are based on the natural grouping of the data. NBC can also identify breakpoints by picking the class breaks that group similar values and maximize the differences between classes, and the features are divided into classes whose boundaries are set where there are relatively big jumps in the data values. This study applied the NBC to discrete computed values through analyzing natural properties of the computed values to line out dividing points between clusters.

Weightage Assigned

Selected indicators were analyzed using Statistical Package for the Social Sciences (SPSS) software. The cut if the value was used as 1.0 for eigenvalues and a total of three PCs were extracted (Table 3), which accounted for 74% of the total variance.

Table 3: Eigenvectors of the correlation matrix of the indicators

Indicators	PC1	PC2	PC3
Soil	0.351241	0.675620	0.120301
NDVI change	0.026287	0.513143	0.091370
Average max temperature	-0.407230	0.296385	0.052774
Dry season GW level	0.082766	0.541383	0.096398
Salinity	0.100161	0.550081	0.097947
CDD	0.474662	0.737331	0.131289
CWD	-0.207800	0.396099	0.070529
Population density	0.339480	0.669740	0.119253
Population density change	0.266377	0.633188	0.112745
Road density	0.206266	0.603133	0.107393

Finally, Table 4 represents the weight of every indicator and this weight of each factor was calculated following equation:

$$Y_{ij} = \frac{X_{ij} - X_{min,j}}{X_{max,j} - X_{min,j}} \qquad (4)$$

Where Y_{ij} represents the standardized value of factor j of grid i, varying from 0 to 1, X_{ij} represents the measured value of factor j of grid i, and $X_{min,j,}$ and $X_{max,j}$ represents the minimum and maximum value of factor j of grid i, respectively.

Table 4: The weight of every indicator

Indicators	Weight
Soil	0.120301
NDVI change	0.091370
Average max temperature	0.052774
Dry season GW level	0.096398
Salinity	0.097947
CDD	0.131289
CWD	0.070529
Population density	0.119253
Population density change	0.112745
Road density	0.107393

Vulnerability Assessment Following IPCC And PCA Methods

The vulnerability can be calculated from indicators and in the linear form of exposer, sensitivity, and adaptive capacity according to IPCC TAR. The formula according to TAR (IPCC, 2007) is described as

Vulnerability = Exposure × Sensitivity−Adaptive Capacity

In IPCC AR4, vulnerability is defined as a function of exposure, sensitivity, and adaptive capacity. Vulnerability according to IPCC AR5 is computed as a linear relation of sensitivity and adaptive capacity. The formula for the vulnerability used for this study is:

Vulnerability = Sensitivity−Adaptive Capacity (Hoegh-Guldberg et al., 2014)

For our study purpose, the selected indicators are sensitive to the environment. As a result, the integration of our all indicators represents the environmental vulnerability of our study area. The integration process was done following eq. 5

In this study, every factor was assigned weight using PCA. The environmental vulnerability assessment map was created based on indicators weight with the support of the algebraic computation as given in eq. 5. The higher the environmental vulnerability value represents the more vulnerability of the environment.

$$\text{Environmental vulnerability} = \sum B_1 \times B_2 \times \dots\dots\dots\dots\dots\dots \times B_n \qquad (5)$$

Where B is the major groups of indicators.

$$B = \sum_{i=1}^{n} v_i \times w_i \qquad (6)$$

Result

The generated map for the individual indicator is divided into five vulnerability groups consisting of very low, low, medium, high, very high vulnerabilities with an equal interval of their collected data. The environmental vulnerability map is also assorted into five vulnerability groups consisting of very low, low, medium, high, very high vulnerabilities with an interval of 0-0.05, 0.05-0.4, 0.4-0.5, 0.5-0.6, 0.6-1.0 respectively.

Spatial Distribution of Indicators

Surface soil plays a vital role in growing plants and vegetation and reducing topsoil erosions. The compacted properties of soil help to prevent erosion. The higher water holding capacity of soil can lead to land improvement. From our analysis, it was found that 62.5% of soil is clay, 32.5% is clay loam and 5% is sandy (Figure 3(a)). From the agricultural importance, soil quality is favorable to the environment in this area.

Vegetation helps in stopping environmental degradation and loss of biodiversity. Climate change-related sea level rise and saline intrusion are likely to create an adverse impact on present vegetation type. The rapid vegetation change hampers the present eco-environmental behavior. NDVI changes had been measured from the difference of 2001 to 2011 vegetation cover. Within 11 years difference, about most of the area is observed moderate to high vegetation change (figure 3(b)). The eastern part of the area shows the decrease of vegetation whereas the western part shows the increase of vegetation. This is very concern for environmental vulnerability assessment.

Groundwater has been depleting at an alarming rate due to a lack of fresh surface-water availability in the coastal zone. A high level of saline intrusion in the surface water makes it impossible to use for irrigation and household purpose. Population stress and demand is mainly responsible for groundwater depletion. Prolonged groundwater depletion was found in the landward part of the study area as urbanization and population density is higher in that part (figure 3(c)).

The major crop of Bangladesh is rice, which is vulnerable to increased temperature. At the high ranges of temperature, the rice crops drop their yield (Rahman et al., 2007). Due to the climate change impact, the overall temperature is increased in this country. The spatial variation of temperature can be observed in the South-west region (Figure 3(d)). About 50% of the area on average experience more than 30°C temperature over the year.

Cumulative Dry Day (CDD) means to sum up of consecutive dry days of a year. With the increase of temperature, the CDD is also increasing which will eventually make the environment more vulnerable. The soil loses enough moisture and salinity intrusion increases if the CDD increases. It has been observed that the eastern seaward part of the Southwest region has a moderate to a high level of vulnerability due to an increase of CDD (Figure 3(e)).

Cumulative Wet Day (CWD) is the sum-up of consecutive wet days of a year. With the increase of CDD, the CWD decreases and putting the environment at risk. Without enough rainfall, surface water dried up followed by lower recharge, excessive pumping of groundwater for irrigation and drinking purposes, and hot climatic conditions. The salinity level increases due to the low flow of freshwater from upstream. The western landward area shows a high value of CWD than other parts of this region (Figure 3(f)).

The salty water from the sea intrudes to fresh water and increases the level of salinity. This becomes extreme when the upstream freshwater flow reduces. Surface water is very important for irrigation, aquaculture, and water-related livelihoods. Salinity makes it impossible to be used for different purposes. This will result in the reduction of freshwater crops such as rice. In the southwest region of Bangladesh, the saline intrusion level is very high compared to the whole country. Especially the adjacent part of the Sunderbans Mangrove forest in Southern coastal shows a high level of environmental vulnerability due to high salinity (Figure 3(g)).

Road density is taken into consideration for environmental vulnerability assessment because pollution like fuel and gas emissions from traffic congestion is generated on the roads. As the selected study area is mostly rural, road density is low in most parts (Figure 3(h)). Big cities have a medium to very high road density and areas closer to Sundarbans have very low road density. Road density is followed by the high population density, urbanization and coastal development, and increase of tourist number.

The anthropogenic development and urbanization may create various kinds of pollution, such as disposal of household waste, uncontrolled construction, and emission from motor vehicles. Land used for other purposes is needed to be changed to residential land due to urbanization. The high density of the population is observed in the urban area. It is observed that population density is relatively low to medium in most parts of the Southwest zone as Salinity level has increased in that area over the past decades (Figure 3(i)). High density is found only in some important cities where industrialization and economic development have flourished. The uncontrolled growth of the population creates a negative impact on the environment.

In the Southwest region, the population change from 2001 to 2011 has been calculated. Most of the area shows medium to high population change (Figure 3(j)). The reason for the changes is due to the high salinity rate in many parts of this region. This can be the indication that the environment is gone in adverse for people to live. Sometimes people have migrated to big cities and other areas due to the adverse impact of salinity and difficulty in livelihoods.

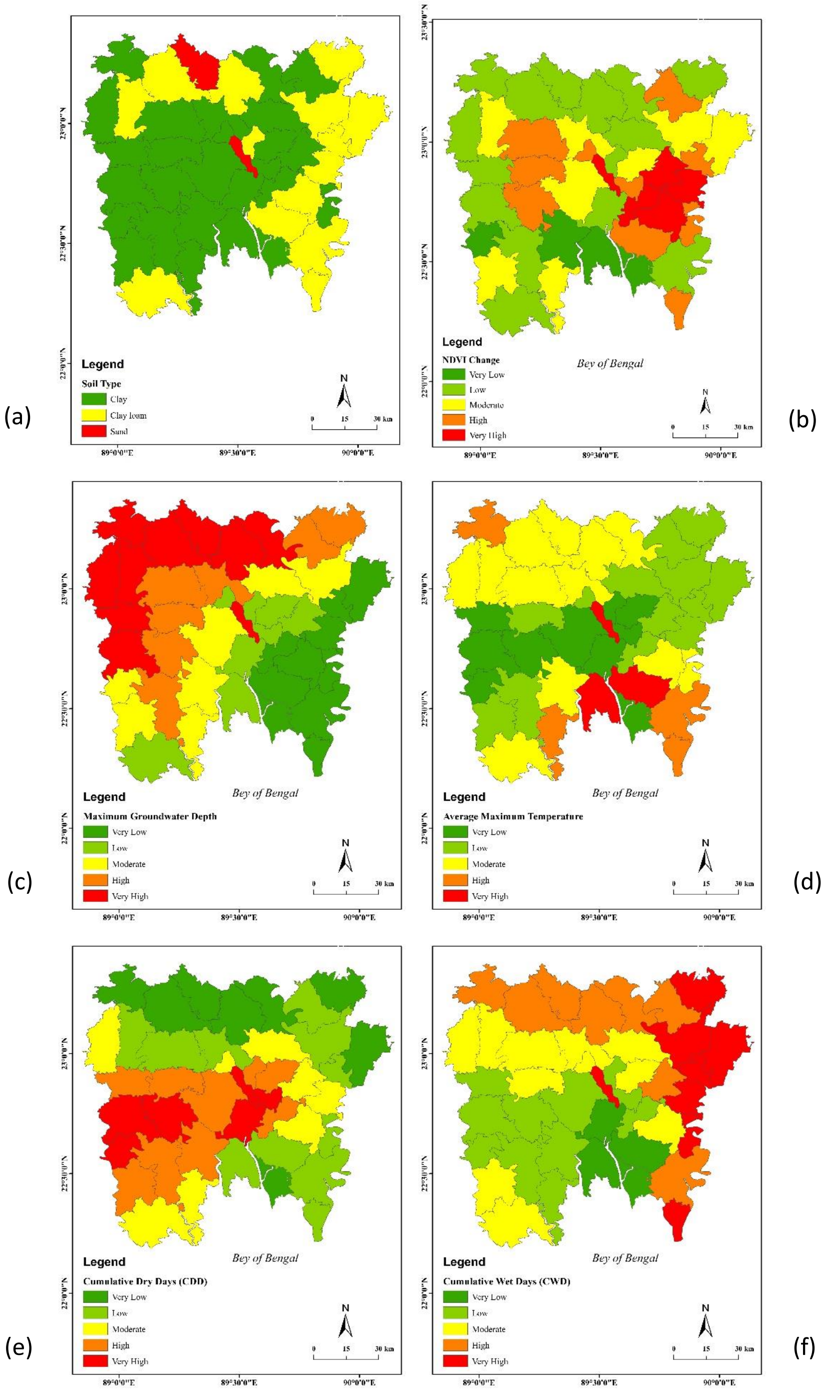

Figure 3. Spatial distribution of indicators: a) Soil type, b) NDVI change, c) Maximum Groundwater level, d) Average maximum temperature, e)CDD, f) CWD, (continues)

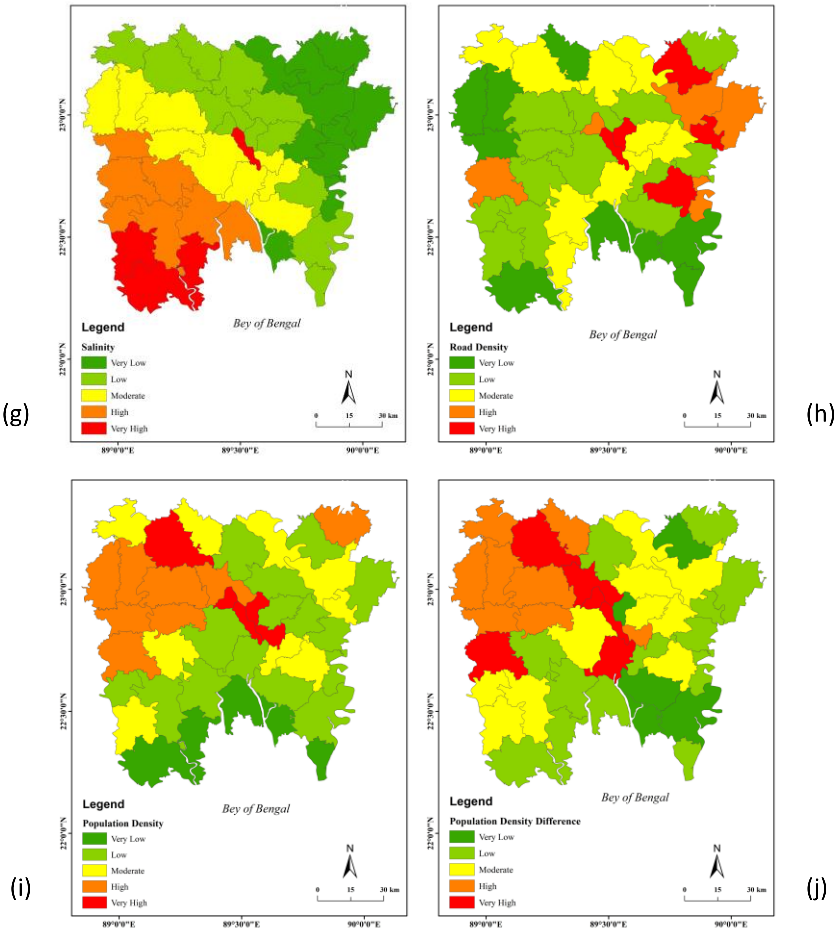

Figure 3. Spatial distribution of indicators: g) Salinity, h) Road density, i) Population density, j) Population density change

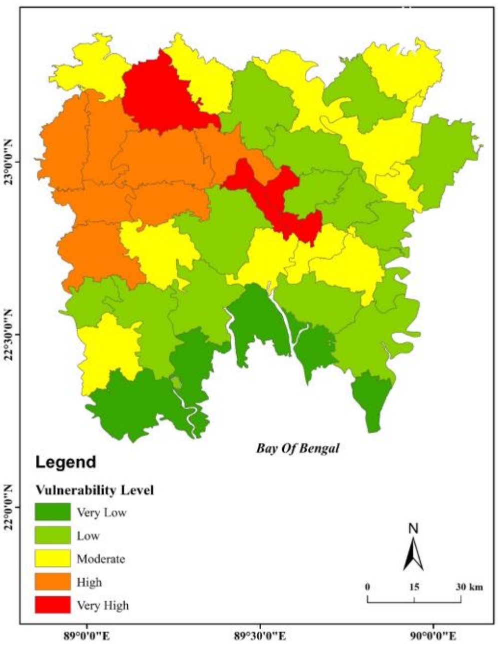

Figure 4. Spatial distribution of Environmental vulnerability

Driving Indicators in Environmental Vulnerability

From the spatial analysis, it has been seen that the vulnerability groups representing very low, low, medium, high, and very high contain 10%, 35%, 28%, 17%, and 10% of the Upazilas, respectively. The result in Figure 4 shows that the areas with very high and high levels of vulnerability are situated on the most landward side of the South-west coastal region whereas, the areas with a low and very low level of vulnerability are on the most seaward side and situated next to the Sundarbans mangrove forest. The seaward part has a relatively high salinity level and also decreasing population density. As a result, relatively low population density can be seen in this region. The low environmental vulnerability in this region is associated with low population density, low road density, and low values of CWD & CDD. On the other hand, urbanization and economic development have made the landward side more environmentally vulnerable.

Conclusion

The geological features of Bangladesh make it more vulnerable to the environment. It has a long coastline of 710 km and a vast population. The limited usable landmass force people to live close to the coast with lots of difficulties. This research considered ten indicators for assessing regional environmental vulnerability. GIS and RS techniques are integrated with the PCA to determine the weights of ten indicators. Comparing to other traditional methods, these techniques allow us to integrate various spatial information. The results show that more than half of the area is under the moderate to high-level environmental vulnerability zone. This scenario is very alarming. There should be monitoring of the condition of selected indicators so that vulnerability can be minimized in the South-west region. The framework shown in this paper is a modern and heuristic tool for a better understanding of environmental vulnerability. This study can be applied at different spatial and temporal scales considering relevant indicators for region-specific. The study has some limitations too. The data collected mostly from 2011 due to the unavailability of recent data. Recent data can make the study more appropriate. Also, we couldn’t get the migration data which can add a new dimension to the assessment. 30m resolution DEM is used for NDVI data. By using higher resolution the data set can be improved. There are only 2-3 weather stations in the southwest region which makes the data availability limited. In this study, PCA is used whereas the data set was not too large. Thus by overcoming the limitations we can observe and understand the impacts on the environment. With the available robust climate change model, future research might incorporate climate change into the environmental vulnerability framework. This research also a useful and effective tool that can provide policy-guidance for environmental conservation and management to reduce environmental vulnerability.

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