

Assessing Spatial Vulnerability of Bangladesh to Climate Change and Extremes: A Geographic Information System Approach

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Research Article

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Abstract

Regarding climate change, the world's most discussed issue for the last few decades, countries like Bangladesh are always noteworthy due to its susceptibility resulting from its geography, hazard proneness, and socioeconomic condition. Thus, this aimed to justify the hypothesis that Bangladesh has spatial diversity in sectors of Climate Change Vulnerability (CCV) by identifying the sectors of vulnerability and visualizing the spatial distribution of vulnerability through multivariate geospatial analysis in the GIS environment. For an integrated assessment of CCV, 38 indicators (socio-economic and biophysical) have been incorporated in the IPCC framework in raster form. Test statistics have shown Kiser-Meyer-Olkin (KMO) value is 0.73 and the p-value of Bartlett's sphericity is 0. The principal component analysis resulted in 6 principal components with 73.52% total explained variance. Sectors of CCV are the Climatic extreme event vulnerability (PC1), Meteorological shift vulnerability (PC2), Infrastructure and demographic vulnerability (PC3), Ecological vulnerability (PC4), Flood vulnerability (PC5), and Economic vulnerability (PC6) with Cronbach's alpha 0.90, 0.81, 0.88, 0.72, 0.72, and 0.66 respectively. Among 3 clusters (Jenks Natural break) of weighted averaged indices, the highly vulnerable cluster has shown that the PC1 has the highest magnitude with a score of 0.53–0.87, while the PC5 has the highest spatial coverage with 24 districts. The present study however is a new edition in climate vulnerability assessment in Bangladesh since it encompasses multivariate spatial analysis to demonstrate countrywide CCV. This study should be an important tool for setting adaptation and mitigation strategies from the root level to policymaking platforms of Bangladesh.

1. Introduction

In the present century, climate change is reportedly the greatest threat to our planet Earth. Climate change affects various aspects of the Earth system including weather, hydrology, ecology, and environment (Rahman and Lateh 2017). When climate parameters show a persistent shift (for a decade or longer) in the mean state which can be tested statistically, it can be termed as climate change (IPCC 2007). The standard period defined by the World Meteorological Organization for identifying changes in the state of the climate is 30 years (Javid et al. 2019). The Intergovernmental Panel on Climate Change (IPCC) has observed significant trends in temperature and precipitation around the world but with different magnitudes (IPCC 2014). Globally surface temperatures are rising though it is not uniform all over the world (IPCC 2007, Kerr 2009, Lorentzen 2014, Nick et al. 2009). The average temperature of the Earth risen approximately 0.85 °C from 1880 to 2012 and would increase between 0.3 and 4.8 °C by the end of the twenty-first century (IPCC 2013). Moreover, there are shreds of strong evidence that fluctuations in both global and regional rainfall patterns have already taken place along with global warming (Chadwick et al. 2016, Dore 2005, Feng et al. 2013). However, the degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes is termed as climate change vulnerability (IPCC 2007). In terms of climate change, low GDP countries are more vulnerable than higher ones, mainly because of the limited economic capacity to adapt to the impacts of climate change in the low GDP world (IPCC 1996). Particularly, countries where livelihoods are

mostly natural resource-dependent, are readily at risk to the negative impacts of forthcoming events from climate change (Heltberg and Bonch-Osmolovskiy 2011). Socioeconomic systems are more vulnerable in lower-income countries as the economic and institutional circumstances are not strong enough, additionally, the society and its interaction with the climate affect the climate change impact along with the biophysical characteristics (Fischer et al. 2005, IPCC 2014). Additionally, coastal countries are vulnerable to climate change since the sea-level rise and saltwater intrusion, directly and indirectly, affect water quality and quantity (Iyalomhe et al. 2015). Fluctuations in cyclone and precipitation patterns as a result of global temperature rise also make coastal regions vulnerable to climate change (Moser and Davidson 2016). Moreover, extreme climatic events including storm surge and coastal erosion affect various aspects of the coastal region especially the agricultural sector (Barbier 2015, Neumann et al. 2015, Glibert et al. 2014).

Bangladesh is among the most vulnerable countries in the world in the context of climate change and climate variability, extreme climatic events have become very frequent in the country (Uddin et al. 2019). With a fast-growing population at a rate of 1.37 percent, currently over 160 million with 1015 per km² (Dewan et al. 2012, DoE 2012), Bangladesh is expecting to be added by 20 million people (with 1200 per km²) by 2025 (Shaw 2015). The country is highly exposed to extreme climate conditions, including floods, cyclone-induced storm surge, coastal floods, riverbank erosion, drought, and an increasing trend of sea-level rise, saline water intrusion, and many more natural hazards (Dasgupta et al. 2014, Ruane et al. 2013). The loss of lives and assets is also very high in Bangladesh compared to other countries. For example, Cyclone Sidr in 2007 destroyed the entire economy of Bangladesh, and the total damages amounted to US\$ 1.67 billion (Hossain et al. 2020). The current incidence of floods in the northern part of Bangladesh and tropical Cyclone Mora affected an estimated 3.3 million people and 562,594 ha of crops in 2017 (DDM 2017). About 50 percent of the total cyclone death in the world occurs in this country (Haque et al. 2019). In the Long-Term Climate Risk Index (CRI), Bangladesh is 13th among the most affected countries concerning extreme events that occurred in the last two decades (Germanwatch 2021). The Notre Dame Global Adaption Index has categorized Bangladesh a highly vulnerable to climate change as well as ill-prepared to deal with its impacts (The Washington Post 2015). Bangladesh not only lies in the ranking of the most extreme weather-occurring countries as shown by the DW (2018) but also demonstrates a significant variation in both temperature and rainfall across the country as observed by Rahman and Lateh (2017). As a low-lying country on a mega delta, Bangladesh is particularly exposed to global sea-level rise that is caused by thermal expansion (warmer oceans expand) and by melting of glaciers, polar ice caps, and ice-sheets increasing the overall volume of the oceans (Das et al. 2020, ICCCAD 2019). Bangladesh has always been a disaster-prone country, and in addition to long-term changes to average climatic conditions, climate change is also causing more unpredictable and more extreme weather, leading to more frequent and/or more severe disasters (UNICEF 2016). The assessment of climate variability and change on the country level is a crucial issue because local and regional climate change often does not match the global climate change (Davies and Midgeley 2010). A local-level assessment improves the understanding of long-term climate variability and change and identifies the drivers of change at the country level or local scales (Ericksen et al. 2011). Vulnerability assessment is

very essential in the context of climate change as it paves the way for assessing adaptation options (McInnes et al. 2013). Vulnerability assessment is a matter of integrating natural processes, socioeconomic conditions, and the mechanisms of responses of the ecological and economic system (Chang and Huang 2015). Since the climate and weather of the country vary with the differences in geography, any study regarding climate change vulnerability would not be fruitful without spatial consideration in profiling vulnerability indicators (Abson et al. 2012, Davies and Midgeley 2010). It's worth mentioning that diverse geographical features, as well as heterogeneous climatic conditions, characterize Bangladesh (Rashid 1991). Though several studies have already been done regarding climate change vulnerability in different parts of Bangladesh (Ahmed et al. 2013, Ahsan and Warner 2014, Dasgupta et al. 2010), not covering the whole country. Moreover, the spatial consideration of vulnerability indexing using GIS is not introduced yet, except for a particular locale (Uddin et al. 2019) and particular sectors (Roy and Blaschke 2015). Therefore, a countrywide vulnerability assessment using geospatial analysis is worth considering.

In terms of climate change, vulnerability is a measure for risk level assessment as well as a directory to building resilience (Salinger et al. 2005). Vulnerability is the degree of susceptibility or incapability of a system to cope with the adverse effects of climate change, variability, and extremes (IPCC 2014). It is also defined as the ability or inability of individuals or social groups to cope with, recover from, or adapt to, any climate-induced stress (Kelly and Adger 2000). On the other hand, according to IPCC (2007), vulnerability is a function of the character, magnitude, and rate of climate variation to which a system is exposed, its sensitivity, and its adaptive capacity. The degree of climate stress upon a particular unit of analysis can be termed as exposure (Comer et al. 2012). Further, exposure can be defined as the experiences of disturbances in the internal and external system (Abson et al. 2012). The reaction of a system to climate hazards is called sensitivity (Preston and Stafford-Smith 2009). Sensitivity is variable as it depends on location, sectors, and population. According to Gallopín (2003), sensitivity is the degree to which a system is changed or affected by an internal or external disturbance or set of disturbances. Adaptive capacity is a significant factor in characterizing vulnerability. The ability of a system to cope with extreme climate variability and to lessen the potential damages is termed adaptive capacity (Adger 2006, Brooks 2003, Burton et al. 2002, Gallopín 2006, Gerlitz et al. 2014, Yohe and Tol 2002). Nonetheless, adaptive capacity is context-specific and varies from country to country, community to community, among social groups and individuals, and over time (IPCC 2001). Though vulnerability assessment is not a new concept, it emerges in the climate science and climate policy application (Füssel and Klein 2006, Uddin et al. 2019), it is the primary step in lessening the impact of the future extreme climate on the socio-ecological system (Adger 2006, Howden et al. 2007). However, there are three conceptual approaches for the assessment of vulnerability, the Socioeconomic approach, the Biophysical approach, and the Integrated assessment approach that combines both socioeconomic and biophysical approaches (Deressa et al. 2008). This study adopts the integrated assessment approach incorporated in the IPCC's AR4 vulnerability framework (GIZ 2014) to understand the potential impact of climate change in Bangladesh. AR4 framework is suitable for vulnerability mapping, especially when following the

integrated assessment approach (Delaney et al. 2021, Bukvic et al. 2020, Macharia et al. 2020, Sherbinin et al. 2019).

There are different tools and techniques available for assessing vulnerability in a particular system. Mapping in Geographic Information System (GIS) is one of them as it is a powerful visualization tool to identify the most susceptible areas from present to future changes in the environment (Delaney et al. 2021, Bukvic et al. 2020, Uddin et al. 2019). The vulnerability mapping makes it easy for government and donor agencies to decide to identify the most vulnerable regions to climate change (Davies and Midgeley 2010, Ericksen et al. 2011, Yusuf and Francisco 2009). To assess a sector-specific vulnerability, there should be a statistical approach to reduce the large dataset into groups of variables. Principal Component Analysis (PCA) is a suitable approach to categorize the set of variables into appropriate sectors known as Principal Components (Thompson 2004, Williams et al. 2012). PCA is a standard modern dimensionality reduction tool that is widely used in almost all disciplines (Blasius 2014, Bro and Smilde 2014, Guillard-Gonçalves et al. 2015, Hair 2010, Kang et al. 2015, Singh and Vedwan 2015), particularly in making decisions based on spatial maps (Okey et al. 2015, Schiavinato and Payne 2015). PCA technique is applied for spatially explicit groups of socioeconomic vulnerability (Miller 2014), poverty (Howe et al. 2013), and health vulnerability (Fisher et al. 2015, Zhu et al. 2014). The principal component analysis is also used to calculate unbiased weight and better data interpretation that minimizes the total sum of the squared perpendicular distance from the points to the line (Rencher 2002). Since PCA serves in both ways, reduces dimension to identify sectors, and gives variable weights, its use in sector-specific spatial vulnerability assessment is appropriate (Kim et al. 2019, Rajesh et al. 2018). However, the number of principal components (PCs) can be determined based on a rule of thumb proposed by Kaiser (1960). According to that rule, a component is retained if its Eigenvalue is greater than unity. Another way of retaining PC is to follow Catell's criterion, where the breakpoint on the Scree plot of eigenvalues is the yardstick (Catell 1966). PCA is performed to calculate the indicator's unbiased weights based on their factor scores and the proportion of variance of each component as described by Zhu et al. (2014) and Jolliffe (2002). On the other hand, Cluster analysis (CA) has been applied to a wide range of research to reveal vulnerability patterns that show typical combinations of the units of analysis based on their attributes. (Bouroncle et al. 2017, Anderberg 2014, Duran and Odell 2013, Tan et al. 2013). In this study, Jenks natural break has been performed for the classification of spatial vulnerability. The Jenks Natural Breaks Classification (or Optimization) system is a data classification method designed to optimize the arrangement of a set of values into natural classes. A Natural class is the most optimal class range found naturally in a dataset. A class range is composed of items with similar characteristics that form a natural group within a dataset (Dent 1999). This classification method seeks to minimize the average deviation from the class mean while maximizing the deviation from the means of other groups. The method reduces the variance within classes and maximizes the variance between classes (Jenks 1967). It is also known as the goodness of variance fit (GVF), which equals the subtraction of SDCM (sum of squared deviations for class means) from SDAM (sum of squared deviations for array mean) (ESRI 2016, Slocum 1999).

Since various extreme climatic events that occur in Bangladesh and the socio-economic condition of the country are not uniform all over the country, the vulnerability to climate change and extremes should also be diverse in terms of sectors and geography. Therefore, the present study is based on the rational hypothesis that Bangladesh has spatial diversity in the sectors of climate change vulnerability. And thus, this study will answer a couple of questions: what are the sectors of climate change vulnerability (CCV) in Bangladesh, and how these sectors of vulnerability are distributed geographically? To answer the research question, this study aims to identify the sectors of vulnerability through geospatial analysis and visualize the spatial vulnerability in the GIS environment. A sectoral vulnerability index helps in decision-making to identify proper measures of adaptation. However, the present study considers those unmet exigencies and provides potential implications for future decision-making and policymaking.

2. The Study Area

The spatial extent of the study area is between 20° 34' N to 26° 38' N latitude and 88° 01' E to 92° 41' E longitude (Fig. 1) with an area of 144,000 km² (BBS 2012). Concerning global warming and climate change, the study area Bangladesh is one of the most vulnerable countries in the world due to its least capacity to address the devastating impacts (IPCC 2007). Recently, Bangladesh is experiencing higher temperatures, more variability in rainfall, more extreme weather events, and sea-level rise. Bangladesh is highly vulnerable because it is low-lying, located on the Bay of Bengal in the delta of the Ganges, Brahmaputra, and Meghna, and also densely populated. Since agriculture is the mainstay of the economy of Bangladesh, its agriculture and water sectors are very sensitive to impacts of the climate change.

3. Materials And Methods

3.1 Indicator selection and data collection

Many studied climate change vulnerabilities using social, economic or biophysical indicators (Liu et al. 2008, Metzger and Schröter 2006, Stelzenmüller et al. 2010). However, for the present study, 30 socioeconomic indicators have been selected based on the review of existing literature and data availability (Table 1), which have been obtained from the Bangladesh Bureau of Statistics (BBS 2016, 2013, 2012). Again, referring to existing literature and data availability, 12 biophysical indicators have also been selected from different spatial and nonspatial sources (Table 1). The variability in the coefficient of temperature and precipitation has been extracted from the work of the Institute of Water and Flood Management (IWFM 2014). Then they have been incorporated with the climatic sub-regions suggested by Rashid (1991). A five-class drought class map of the whole country has been adopted from the Comprehensive Disaster Management Program (CDMP 2006). The cyclone risk map used in this study, a four-class relative risk map, has been adopted from the Center for Environment and Geographic Information Services (CEGIS 2006). The Sea Level Rise (SLR) risk map has been produced from the elevation map collected from United States Geological Survey (USGS). Different types of flood risk maps have been reproduced from the maps of the Bangladesh Agricultural Research Council (BARC 2001) and Bangladesh Water Development Board (BWDB 2010). Erosion-prone areas with relative risks (BWDB

2010) and salinity intrusion maps of 1 to 5 ppt salinity line (SRDI 2010) also have been recreated in this study. Finally, a general hazard class map covering all over the country, with a 1 to 5 relative hazard proneness, has been adopted from Bangladesh Center for Advanced Studies (BCAS 2008). However, the rationale for selecting these indicators is provided in Table 1. Details on the selected indicators including units, vulnerability components, themes, and data sources have been mentioned as supplementary (see Appendix A).

Table 1 Initially selected indicators of CCV with the rationale of selection. The column “Sign” indicates the relation of each indicator with vulnerability. The first 30 are socioeconomic indicators, 31 to 42 are biophysical indicators.

No.	Indicators	Rationale of Selecting the Indicator	Sign
1	Literacy rate	Increases adaptive capacity by allowing access to information.	-
2	Dependency ratio	Lessens social capacity to adapt to extreme events.	+
3	Irrigation	Ensures food security thus increases adaptive capacity.	-
4	School	Increases resilience by providing infrastructural support.	-
5	Shelter	Provides shelter and infrastructural support to the affected.	-
6	Roads	Increases mobility and communication capacity during emergencies.	-
7	Health institutes	Strengthens health resilience during emergencies.	-
8	Electricity	Ensures socio-economic capacity and reduces vulnerability.	-
9	Tube well	Lessens drinking water stress during and after a disaster situation.	-
10	Drinking water source	Reduces susceptibility to climate change-associated diseases.	-
11	Away population	Enables economic capacity building.	-
12	Household	Increases the adaptive capacity of a certain community.	-
13	Drought affected HHs	Increases vulnerability by mainly affecting agricultural production.	+
14	Poverty	Intensifies risk due to higher exposure to hazards.	+
15	Television	Plays an important role in forecast and awareness-raising.	-
16	Radio	Enhances emergency preparedness and risk reduction.	-
17	Fuelwood dependency	Compromises food security, thus increases vulnerability.	+
18	Disability	Obstructs mobility and increases sensitivity.	+
19	Female HH head	Reduces gender disparity and increases the resilience of women.	-
20	Population density	High-density compromises quality housing and living standards.	+
21	Injury in NH	Increases climate change susceptibility of humans.	+
22	Crop damage	Decreases agricultural resilience and food security.	+
23	Household damage	Increases the overall physical vulnerability of a community.	+
24	Tornado affected HHs	Damages infrastructure and rural houses.	+

25	Agriculture dependency	Increases susceptibility when hazards destroy croplands.	+
26	Storm affected HHs	Increases the physical vulnerability of the community.	+
27	Salinity affected HHs	Degrades quality of water for drinking and agricultural production.	+
28	Cyclone affected HHs	Increases the risk of coastal communities causing destruction.	+
29	Flood-affected HHs	Damages road, infrastructure, flood embankments, and rural houses.	+
30	Erosion affected HHs	Shoreline erosion and riverbank erosion increase vulnerability.	+
31	Maximum Temperature	Temperature changes are considered increasing exposure.	+
32	Minimum Temperature	Temperature changes are considered increasing exposure.	+
33	Precipitation	Changes in precipitation patterns are considered increasing exposure.	+
34	Drought	Increases exposure by mainly affecting agricultural production.	+
35	Hazard Class	Increases exposure and risks of damage all over the country.	+
36	Tidal Flood	Increases exposure and the losses of the coastal community.	+
37	Sea Level Rise	Sea level rise may trigger all other exposure factors on the coast.	+
38	Cyclone	Destroys houses, assets, agriculture, and lives.	+
39	Salinity Intrusion	Degrades quality of water for drinking and agricultural production.	+
40	Flush Flood	Damages roads, infrastructure, and rural houses in the hilly regions.	+
41	River Flood	Damages road, infrastructure, flood embankments, and rural houses.	+
42	Erosion	Shoreline erosion and riverbank erosion increase exposures.	+

HH = Household, NH = Natural Hazard,

3.2 Preparation of raster datasets

All socioeconomic data have been incorporated into the GIS database to generate vector maps of all indicators. A brief description of the selected indicators is given in Table 1. Since data from different BBS publications come with different units, there is a necessity of transforming some units to the desired form

that can easily interpret vulnerability. This transformation includes percent, normalizing with population, and normalizing with the area as done by Uddin et al. (2019). After transforming into these desired units of measurement, all socioeconomic indicators have been incorporated into the district-wise GIS database. On the other hand, all the biophysical data were collected in the form of different published digital maps. These maps have been incorporated into the database with relative scales. For the suitability of spatial analysis, all vector maps from created databases, both from socioeconomic and biophysical, were converted to raster datasets of uniform resolution (see Fig s1, Fig s2, Fig s3, Fig s4, and Fig s5 in the Online Resource 1). However, for GIS analysis, ArcGIS 10.5 desktop version is used throughout the present study.

3.3 Rescaling of datasets

At that point, to avoid the influence of one variable to other variables and create a stronger relationship amongst the variables, all raster datasets have been rescaled to 0 – 1 (Quackenbush 2002). It's called maximum-minimum normalization. A similar approach has been followed in developing the human development index and life expectancy index (Coulibaly et al. 2015, Piya et al. 2012, UNDP 2007). Standardization, another data rescaling technique commonly used before PCA, has not been considered since most of the variables in the dataset are not normally distributed. However, for the normalization of all raster datasets in a single command, an ArcGIS model has been built with the Raster Calculator tool and raster iterator using the database as the model Workspace (see Appendix B).

3.4 Removal of insignificant variables

For a meaningful PCA, the sample database must not contain any insignificant variables that have no or very negligible relations with the rest of the variables. The presence of such insignificant variables can make the process of pattern identification futile. Therefore, variables that have no or very poor value of correlation coefficients must be eliminated from the database. For this purpose, a correlation matrix of all raster datasets has been calculated using the Band Combination Statistics tool of ArcGIS. Examining the correlation matrix, variables with coefficients $< |0.3|$ with most of the variables have been removed from the initially selected sample datasets (see Appendix C). Moreover, variables with higher coefficients but with a very negligible number of other variables (less than 3) have also been eliminated.

3.5 Test of sampling adequacy and sphericity

There are some established test statistics for determining the suitability of sample datasets before PCA. These tests include the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy. The KMO value ranges from 0 to 1, and a value greater than 0.50 indicates the sample is adequate thus is considered suitable for PCA (Ledesma and Valero-Mora 2007). Another test statistic is Bartlett's test of Sphericity which tests the hypothesis that the correlation matrix is an identity matrix, which would indicate that variables are unrelated and therefore unsuitable for structure detection. In this test, the level of significance should be less than 0.05 for the chi-square statistic and the degree of freedom of the sample datasets (Uddin et al.

2019). In this study, KMO test of adequacy and Bartlett's test of sphericity have been calculated manually (see Appendix D).

3.5 Principal Component Analysis (PCA)

Once the database has been normalized and test statistics have been performed, Principal component analysis (PCA) of normalized raster datasets have been performed using the Arcpy, which has resulted in a multi raster band (each band for each PC), and a text (".asc" or ".txt") file containing PCA result. ArcPy is a Python site package that provides a useful and productive way to perform geographic data analysis, data conversion, data management, and map automation with Python.

3.5.1 PC retention

PCs have been retained by Catell's test which determines the number of components to retain by a breakpoint on the Scree Plot from eigenvalues, also known as the elbow method (Catell 1966). Kaiser's criterion is another commonly used PC retention technique, by which PCs with eigenvalues greater than unity are retained (Kaiser 1960). However, Kaiser's criterion could not be followed in this study since the PCA eigenvalues are in normalized form. Therefore, Catell's test on the Scree plot has been performed which has been cross-checked by another criterion that is the total explained variance should be higher than 70% (Kaiser 1966, Uddin et al. 2019).

3.5.2 Varimax rotation

Once the number of PCs has been retained then it's time to maximize the variances to get the most out of PCA. Varimax rotation of component loadings is thus a common practice in PCA-based studies. Varimax rotation keeps the total explained variance constant and increases the explained variances of PCs with smaller eigenvalues towards the most stable scenario (Rajesh et al. 2018). The varimax rotation has been performed in Excel using the Real statistics resource pack software (Zaiontz 2020). The largest absolute values of varimax rotated loadings are used as weights of variables and also used for grouping variables into the retained PCs.

3.6 Test of internal consistency of PCs

Before aggregating the indicators into PC groups, the internal consistency of each PC has been tested. There are different test statistics available for determining the internal constancy and reliability of multiitem bipolar scales, the Cronbach's alpha is one of them (Chronbach 1951). The statistic "typically" ranges from 0.00 to 1.00, but a negative α value can occur when the items are not positively correlated among themselves. The size of alpha depends on the number of items in the component but 0.65 to 0.80 is often considered adequate for a scale used in human dimensions research (Vaske et al. 2016). Rajesh et al. (2018) and others have used Chronbach's alpha to measure the internal consistency of components in vulnerability assessment earlier. In this study, Cronbach's alpha has been calculated manually (see Appendix E).

3.7 Aggregation of variables

However, to measure sector-specific vulnerabilities, the normalized raster of the same profile or PC have been aggregated after multiplication with their respective unbiased weights (retrieved from PCA). Before aggregating, the indicators of negative relations with vulnerability (according to Table 1) have been inversed using “1 – normalized raster” as the map algebra expression in the raster calculator. Indicators of the same profile have been aggregated using Eq. 1, as done by Uddin et al. (2019) using the raster calculator,

$$\text{Weighted Average} = \frac{X_1 \times W_1 + X_2 \times W_2 + \dots + X_n \times W_n}{W_1 + W_2 + \dots + W_n} \quad (1)$$

Where, X = raster name, and W = weight of raster.

3.8 Clustering of aggregates

Finally, the clusters in sector-based indexed vulnerability maps have been identified using the Jenks natural break, a Cluster analysis (CA) method. This CA method is the default classification method in ArcGIS which is suitable for classifying thematic maps with higher variance (ESRI 2016). Three classes, namely High, Low, and Moderate, have been identified for all sectors and then numbers of districts have been counted for every class using the zonal statistics tool.

4 Results

4.1 From indicators to vulnerability sectors

The focal analytical approach for the present study is the PCA. However, some test statistics have been performed over the sample datasets to ensure PCA suitability beforehand. Examining the correlation matrix of initially selected 42 raster datasets (Table 1), 4 indicators have been eliminated due to insignificant correlations. The remaining 38 indicators (Table 3) have been considered for the test of sampling adequacy and sphericity. Sampling adequacy has been tested through the KMO statistic which gave an approximate value of 0.73 for all datasets. KMO of individual indicators has also been examined and found all indicators have KMO > 0.5 depicting adequacy of the sample datasets. Bartlett's test of sphericity gave a p-value very close to 0.000 which also indicates the suitability of the sample datasets for PCA.

4.1.1 Retention of principal components

To reduce the total number of variables into a smaller number of components (PCs) and to retain relevant useful information of the dataset, PCA has been performed. Now, PCs can be retained by using the rule of thumb established by Kaiser (1960), which uses “eigenvalues greater than 1” as the criteria. Since the analysis of the present study has been designed and performed over normalized datasets, eigenvalues

generated through PCA are also normalized, thus, Kaiser's criterion cannot be followed directly to retain components. However, Cattell (1966) established that a significant break on the Scree plot generated with eigenvalues indicates the number of PCs to retain, which is another commonly used criteria in PCA-based studies. In this study, 6 principal components have been retained as shown in Fig. 3 following Catell's criterion. The overall explained variance for the retained PCs is 73.52%, where PC1 explains 33.30%, PC2 explains 14.51%, PC3 explains 9.90%, PC4 explains 6.50%, PC5 explains 4.94%, and PC6 explains 4.37% of the total variance (Table 2).

4.1.2 Identification of CCV sectors and variable weights

Considering the highest varimax rotated component loadings derived from Eigenvectors from each PC, 6 vulnerability profiles, as well as unbiased weights for each indicator, have been retained (Table 3). However, from this finding, it can be said that there are 6 sectors of the climate change vulnerability of Bangladesh. Thus, it answers the first question of the research problem. It also sets the base for the justification of the hypothesis.

The PC1 has been named Climatic Extreme Event Vulnerability since this group mainly consists of indicators associated with extreme weather and climatic events. This component has 9 indicators highly loaded: Flood and/or cyclone shelter, Number of houses damaged by previous extreme events, Number of households affected by storms, Number of households affected by salinity intrusion, Number of households affected by cyclones, Hazard classes, Sea level rise risk, Cyclone risk, and Salinity intrusion proneness. The PC2 has been named Meteorological Shift Vulnerability since indicators associated with fluctuations of shifts in meteorological conditions constitute this group. It has 5 indicators highly loaded: Number of drought-affected households, Number of tornado-affected households, Coefficients of change in average maximum temperature, Coefficients of change in average minimum temperature, and Coefficients of change in average precipitation. Most of the structural and demographic indicators considered in the present study constitute the PC3, hence it is named Infrastructure and Demographic Vulnerability. The 12 indicators highly loaded for this component are Literacy rate, Number of primary schools, Road network, Number of health institutes, Number of households with electricity connections, Number of households with in house or close (within 200 m) drinking water source, Total number of houses, Access to television, Access to radio, Percent of disabled people, Number of households with female head, and Population density. The 6 indicators namely Irrigation coverage, Number of households with tube well, Number of households dependent on fuelwood for cooking, Number of people injured in natural previous natural hazards, Number of households dependent on agriculture for primary income, and Number of flood-affected households have the highest loadings for the PC4. This sector has been named Ecological Vulnerability since it contains agriculture and water-related indicators. The PC5 has been named Flood Vulnerability because it contains all flood indicators. The 3 flood indicators highly loaded are Tidal flood risk areas, Flush flood risk areas, and River flood risk areas. Finally, the PC6 has been named Economic Vulnerability since it contains indicators that are directly related to the economic condition. The Economic Vulnerability sector has 3 indicators highly loaded: Dependency ratio (percent of people without income), Percent of away people, and Percent of people below the poverty line.

Table 2 Explained variance of the first 6 PCs, retained through Catell’s criterion, along with their eigenvalues.

Principal component	Eigenvalue	Explained variance (%)	Total variance explained (%)
PC1	0.372	33.30	73.52
PC2	0.162	14.51	
PC3	0.110	9.90	
PC4	0.072	6.50	
PC5	0.055	4.94	
PC6	0.049	4.37	

Table 3 The 38 indicators used in the PCA. Retained 6 PCs with absolute values of varimax rotated loadings. Bold values indicate the highest loadings of indicators and thus are the unbiased weights.

No	Indicator	PC1	PC2	PC3	PC4	PC5	PC6
1	Literacy rate	0.057	0.011	0.072	0.061	0.002	0.065
2	Dependency ratio	0.026	0.001	0.039	0.008	0.005	0.127
3	Irrigation	0.046	0.052	0.049	0.063	0.015	0.003
4	School	0.006	0.015	0.112	0.036	0.015	0.016
5	Shelter	0.098	0.069	0.047	0.010	0.011	0.037
6	Roads	0.021	0.033	0.089	0.061	0.013	0.028
7	Health institutes	0.006	0.014	0.041	0.033	0.001	0.039
8	Electricity	0.017	0.008	0.142	0.025	0.017	0.027
9	Tube well	0.018	0.065	0.029	0.090	0.032	0.063
10	Drinking water source	0.108	0.065	0.123	0.093	0.039	0.015
11	Away population	0.000	0.003	0.034	0.027	0.009	0.048
12	Household	0.000	0.000	0.070	0.012	0.005	0.016
13	Drought affected	0.015	0.079	0.048	0.004	0.004	0.018
14	Poverty	0.017	0.017	0.033	0.001	0.028	0.119
15	Television	0.026	0.013	0.078	0.006	0.005	0.068
16	Radio	0.027	0.021	0.114	0.051	0.002	0.019
17	Fuelwood dependency	0.078	0.065	0.081	0.131	0.039	0.019
18	Disability	0.016	0.005	0.070	0.011	0.013	0.018
19	Female HH head	0.012	0.017	0.089	0.022	0.018	0.066
20	Population density	0.002	0.006	0.053	0.005	0.002	0.013
21	Injury in NH	0.065	0.011	0.000	0.098	0.008	0.018
23	Household damage	0.110	0.005	0.025	0.029	0.001	0.008
24	Tornado affected HHs	0.009	0.035	0.014	0.030	0.007	0.010
25	Agricultural dependency	0.020	0.004	0.023	0.104	0.001	0.013
26	Storm affected HHs	0.116	0.011	0.017	0.022	0.017	0.012
27	Salinity affected HHs	0.051	0.013	0.011	0.015	0.006	0.037
28	Cyclone affected HHs	0.106	0.022	0.019	0.008	0.001	0.003
29	Flood affected HHs	0.012	0.017	0.015	0.093	0.011	0.028

31	Maximum Temperature	0.090	0.251	0.061	0.047	0.019	0.013
32	Minimum Temperature	0.054	0.133	0.009	0.016	0.030	0.023
33	Precipitation	0.074	0.250	0.074	0.035	0.023	0.017
35	Hazard Class	0.144	0.046	0.010	0.023	0.057	0.032
36	Tidal Flood	0.145	0.005	0.002	0.007	0.175	0.005
37	Sea Level Rise	0.210	0.013	0.044	0.043	0.024	0.025
38	Cyclone	0.192	0.103	0.017	0.054	0.013	0.012
39	Salinity Intrusion	0.169	0.022	0.016	0.004	0.022	0.039
40	Flush Flood	0.013	0.010	0.005	0.014	0.089	0.025
41	River Flood	0.020	0.047	0.009	0.026	0.184	0.010
<i>Eigen values</i>		<i>0.25</i>	<i>0.19</i>	<i>0.13</i>	<i>0.09</i>	<i>0.09</i>	<i>0.06</i>

HH = Household, NH = Natural Hazard, Bold indicates weights of variables, Italics indicates eigenvalues

4.2 Spatial climate change vulnerability of Bangladesh

Once CCV sectors have been identified from the outcomes of PCA, each sector has been tested if their indicators have internal consistency, or in another word whether the sector is reliable or not. The test statistic Cronbach's alpha has been determined more than 0.6 for all sectors (Table 4), which depicts the reliability of all sectors. Then indicators of all sectors have been aggregated through the weighted average to get indexed vulnerabilities which is the final result of the present study. The 6 indexed CCV maps for each PC with three clusters have been shown in Fig 4. These maps show a clear spatial variation in different sectors of the vulnerability of Bangladesh which answers the second question of the research problem. Therefore, the rational hypothesis that Bangladesh has spatial diversity in factors of vulnerability is justified.

Table 4 Test of internal consistency of sectors of CCV through Cronbach's alpha.

PCs	CCV sectors	Items	Cronbach's α
PC1	Climatic extreme event vulnerability	9	0.90
PC2	Meteorological shift vulnerability	5	0.81
PC3	Infrastructural and demographic vulnerability	12	0.88
PC4	Ecological vulnerability	6	0.72
PC5	Flood vulnerability	3	0.72
PC6	Economic vulnerability	3	0.66

4.2.1 Climatic extreme event vulnerability

The climatic extreme event vulnerability or PC1 consists of indicators associated with extreme weather and climatic events that are very common in Bangladesh. Especially the coastal regions are readily very much vulnerable to climate change due to the sensitivity of the coastal ecosystem and its dependent community. However, from Fig. 4(a), it has become obvious that the coastal regions of the country are highly vulnerable due to climatic extreme events. PC1 consists of variables like cyclone, sea-level rise, salinity, and general hazard classes which make the coastal regions of Bangladesh highly exposed to climatic extreme event vulnerability. On the other hand, shocks to previous natural hazards and climatic extreme events, like cyclones, storms, salinity, etc. caused damage to lives and resources especially damaged households. Such a phenomenon makes the coastal region of Bangladesh more sensitive to extreme weather and climatic events. In this study, this sector (PC1) has only one adaptive capacity: cyclone and flood shelters which play a very significant role in reducing vulnerability to extreme events. However, regions apart from the coast of the Bay of Bengal have been found moderately vulnerable, whereas, only high lands are less vulnerable to extreme climatic events (Fig. 4(a)). The higher lands of the Barind tract and Madhupur tract, Sylhet and Chittagong hill tracts, and a part of Himalayan piedmont plains are less vulnerable (Fig. 4(a)).

4.2.2 Meteorological shift vulnerability

Important meteorological indicators like temperature and precipitation coefficient are components of this vulnerability sector, which are vital to the phenomenon of climate change. Variability in temperature and precipitation coefficient bring various types of meteorological hazards like meteorological drought and tornado increasing the exposure to climate change and extremes. Moreover, variability in temperature directly causes various human health issues due to heat stress. The PC2 contains indicators that are spatially variable keeping in correspondence to the climatic sub-regions of Bangladesh such as temperature and rainfall. Drought-affected households and tornado-affected households are also limited to certain regions, making them highly sensitive to meteorological shifts, which are aligned with the climatic sub-regions of Bangladesh. PC2 does not have any variables that increase adaptive capacity and decrease vulnerability to climate change. Fig. 4(b) shows that all of the coastal regions, Chittagong hill tracts, the northern part of the north region, and the western region of the country are highly vulnerable to weather shifts or meteorological shifts. On the other hand, the mid-south region has been found mainly low vulnerable to weather shift and meteorological variability, while, the north-eastern and north-western regions have been demonstrated as moderately vulnerable (Fig. 4(b)).

4.2.3 Infrastructure and demographic vulnerability

Infrastructure and information play a vital role in enhancing the adaptive capacity for facing climate change impacts. In this study, the PC3 consists of infrastructure, information, and demographic variables that have effects on CCV. Mainly the southeast and the northeast region, and part of the north region are highly vulnerable to climate change and extremes due to infrastructure inadequacy, demography, and information susceptibility (Fig. 4(c)). Fig. 4(c) also shows that the rest of the mid and east region of the

country is moderately vulnerable, and the western part is low vulnerable in this sector. Adaptive capacity indicators like literacy rate, primary schools, road network, health institutes, electricity connections, drinking water source, number of houses, television, and radio decrease vulnerability to climate change and extremes. Percent of disabled people, number of households with female head, and population density are sensitivity related indicators which also increases climate change vulnerability.

4.2.4 Ecological vulnerability

Ecological vulnerability or PC4 has tube well and irrigation coverage which increase the adaptive capacity of the region resulting in a decrease in vulnerability. Fuelwood dependency for cooking and agricultural dependency for livelihood increases the exposure to ecological vulnerability. The number of flood-affected households and injuries in previous extreme events are sensitivity-related indicators and thus they increase vulnerability. Fig. 4(d) depicts that most eastern regions, southwest regions, and part of northern regions are highly vulnerable to Ecological vulnerability. The midsouth and northwest regions are moderately vulnerable, and the rest of the regions of the country are low vulnerable to ecological vulnerability to climate change (Fig. 4(d)).

4.2.5 Flood vulnerability

Bangladesh is a flood-prone country as a whole because floods of different forms and magnitude visit this country every year with spatial variability. Floods in Bangladesh are mainly linked with its geography. PC5 or flood vulnerability is composed of 3 forms of common floods in Bangladesh. All three flood indicators increase the exposure of Bangladesh to climate change and thus increases the vulnerability. As shown in Fig. 4(e), the coastal region, the northeastern hilly region, and the middle region are found highly vulnerable to CCV due to flooding. In a nutshell, Bangladesh is overall vulnerable due to flooding all over the country except hilly regions of the southeast and northwest (Fig. 4(e)).

4.2.6 Economic vulnerability

Since Bangladesh is among the lower-income countries of the world, economic condition is a vital consideration while studying climate change vulnerability. The strong economic condition of a country decreases the level of vulnerability because the capability to adapt to climatic and weather extreme events directly depends on the economy. However, dependency ratio, away-population, and poverty constitute the economic vulnerability of Bangladesh to climate change and extremes. Dependency ratio and poverty percentage increases exposure to the impacts of climate change and thus increase the level of vulnerability. The away population on the other depicts the better economic condition and increases adaptive capacity to climate change and extremes. Fig. 4(f) shows the spatial distribution of the vulnerable zones in different magnitudes. Hilly region of the southeast, some districts in the mid-south and the southwest are mainly highly vulnerable. Mostly, Bangladesh has moderate to high CCV due to economic incapacity (PC6) as a whole (Fig. 4(f)).

4.3 Overview of CCV sectors and clusters

4.3.1 Magnitude of vulnerability

Clustering helps to interpret results from spatial analysis more lucidly. The main result of the study, sectoral CCV maps, thus has been undertaken a clustering process which is also a spatial analysis. Outputs from clustering have not only divided Bangladesh into vulnerability classes but also have given interesting insights about the sectors of CCV. Fig. 5 shows the cluster ranges of all sectors in which the indexed CCV maps have been classified. PC1 or climatic extreme event has an index ranging from 0.07 to 0.87, having the highest upper value among all sectors (Fig. 5). Meteorological shift (PC2) has an index ranging from 0.09 to 0.78 which has the second-highest upper value. Similarly, economic vulnerability (PC6), flood vulnerability (PC5), infrastructure and demographic vulnerability (PC3), and ecological vulnerability (PC4) decrease with upper index value respectively (Fig. 5).

The CCVI has been calculated with maximum-minimum normalized datasets hence the index value ranges also lie between 0 and 1. Index value close 1 indicates the higher intensity of vulnerability of certain sectors. Therefore, it can be said that climatic extreme event is the most severe sector of vulnerability in Bangladesh in terms of vulnerability level (Fig. 6(a)). Similarly, considering the level of vulnerability, the meteorological shift is the second most severe CCV sector. Economic vulnerability and flood vulnerability are in third and fourth place in the severity scale respectively with almost similar index ranges. Infrastructure and demography and ecological vulnerability are the fifth and sixth most severe CCV sectors with almost similar index ranges (Fig. 6(a)).

4.3.2 Coverage of vulnerability

Calculation of zonal statistics over vulnerability clusters shows 8 districts of Bangladesh are highly vulnerable due to extreme climatic events (PC1), 10 districts are moderately vulnerable, and the rest 46 are low vulnerable (Fig. 5). The number of districts highly vulnerable due to meteorological shift (PC2) is 17, moderately vulnerable 22 and 27 districts are low vulnerable as shown in Fig. 5. Considering the PC3 or infrastructure and demographic vulnerability, 22 districts of Bangladesh are vulnerable to climate change, 23 and 19 districts are moderate and low vulnerable respectively (Fig. 5). The figure also shows the number of districts in each vulnerability class due to ecological reasons (PC4) and 16 districts are highly vulnerable to climate change and extremes, while 24 for each moderate and low vulnerability. Due to flooding (PC5), 24 districts of Bangladesh are highly vulnerable to climate change, while 18 districts are moderately vulnerable and the rest 22 are low vulnerable (Fig. 5). Economic conditions (PC6) make 15 districts highly vulnerable to climate change and extremes, the number of moderate and low vulnerable districts are 32 and 17 respectively as illustrated in Fig. 5.

However, Fig. 6(b) clearly shows that the highest number of highly vulnerable districts are the result of PC5 or flooding across the country, the second-highest number of highly vulnerable districts are the result of PC3 or infrastructure, and demographic vulnerability. PC2 or meteorological shift, PC4 or ecological, and PC6 or economic vulnerability show almost similar attitudes containing third, fourth, and fifth-highest numbers of districts (Fig. 6(b)). On the other hand, the lowest number of highly vulnerable districts are the result of PC1 or climatic extreme events (Fig. 6(b)). Therefore, it can be said that flooding is the most

dominant and climatic extreme event is the least dominant sector of vulnerability to climate change and extremes in terms of area coverage.

5 Discussion

The present study started with a goal to justify the hypothesis that Bangladesh has variability in climate change vulnerability both in terms of sectors and spatiality. Principal Component Analysis (PCA), a multivariate spatial analysis of geographic datasets in a GIS environment, has been used in this study which reduced the dimensionality of datasets from 38 CCV indicators to 6 CCV sectors (PCs). PCA has been used for this purpose for decades, still, it's a common practice as done by Gupta et al. (2020). However, vulnerability sectors have been identified by interpreting the items or variables that constitute each PC. The six sectors identified are Climatic Extreme Event, Meteorological Shift, Infrastructure and Demography, Ecology, Flood, and Economic vulnerability. Uddin et al. (2019) have identified CCV sectors of southwest coastal Bangladesh using a similar approach but with different data types and analytical environments. Hence, this finding answers the first research question that what are the sectors of CCV in Bangladesh, as stated earlier.

Climatic extreme events resulted in high vulnerability mainly in the coastal regions of Bangladesh. A total of 18 districts adjacent to and close to the Bay of Bengal were found moderate to highly vulnerable to climatic extreme events. This indicates that this sector of CCV is related to the ocean. However, indicators in this sector also depicted the same message, since this sector is the aggregate of the cyclone, storm surge, salinity intrusion, and sea-level rise related indicators. These events are simultaneously very acute and chronic in the coastal regions of Bangladesh (Das et al. 2020, ICCCAD 2019, Roy and Blaschke 2015, Dasgupta et al. 2014). The sector identified next is the Meteorological Shifts which resulted in high vulnerability in the southeast and northern climatic subregions of Bangladesh. The characteristic indicators of this CCV sector are average precipitation, average maximum temperature, and average minimum temperature related. Rahman and Lateh (2017) and IWFm (2014) identified the shifts in meteorological indicators considering the climatic sub-regions of Bangladesh. Finding from this study also showed an alignment of meteorological shift vulnerability with the climatic subregions demarcated by Rashid (1991). Infrastructure and Demographic vulnerability came high in the coastal districts, districts of the haor basin, and some northern districts. The midsouth districts and hilly districts of the southeast are mainly moderately vulnerable to CC for infrastructure and demographic incapacity. The ecological vulnerability is mainly an aggregate of dependency on agriculture and dependency on fuelwood. Both of these indicators are very vital for CCV study since climate change impacts have very severe effects on them (Barbier 2015, Neumann et al. 2015). The ecological vulnerability had high scores in districts of the southwest and eastern regions. However, Infrastructure and demographic vulnerability and ecological vulnerability showed spatial distributions that can better explain with units of observation for socioeconomic data which was the district in the present study. Flood vulnerability is composed of three major forms of flooding in Bangladesh. Unlike other sectors of vulnerability flood vulnerability showed a different pattern in spatial distribution. Riverine areas and floodplains, coastal areas, and haor basins with adjacent hilly regions are moderate to highly vulnerable to climate change impacts resulting

from river flood, tidal flood, and flush floods respectively. These three forms of common floods resulted in devastating losses of lives and resources throughout history (DDM 2017). However, this sector of vulnerability showed spatial alignment with the flood risk map of BARC (2001). The economic vulnerability aggregated poverty and employment-related indicators of CCV. This sector scored moderate to high in the mid, northeast, and southeast districts except Dhaka and Chittagong districts. On the other hand, districts in the western strip are mainly less economically vulnerable except Satkhira, Nawabganj, and Naogaon districts. However, from the discussion, it can be said that sectors of CCV showed mainly two types of spatial characteristics, the socioeconomic sectors with district-wise spatial variability, and the biophysical sectors with spatial variability along physiography and climatic subregions of Bangladesh. In a nutshell, this study answers the second research question of how the sectors of CCV are distributed geographically, and thus the rational hypothesis that Bangladesh has spatial diversity in the sectors of climate change vulnerability is tested true.

Results from the present study gave another insight about CCV sectors, that is the magnitude of vulnerability. Considering the sector scores from CCV indices the highest magnitude has been found in climatic extreme events. In the past extreme events proved to be very severe in terms of damages caused (Haque et al. 2019, DDM 2017). The geographic setting of Bangladesh also poses an inherent threat from climatic and weather extreme events (UNICEF 2016). The second most severe vulnerability sector found in this study is meteorological shifts. Meteorological shifts in Bangladesh resulted in droughts of varying magnitude along with different climatic subregions (Rahman and Lateh 2016), and the future has been predicted as concerning too (Khan et al. 2020). Subsequently, economic vulnerability, flood vulnerability, infrastructure and demographic vulnerability, and ecological vulnerability came respectively in terms of severity. On the other hand, considering the spatial coverage, that is the number of districts covered by each cluster, flood vulnerability had the highest magnitude. Almost all regions of the country showed moderate to high vulnerability to climate change due to flooding. Flooding has always been the most spatially extensive hazardous event in Bangladesh and it has been long-established (DDM 2017, Dasgupta et al. 2014). Infrastructure and demographic vulnerability, meteorological shift vulnerability, ecological vulnerability, economic vulnerability, and climatic extreme event vulnerability decreasingly stood next in terms of coverage. Here, extreme climatic event vulnerability showed an interesting characteristic regarding magnitude. Though this CCV sector has the highest score of vulnerability this sector is constrained in the smallest coverage, that is the coastal regions. Therefore, it can be said that coastal Bangladesh poses the most intense form of vulnerability to climate change impacts.

Findings from this study would help improve the current adaptation and mitigation strategies adopted in the current climate policy of Bangladesh, since two major aspects of CCV, the sectoral aspect and the spatial aspect, have been portrayed in this work. The sectoral aspect of vulnerability to climate change would help understand and prioritize options of adaptation and mitigation to climate change impacts. Six identified sectors with different biophysical characteristics suggest different sets of adaptation and mitigation options in Bangladesh. Further study on each sector of climate change vulnerability, identified in this study, will give clear accounts of specific strategies. On the other hand, the magnitude of vulnerabilities, as discussed earlier, will guide to prioritization of the implementation of adaptation and

mitigation strategies in Bangladesh. Which again requires a further study on specific sectors and current strategies. The second aspect of CCV from this study, which is the spatial variability, will help decision-makers and policy makers to initiate and strengthen the implementation of strategies related to climate change adaptation and mitigation in the right places. However, to identify all the particulars of strategies further study will be needed as well as the mainstreaming of these studies on the climate policy and development of Bangladesh.

6 Conclusions

The present study findings eloquently expressed the climate change vulnerability for different sectors. The study findings specifically focused on the retention of unbiased weights for indicators, the identification of vulnerability profile, and finally the aggregation of sector-specific indicators to demonstrate a countrywide spatial climate change vulnerability. Assessment of vulnerability to climate change has been introduced in a new and interesting way through considering countrywide spatial variation. 38 out of 42 initially selected variables have shown stronger inter relations and tested suitable for PCA though Kaiser-Meyer-Olkin test of sampling adequacy ($KMO = 0.73$) and Bartlett's test of sphericity ($p = 0$). All relevant raster datasets of indicators have been incorporated in the IPCC framework, to assess spatial vulnerability to climate change for 6 different Principal Components (PCs), responsible for more than 73.5% of accumulative variability of the total dataset. All identified sectors have been tested internally consistent with their items or indicators since Cronbach's alpha is greater than 0.65 for each PC.

The climatic extreme event vulnerability (PC1) has shown 8 districts of the coastal region have been highly vulnerable to climate change. The PC2, which has been defined as the meteorological shift vulnerability, shows the south-eastern and northern climatic sub-regions consisting of 17 districts are highly vulnerable. Most regions of the country have been found moderate to highly vulnerable to infrastructure and demographic vulnerability (PC3), especially 22 districts from the southeast, northeast, and northern regions have high vulnerability. 16 peripheral districts from the southwest, southeast, northeast, north, and western region have been found scoring high in PC4 or ecological vulnerability. PC5 or flood vulnerability has been found high in the coastal region, the northeastern hilly region, and the middle region consisting of 24 districts. The economic vulnerability (PC6) has been found high in 16 districts from different parts of Bangladesh. Aside from the spatial variability of climate change vulnerability, this study has also revealed that the climatic extreme event vulnerability is of the highest magnitude and the meteorological shift vulnerability is of second highest. Regarding the coverage of vulnerability, flood vulnerability has come first since it covers more districts than any other vulnerability sector.

The present study has been accomplished with a comprehensive framework and a rigorous methodology, which presents the countrywide vulnerability to climate change based on sectors of vulnerability and could be a new source of ideas. Findings from this study, which are mainly maps, have scopes to be referenced for further studies. This study can also be an essential tool for mitigation and adaptation

measures of climate change impacts from the root level to the policymaking level. Identified sectors of vulnerability, and their spatial distribution, magnitude, and coverage suggest that mitigation and adaptation measures for the forthcoming climate change impacts should be sector-specific, location-specific, and priority-based. However, this study has not addressed the particulars of adaptation and mitigation strategies, rather has enlightened the sectors and spatiality of climate change vulnerability in Bangladesh.

The present study had a limitation of data quality since all the datasets used were collected from several secondary sources. Precisely, spatial data or maps were collected from websites of many governments and non-government organizations and agencies, where the datasets were not presented in a very structured way and with metadata information. Spatial resolutions of collected maps were also a constraint that needed to be handled carefully. Another shortcoming of the study was the poor temporal validity since most of the socioeconomic data used were from the Census of 2011, and no updated data will be available until the next census. Key statistical procedures of the study have been performed in the ArcGIS software as spatial analysis. Since spatial analysis in ArcGIS software does not provide all statistical capabilities, different test statistics were performed manually in which may affect the accuracy of testing.

Declarations

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Md. Golam Azam: Conceptualization, Methodology, Software, Formal analysis and investigation, Writing - original draft preparation, Visualization, Writing - review and editing.

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Figures

Figure 1

Location of the study site, Bangladesh, in the context of the World. The world map illustrates the Global Climate Risk Index (CRI). Bangladesh and adjacent regions (inset) are portrayed on the global DEM of SRTM with climatic subregions of Bangladesh.

Figure 2

Process flow diagram showing comprehensive methodology and procedural hierarchy for the present study

Figure 3

(a) Scree plot of the Eigenvalues of components. The 6th component (red) showing a breakpoint in the line which, according to Catell (1966), indicates that the first six PCs are responsible for most of the variability. (b) Pareto chart portraying variances explained by retained components with higher Eigenvalues. As a whole, 6 PCs explain 73.52% of the total variability.

Figure 4

The spatial climate change vulnerability of Bangladesh. Vulnerability sectors have been selected based on retained principal components.

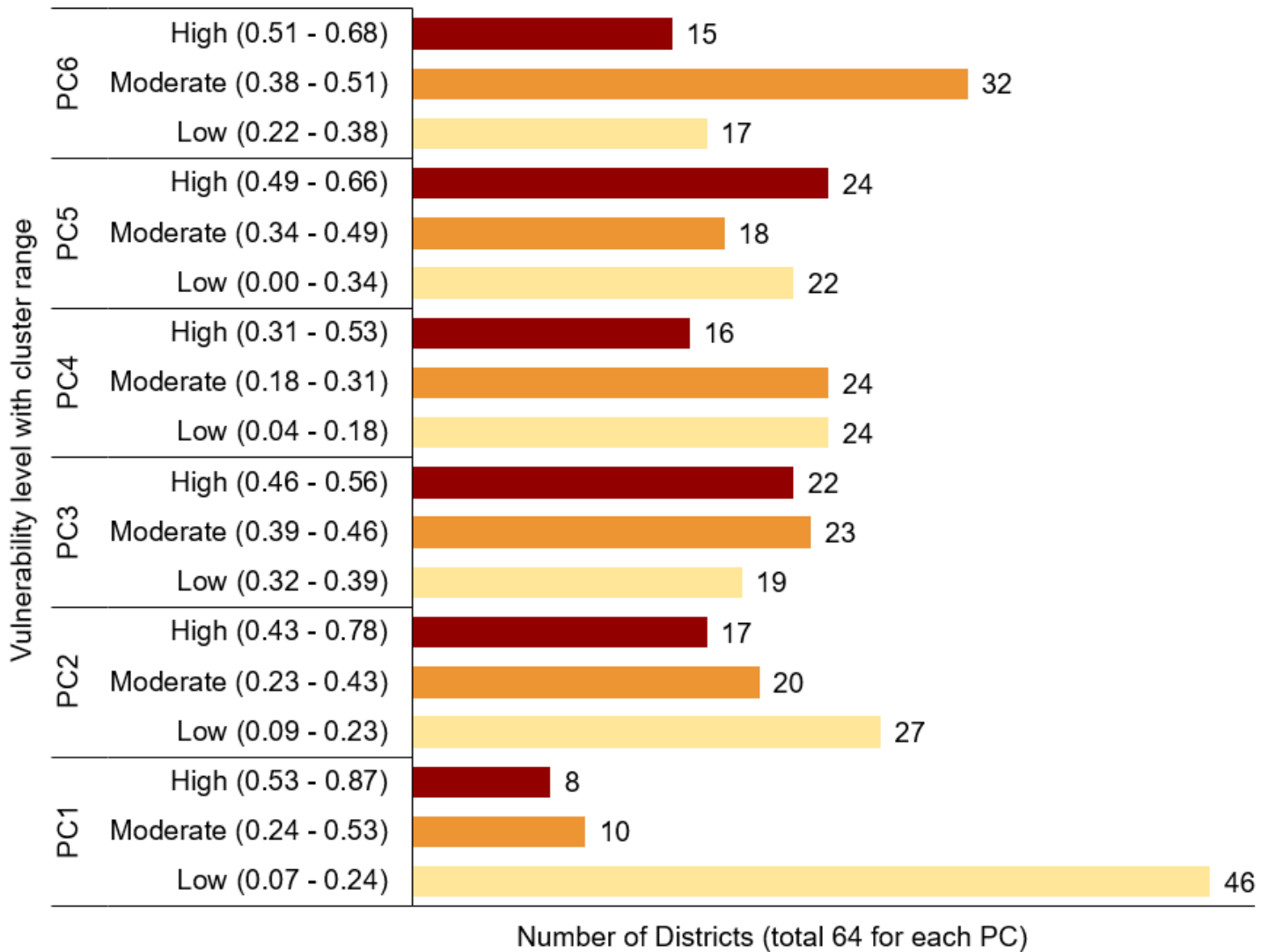


Figure 5

Classification of 64 districts according to different vulnerability sectors (PCs) using Jenk's natural break clustering

Figure 6

Overview of vulnerability sectors in terms of severity and coverage for the "high vulnerability" cluster. (a) Illustrating the severity of CCV sectors by upper values of CCVI in each sector. (b) Illustrating coverage of CCV sectors by numbers of highly vulnerable districts in each sector.

Supplementary Files

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- [Appendix.docx](#)
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