Mitig Adapt Strateg Glob Change (2022) 27: 38
https://doi.org/10.1007/s11027-022-10013-w

ORIGINAL ARTICLE

Assessing spatial vulnerability of Bangladesh to climate change and extremes: a geographic information system approach

Md Golam Azam[1,2] · **Md Mujibor Rahman**[1]

Received: 30 May 2020 / Accepted: 9 June 2022 / Published online: 9 July 2022

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 study 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 (socioeconomic and biophysical) have been incorporated in the IPCC framework in raster form. Test statistics have shown that Kaiser–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 coastal vulnerability (PC1), meteorological shift vulnerability (PC2), infrastructure and demographic vulnerability (PC3), ecological vulnerability (PC4), pluvial 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 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.

Keywords Climate change vulnerability (CCV) · Bangladesh · Geographic Information System (GIS) · Multivariate spatial analysis · Principal component analysis (PCA) · Vulnerability mapping

✉ Md Golam Azam
mdg0azam@outlook.com

Md Mujibor Rahman
mujib@es.ku.ac.bd

[1] Environmental Science Discipline, Khulna University, Khulna 9208, Bangladesh

[2] Remote Sensing, Center for Environmental and Geographic Information Services (CEGIS), Dhaka, 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 rose 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 surges 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 exposed 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 km^2 (Dewan et al. 2012; DoE 2012), Bangladesh is expecting to be added by 20 million people (with 1200 per km^2) by 2025 (Shaw 2015). The country is highly exposed to extreme climate conditions, including floods, cyclone-induced storm surges, 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 as highly exposed to climate change as well as poorly 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 is 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 cover 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 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 socio-economic approach, the biophysical approach, and the integrated assessment approach, that combine 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 Cattell's criterion, where the breakpoint on the scree plot of eigenvalues is the yardstick (Cattell 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).

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 km^2 (BBS 2012). Concerning global warming and climate change, the study area Bangladesh is one of the most exposed 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. Likewise, the country is highly exposed to climate change impacts 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 subregions 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 the 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 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,

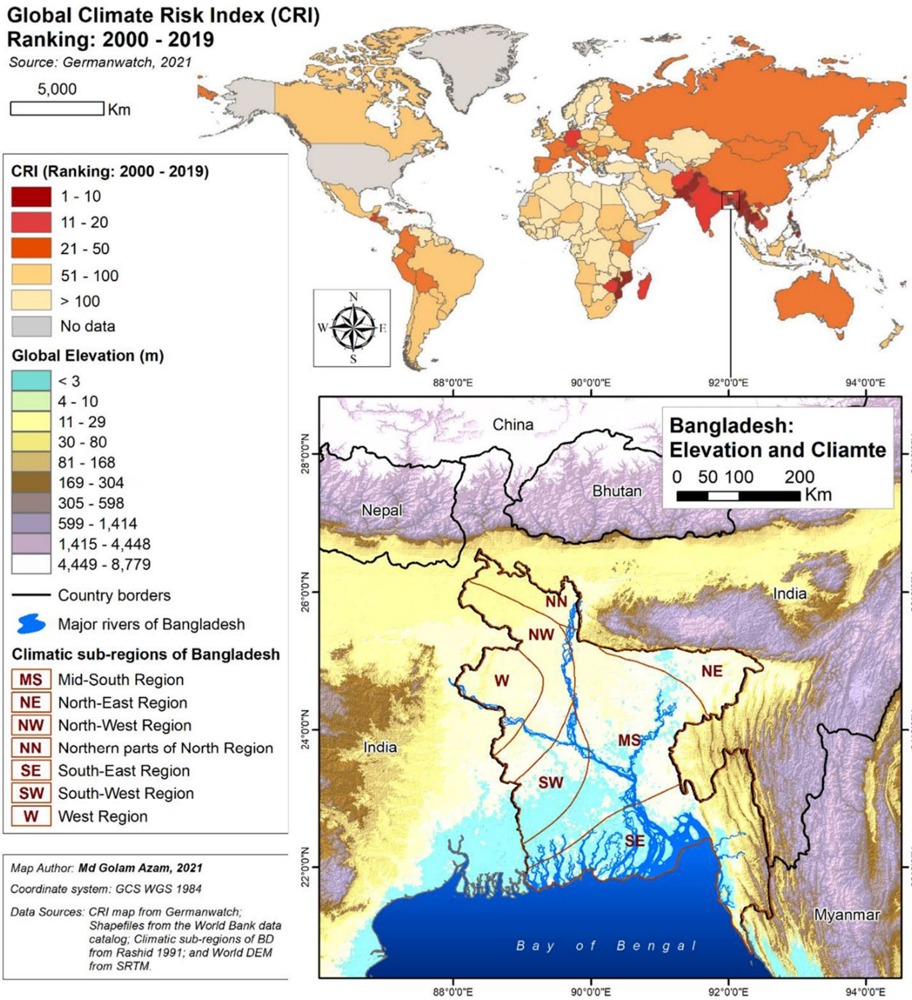

Fig. 1 Location of the study site, Bangladesh, in the context of the world. The world map illustrates the Global Climate Risk Index (CRI). Bangladesh and adjacent regions (inset) are portrayed on the global DEM of SRTM with climatic subregions of Bangladesh

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 1).

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

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 increasing 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 increasing 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

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 among the variables, all raster datasets have been rescaled to 0–1 (Quackenbush 2002). It is 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 2).

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 3). 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 that the sample is adequate and 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, the KMO test of adequacy and Bartlett's test of sphericity have been calculated manually (see Appendix 4).

3.6 Principal component analysis (PCA)

Once the database has been normalized and test statistics have been performed, principal component analysis (PCA) of normalized raster datasets has 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.

3.6.1 PC retention

PCs have been retained by Cattell'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 (Cattell 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, Cattell'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% (Uddin et al. 2019).

3.6.2 Varimax rotation

Once the number of PCs has been retained, then it is 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.

3.7 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 (Cronbach 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 Cronbach'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 5).

3.8 Aggregation of variables

However, to measure sector-specific vulnerabilities, the normalized raster of the same profile or PC has 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,

$$Weighted\ Average = \frac{X_1 \times W_1 + X_2 \times W_2 + \ldots + X_n \times W_n}{W_1 + W_2 + \ldots + W_n} \tag{1}$$

where X = raster name and W = weight of raster.

3.9 Classification of aggregates

Finally, the aggregates have been classified into three classes following an equal interval classification method as done by Das et al. (2020). 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 (Fig. 2).

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

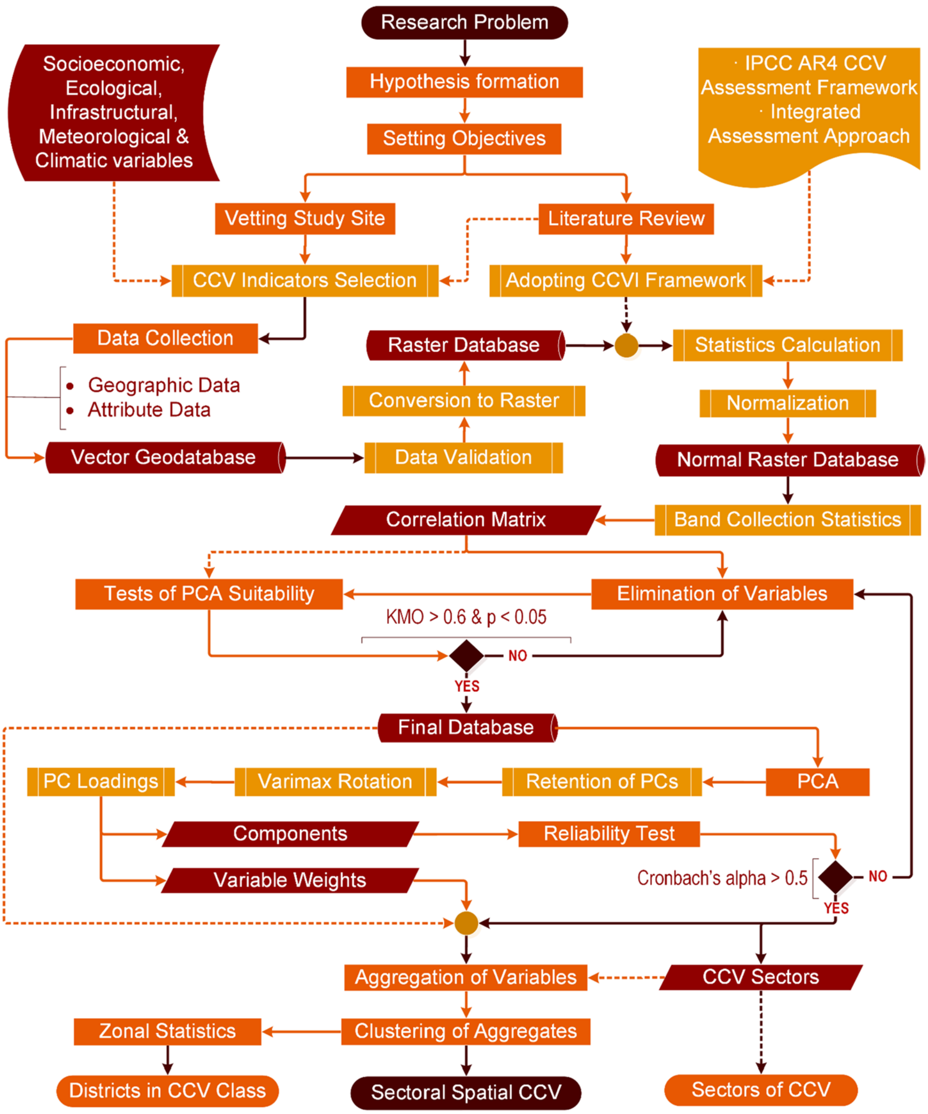

Fig. 2 Process flow diagram showing comprehensive methodology and procedural hierarchy for the present study

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 Cattell'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).

Table 2 Explained variance of the first 6 PCs, retained through Cattell'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	

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 coastal 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 within 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 pluvial vulnerability because it contains all flood indicators which are direct results of rainfall. 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 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
Eigen values		*0.25*	*0.19*	*0.13*	*0.09*	*0.09*	*0.06*

HH household, *NH* natural hazard; bold indicates weights of variables; italics indicates eigenvalues

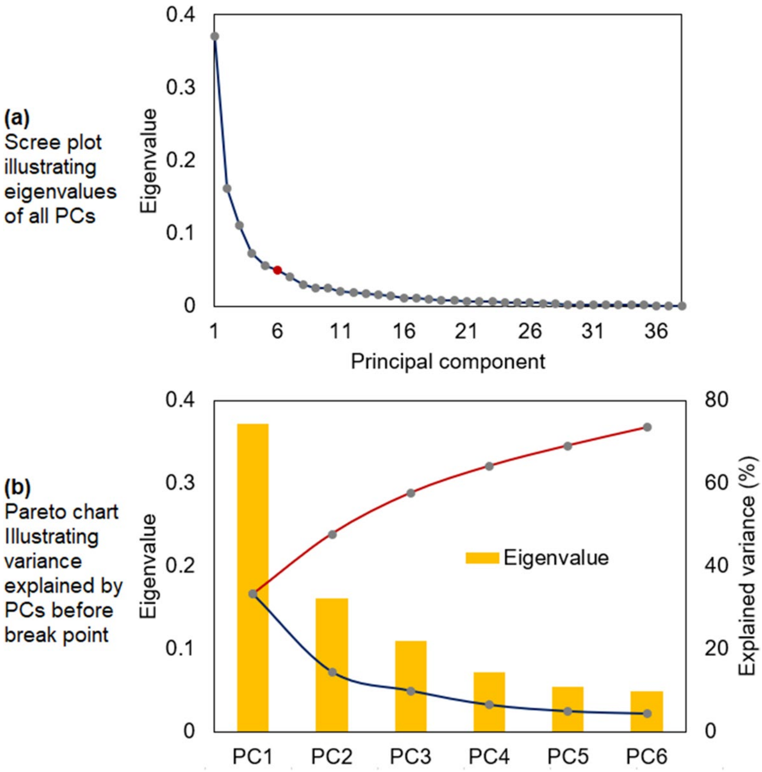

Fig. 3 **a** Scree plot of the eigenvalues of components. The 6th component (red) shows a breakpoint in the line which, according to Cattell (1966), indicates that the first six PCs are responsible for most of the variability. **b** Pareto chart portraying variances explained by retained components with higher eigenvalues. As a whole, 6 PCs explain 73.52% of the total variability

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 words 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

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

PCs	CCV sectors	Items	Cronbach's α
PC1	Coastal 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	Pluvial vulnerability	3	0.72
PC6	Economic vulnerability	3	0.66

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.

4.2.1 Coastal vulnerability

The coastal vulnerability or PC1 consists of indicators associated with extreme weather and climatic events that are very common in Bangladesh. Especially the coastal regions are

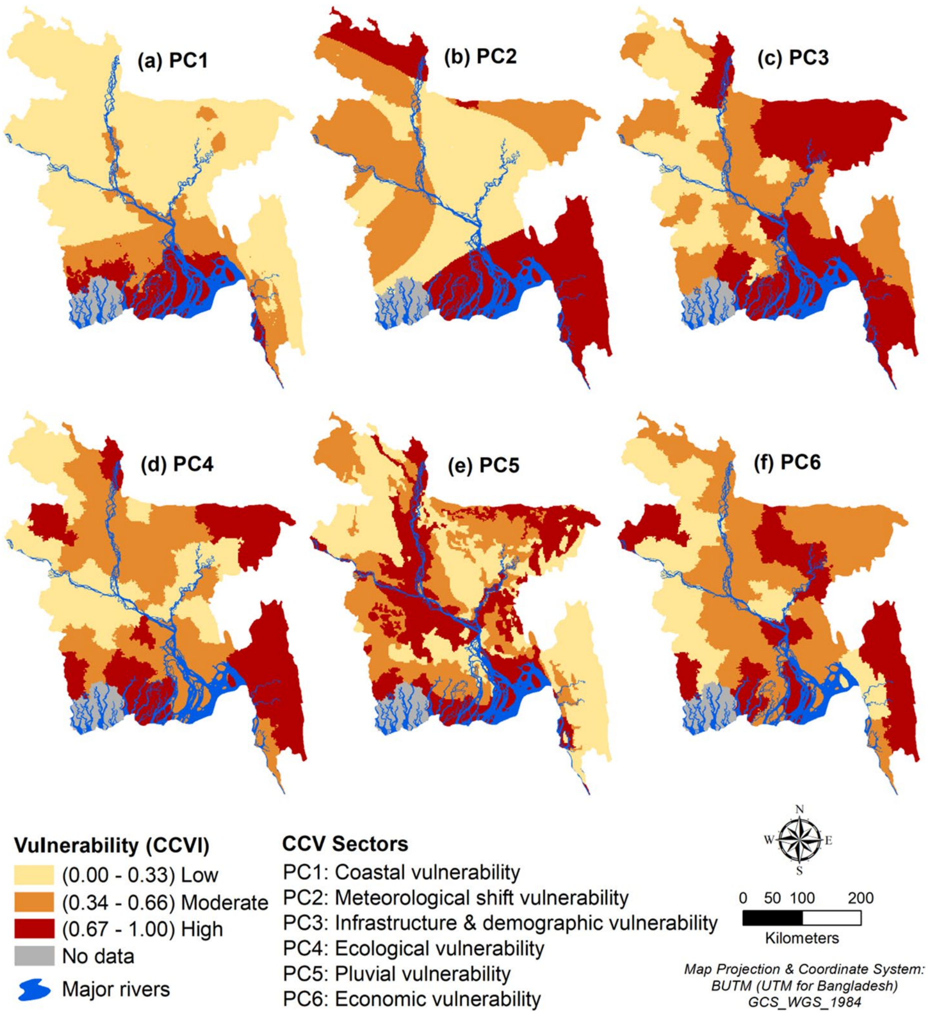

Fig. 4 The spatial climate change vulnerability of Bangladesh. Vulnerability sectors have been selected based on retained principal components

readily very much susceptible to climate change due to the exposure of the coastal ecosystem and the sensitivity of its dependent community. However, from Fig. 4a, it has become obvious that the coastal regions of the country are highly vulnerable due to climatic extreme events in the coastal region. PC1 consists of variables like cyclone, sea-level rise, salinity, and general hazard classes which make the coastal regions of Bangladesh highly exposed to coastal vulnerability. On the other hand, shocks to previous natural hazards and climatic extreme events, like cyclones, storms, and salinity, 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. However, this sector (PC1) has only one adaptive capacity indicator in the present study, cyclone and flood shelters, which play a very significant role in reducing vulnerability to extreme events. Regions apart from the coast of the Bay of Bengal have been found moderately vulnerable, whereas higher lands are less vulnerable to coastal climatic events (Fig. 4a). 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. 4a).

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 subregions 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 subregions of Bangladesh. PC2 does not have any variables that increase adaptive capacity and decrease vulnerability to climate change. Figure 4b 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 northeastern and north-western regions have been demonstrated as moderately vulnerable (Fig. 4b).

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. Though these variables are from different themes and dimensions, the PCA suggested the aggregation of all these indicators to form a single group. 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. 4c). Figure 4c 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 that 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. Figure 4d depicts that most eastern regions, southwest regions, and part of northern regions are highly vulnerable to ecological vulnerability. The mid-south 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. 4d).

4.2.5 Pluvial 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 pluvial 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 increase the vulnerability. As shown in Fig. 4e, 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. 4e).

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 directs 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 increase 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. Figure 4f shows the spatial distribution of the vulnerable zones in different magnitudes. Hilly region of the southeast and 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. 4f).

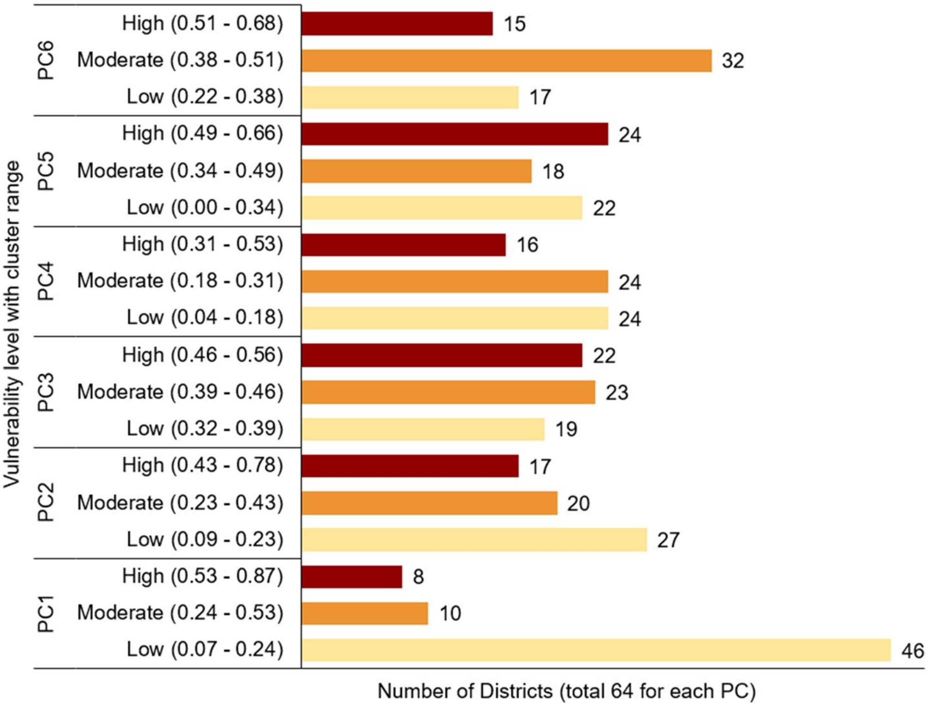

Fig. 5 Classification of 64 districts according to different vulnerability sectors (PCs) using Jenks natural break clustering

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. Figure 5 shows the cluster ranges of all sectors in which the indexed CCV maps have been classified. PC1 or coastal vulnerability 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), pluvial 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 to 1 indicates the higher intensity of vulnerability of certain sectors. Therefore, it can be said that coastal vulnerability is the most severe sector of vulnerability in Bangladesh in terms of vulnerability level (Fig. 6a). Similarly, considering the level of vulnerability, the meteorological shift is

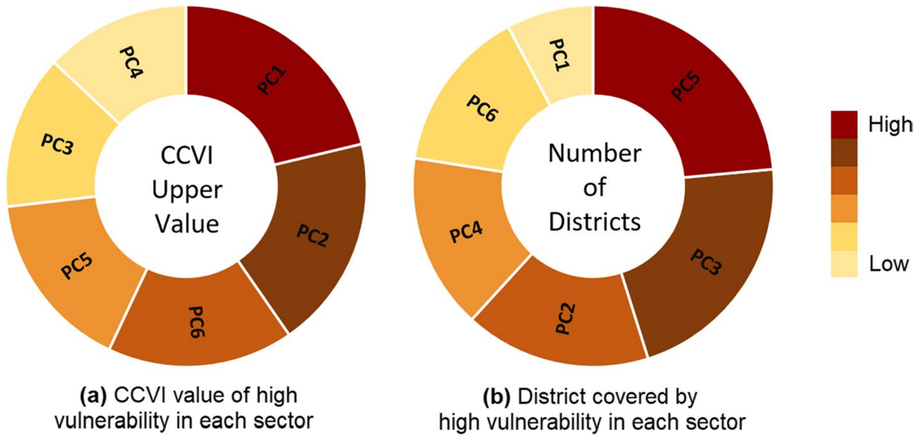

Fig. 6 Overview of vulnerability sectors in terms of severity and coverage for the "high vulnerability" cluster. **a** Illustrating the severity of CCV sectors by upper values of CCVI in each sector. **b** Illustrating coverage of CCV sectors by numbers of highly vulnerable districts in each sector

the second most severe CCV sector. Economic vulnerability and pluvial 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. 6a).

4.3.2 Coverage of vulnerability

Calculation of zonal statistics over vulnerability clusters shows that 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, and a number of moderate and low vulnerable districts are 32 and 17, respectively, as illustrated in Fig. 5.

However, Fig. 6b clearly shows that the highest number of highly vulnerable districts is the result of PC5 or flooding across the country, the second-highest number of highly vulnerable districts is 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. 6b). On the other hand, the lowest number of highly vulnerable districts is the result of PC1 or coastal vulnerability (Fig. 6b). Therefore, it can be said that flooding is the most dominant, and coastal vulnerability 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 is 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 coastal vulnerability, meteorological shift, infrastructure and demography, ecology, pluvial, 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 what are the sectors of CCV in Bangladesh, as stated earlier.

Coastal vulnerability is high 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 coastal vulnerability. This indicates that this sector of CCV is related to extreme events associated with the marine environment. 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. Iyalomhe et al. (2015) also suggested similar indicators to be responsible for the exposure of a coastal region. 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). Ahsan and Warner (2014) and others have found similar findings from their studies coastal regions. Though Bangladesh is a coastal country and claimed to be highly vulnerable to climate change in general, the coastal vulnerability found in this study is not high all over the country. 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 and their related extreme events. Rahman and Lateh (2017) and IWFM (2014) identified the shifts in meteorological indicators considering the climatic subregions 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 mid-south 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 ecosystems (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. Pluvial vulnerability is composed of three major forms of flooding in Bangladesh. Unlike other sectors, pluvial 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 coastal vulnerability. 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, pluvial 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, the pluvial 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 coastal 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 risk reduction 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 to climate change impacts. Six identified sectors with different biophysical characteristics suggest different sets of adaptation and vulnerability reduction 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 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 policymakers to initiate and strengthen the implementation of strategies related to climate change adaptation and building resilience 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. Thirty-eight 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 coastal vulnerability (PC1) has shown that 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 subregions 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. Sixteen peripheral districts from the southwest, southeast, northeast, north, and western region have been found scoring high in PC4 or ecological vulnerability. PC5 or pluvial 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 coastal vulnerability is of the highest magnitude and the meteorological shift vulnerability is of second highest. Regarding the coverage of vulnerability, pluvial 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 risk reduction 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 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 or vulnerability reduction 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 which may affect the accuracy of testing.

Appendix 1 Details of selected indicators

Initially, 42 indicators for climate change vulnerability (CCV) have been selected based on literature review and data availability. The list of all indicators has been mentioned in Table 5 with a description of units, sources of data, theme, and vulnerability components.

Appendix 2. Rescaling of raster datasets: normalization

A maximum-minimum normalization technique (Eq. 2) has been used for all raster datasets using an iterative model (Fig. 7) consisting raster calculator.

$$Normalization = \frac{x - minimum\ of\ x}{maximum\ of\ x - minimum\ of\ x} \tag{2}$$

The map algebra expression used in the above model, a modification of Eq. 2 for the raster calculator, is in the following (Eq. 3).

$$Normalized\ raster = \frac{\varepsilon\%Band_0 1\%\varepsilon - \varepsilon\%Band_0 1\%\varepsilon.minimum}{\varepsilon\%Band_0 1\%\varepsilon.maximum - \varepsilon\%Band_0 1\%\varepsilon.minimum} \tag{3}$$

Appendix 3. Elimination of insignificant variables

As a common practice, the correlation coefficient between − 0.3 and 0.3 is considered insignificant. When a variable has no significant correlation with other variables, or the number of significantly correlated variables is negligible concerning the total number of variables in the dataset, it is considered unsuitable for exploratory factor analysis or principal component analysis (PCA). However, to examine the internal relation of the raster dataset, the following correlation table (Table 6) has been extracted from the "Band collection statistics" tool of ArcGIS.

Here, some variables have negligible or no relation with the rest of the variables in the dataset which are unfavorable for PCA. Hench, we have eliminated them from the dataset, (22) crop damage, (30) erosion-affected households, (34) drought prone areas, and (42)

Table 5 Selected indicators with units, sources, and relation with vulnerability

No	Indicators	Description of units	Sources	Theme	Vulnerability components
1	Literacy rate	Percent of people	BBS 2013	Social	Adaptive capacity
2	Dependency ratio	Percent of people	BBS 2013	Social	Sensitivity
3	Irrigation	Percent of agricultural land covered	BBS 2013	Infrastructural	Adaptive capacity
4	School	No. of govt. primary school per 1000 people	BBS 2013	Infrastructural	Adaptive capacity
5	Shelter	No. of cyclone and/or flood shelter per 1000 people	BBS 2013	Infrastructural	Adaptive capacity
6	Roads	Km of road per 1000 people	BBS 2013	Infrastructural	Adaptive capacity
7	Health institutes	No per 1000 people	BBS 2013	Infrastructural	Adaptive capacity
8	Electricity	Percent of HHs with connection	BBS 2012	Infrastructural	Adaptive capacity
9	Tube well	Percent of HHs with tube well	BBS 2012	Infrastructural	Adaptive capacity
10	Drinking water source	Percent of HHs with drinking water source within 200 m	BBS 2012	Infrastructural	Adaptive capacity
11	Away population	Per 1000 people	BBS 2012	Economic	Adaptive capacity
12	Household	Total number of households	BBS 2012	Economic	Adaptive capacity
13	Poverty	Percent of people below the poverty line	BBS 2012	Economic	Sensitivity
14	Radio	Per 1000 people	BBS 2012	Information	Adaptive capacity
15	Television	Per 1000 people	BBS 2012	Information	Adaptive capacity
16	Agriculture dependency	Percent of HHs depending on farming	BBS 2013	Ecological	Sensitivity
17	Fuelwood dependency	Percent of HHs using wood for cooking	BBS 2013	Ecological	Sensitivity
18	Disability	Percent of people	BBS 2013	Human	Sensitivity
19	Female HH head	Percent of HHs	BBS 2012	Human	Sensitivity
20	Population density	People per square km	BBS 2012	Human	Sensitivity
21	Injury in NH	No of people injured in 2009–2014	BBS 2016	Shocks to natural hazard	Sensitivity
22	Crop damage	Area of cropland damaged in 2009–2014	BBS 2016	Shocks to natural hazard	Sensitivity
23	Household damage	No of HHs destroyed in 2009–2014	BBS 2016	Shocks to natural hazard	Sensitivity
24	Tornado-affected HHs	No of HHs affected in 2009–2014	BBS 2016	Shocks to natural hazard	Sensitivity
25	Drought-affected HHs	No of HHs affected in 2009–2014	BBS 2016	Shocks to natural hazard	Sensitivity
26	Storm-affected HHs	No of HHs affected in 2009–2014	BBS 2016	Shocks to natural hazard	Sensitivity
27	Salinity-affected HHs	No of HHs affected in 2009–2014	BBS 2016	Shocks to natural hazard	Sensitivity

Table 5 (continued)

No	Indicators	Description of units	Sources	Theme	Vulnerability components
28	Cyclone-affected HHs	No of HHs affected in 2009–2014	BBS 2016	Shocks to natural hazard	Sensitivity
29	Flood-affected HHs	No of HHs affected in 2009–2014	BBS 2016	Shocks to natural hazard	Sensitivity
30	Erosion-affected HHs	No of HHs affected in 2009–2014	BBS 2016	Shocks to natural hazard	Sensitivity
31	Maximum temperature	Coefficient of change in 1960–2009	IWFM 2014	Climatic variables	Exposure
32	Minimum temperature	Coefficient of change in 1960–2009	IWFM 2014	Climatic variables	Exposure
33	Precipitation	Coefficient of change in 1960–2009	IWFM 2014	Climatic variables	Exposure
34	Drought	Relative risk map	CDMP 2006	Extreme events	Exposure
35	Hazard class	Relative risk map generalized hazards	BCAS 2008	Extreme events	Exposure
36	Tidal flood	Relative risk map	BARC 2001	Extreme events	Exposure
37	Sea-level rise	Coastal elevation (m)	USGS	Extreme events	Exposure
38	Cyclone	Relative risk map	CEGIS 2006	Extreme events	Exposure
39	Salinity intrusion	The relative risk of ppt of saline intrusion	SRDI	Extreme events	Exposure
40	Flush flood	Relative risk map	BARC 2001	Extreme events	Exposure
41	River flood	Risk map based on inundation height	BWDB 2010	Extreme events	Exposure
42	Erosion	Relative risk map	BWDB 2010	Extreme events	Exposure

HH household, *NH* natural hazard

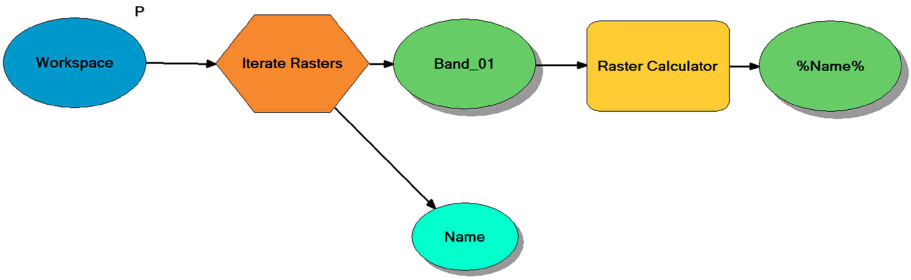

Fig. 7 Iterative model for normalization of raster datasets in a defined workspace

Table 6 Correlation matrix of initially selected 42 indicators (absolute values). Highlighted cells indicate an insignificant relationship

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	1	.44	.25	.13	.35	.10	.47	.55	.18	.14	.43	.34	.19	.26	.30	.70	.16	.12	.27	.41	.07
2		1	.19	.11	.16	.02	.42	.40	.14	.26	.36	.28	.15	.45	.52	.21	.28	.02	.37	.25	.05
3			1	.57	.36	.53	.03	.28	.35	.63	.01	.27	.13	.15	.17	.05	.61	.25	.07	.35	.02
4				1	.14	.74	.19	.71	.40	.69	.16	.63	.17	.28	.41	.53	.52	.58	.49	.58	.13
5					1	.03	.17	.10	.04	.29	.00	.27	.24	.13	.02	.45	.36	.07	.27	.08	.26
6						1	.07	.50	.35	.69	.00	.55	.05	.37	.24	.31	.58	.41	.34	.46	.22
7							1	.43	.44	.01	.30	.57	.17	.09	.28	.53	.07	.28	.01	.47	.05
8								1	.06	.49	.30	.58	.32	.14	.56	.76	.33	.53	.49	.59	.09
9									1	.55	.33	.04	.21	.36	.09	.25	.59	.01	.11	.07	.08
10										1	.01	.37	.03	.30	.31	.10	.83	.35	.19	.36	.04
11											1	.30	.23	.39	.22	.47	.02	.25	.03	.47	.13
12												1	.16	.03	.49	.63	.27	.50	.31	.74	.23
13													1	.02	.21	.32	.09	.13	.19	.14	.03
14														1	.19	.03	.11	.22	.31	.01	.18
15															1	.45	.26	.18	.14	.40	.03
16																1	.11	.50	.51	.62	.01
17																	1	.20	.03	.28	.07
18																		1	.33	.53	.14
19																			1	.29	.04
20																				1	.06
21																					1

erosion prone areas. After the elimination of 4 insignificant variables, the remaining datasets of 38 variables has been considered for further procedures.

Appendix 4. Test statistics

Kaiser–Meyer–Olkin (KMO) test of sampling adequacy:

The Kaiser–Meyer–Olkin (KMO) test is a measure of how suited the dataset is for factor analysis or PCA. The test measures sampling adequacy for each variable in the dataset and the complete dataset. KMO returns values between 0 and 1. KMO values between 0.8 and 1 indicate that the sampling is adequate. KMO values less than 0.6 indicate that the sampling is not adequate and that remedial action should be taken. Some authors put this value at 0.5, and here we have used 0.5 as the lower limit. KMO values close to zero mean that there are large partial correlations compared to the sum of correlations. In other words, there are widespread correlations which are a large problem for factor analysis.

However, individual KMOs can be tested using the correlation and partial correlation (anti-image of correlation) matrices of the dataset with Eq. 4.

Table 6 (continued)

	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42
1	.02	.12	.24	.18	.36	.31	.30	.44	.10	.14	.19	.09	.00	.17	.23	.45	.35	.31	.04	.09	.00
2	.09	.23	.06	.04	.16	.18	.10	.24	.09	.14	.03	.11	.40	.23	.11	.21	.19	.01	.19	.05	.06
3	.05	.28	.13	.19	.40	.23	.44	.32	.03	.52	.32	.55	.12	.15	.14	.23	.48	.30	.04	.29	.00
4	.00	.12	.02	.01	.22	.14	.19	.10	.15	.34	.18	.36	.06	.03	.07	.08	.20	.08	.14	.20	.01
5	.06	.50	.14	.19	.59	.18	.54	.10	.45	.51	.40	.48	.15	.47	.31	.59	.65	.39	.11	.15	.05
6	.11	.15	.20	.19	.30	.15	.29	.37	.18	.47	.38	.46	.04	.03	.02	.13	.36	.18	.21	.24	.03
7	.04	.15	.07	.23	.04	.08	.03	.20	.10	.07	.06	.01	.05	.11	.06	.03	.02	.01	.08	.00	.04
8	.01	.28	.15	.17	.18	.03	.20	.20	.07	.24	.03	.33	.01	.07	.00	.10	.17	.11	.05	.13	.05
9	.15	.18	.22	.20	.03	.23	.10	.19	.13	.41	.34	.35	.22	.11	.21	.08	.20	.02	.22	.30	.11
10	.06	.48	.20	.18	.55	.32	.54	.19	.11	.63	.53	.54	.28	.27	.15	.40	.63	.43	.13	.30	.01
11	.12	.09	.12	.13	.01	.01	.06	.17	.12	.01	.04	.03	.01	.06	.05	.09	.00	.03	.09	.11	.04
12	.10	.03	.15	.01	.08	.04	.10	.13	.35	.19	.08	.20	.00	.05	.03	.02	.10	.09	.07	.03	.03
13	.32	.04	.33	.02	.09	.14	.08	.13	.19	.35	.37	.28	.01	.01	.01	.01	.08	.01	.01	.13	.07
14	.01	.02	.10	.03	.05	.16	.08	.20	.04	.14	.30	.14	.15	.00	.07	.03	.12	.15	.27	.18	.00
15	.09	.25	.08	.08	.28	.02	.16	.11	.22	.15	.02	.12	.16	.09	.13	.18	.16	.06	.14	.03	.04
16	.10	.01	.11	.31	.07	.11	.08	.19	.23	.07	.09	.00	.19	.13	.10	.33	.20	.11	.02	.02	.00
17	.08	.28	.21	.35	.42	.26	.37	.30	.03	.60	.39	.55	.34	.18	.08	.34	.61	.35	.16	.32	.00
18	.01	.19	.02	.06	.10	.21	.22	.04	.08	.18	.10	.20	.08	.11	.18	.03	.14	.22	.03	.00	.03
19	.01	.12	.19	.06	.04	.04	.12	.01	.12	.01	.05	.04	.25	.20	.12	.25	.12	.03	.14	.10	.02
20	.02	.12	.01	.10	.05	.12	.07	.05	.09	.22	.12	.22	.05	.00	.00	.11	.11	.09	.02	.08	.03
21	.24	.50	.12	.23	.15	.18	.15	.60	.55	.08	.04	.03	.05	.22	.29	.23	.17	.27	.20	.11	.00

Table 6 (continued)

	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42
22	1	.18	.28	.05	.09	.32	.03	.35	.56	.20	.16	.18	.00	.16	.12	.07	.00	.09	.02	.21	.09
23		1	.07	.00	.67	.28	.86	.18	.21	.32	.23	.26	.11	.48	.52	.61	.57	.61	.15	.01	.05
24			1	.03	.08	.02	.14	.34	.14	.28	.32	.23	.09	.06	.01	.21	.24	.12	.13	.15	.05
25				1	.16	.04	.16	.50	.07	.16	.09	.13	.17	.04	.06	.24	.24	.13	.04	.12	.03
26					1	.34	.68	.19	.20	.38	.32	.35	.07	.48	.36	.66	.64	.51	.00	.14	.11
27						1	.20	.13	.01	.06	.07	.04	.03	.18	.33	.31	.35	.52	.05	.04	.04
28							1	.20	.05	.42	.34	.40	.08	.48	.48	.62	.64	.62	.06	.10	.06
29								1	.34	.21	.26	.24	.06	.00	.00	.21	.29	.20	.22	.26	.02
30									1	.02	.06	.06	.04	.21	.13	.20	.14	.06	.07	.14	.10
31										1	.81	.92	.15	.34	.16	.34	.68	.36	.09	.31	.00
32											1	.64	.01	.30	.07	.34	.56	.30	.18	.33	.03
33												1	.08	.31	.12	.24	.64	.33	.12	.32	.04
34													1	.20	.18	.25	.22	.16	.08	.11	.02
35														1	.54	.60	.58	.53	.11	.16	.17
36															1	.59	.45	.63	.58	.49	.08
37																1	.74	.66	.12	.01	.08
38																	1	.74	.02	.24	.04
39																		1	.07	.09	.00
40																			1	.41	.01
41																				1	.17
42																					1

$$IndividualKMO = \frac{\sum_{i\neq j} r_{ij}^2}{\sum_{i\neq j} r_{ij}^2 + \sum_{i\neq j} u_{ij}^2} \quad (4)$$

where r_{ij} = correlation coefficients of I with j and u_{ij} = partial variance coefficients of I with j.

Individual KMOs for all variables have been shown in Table 7. Then, the overall KMO of the sample dataset has been tested using Eq. 5.

$$KMO = \frac{\sum_{i\neq j} R_{ij}^2}{\sum_{i\neq j} R_{ij}^2 + \sum_{i\neq j} U_{ij}^2} \quad (5)$$

where R_{ij}= correlation matrix and U_{ij}= partial covariance matrix.

The overall KMO is 0.73 (Table 7), which makes the datasets suitable in terms of sampling adequacy; thus, the datasets are suitable for PCA.

Table 8

Table 7 Calculation of KMO values of individual indicators

Indicators	$\sum_{i\neq j} r_{ij}^2$	$\sum_{i\neq j} u_{ij}^2$	Individual KMO
Literacy rate	3.43	1.61	0.68
Dependency ratio	2.13	1.24	0.63
Irrigation	3.98	0.85	0.82
School	4.79	1.58	0.75
Shelter	3.98	1.03	0.79
Roads	4.45	0.94	0.83
Health institutes	2.12	1.91	0.53
Electricity	4.63	1.03	0.82
Tube well	2.56	2.05	0.56
Drinking water source	6.31	1.18	0.84
Away population	1.60	1.44	0.53
Household	3.78	1.36	0.73
Drought affected	1.16	0.74	0.61
Poverty	1.51	1.35	0.53
Television	2.30	0.98	0.70
Radio	4.24	1.63	0.72
Fuelwood dependency	4.96	1.20	0.80
Disability	2.53	0.75	0.77
Female HH head	1.87	1.44	0.57
Population density	3.59	0.93	0.79
Injury in NH	1.39	1.40	0.50
Household damage	4.37	2.04	0.68
Tornado-affected HHs	1.07	0.68	0.61
Agricultural dependency	1.12	0.88	0.56
Storm-affected HHs	4.39	0.78	0.85
Salinity-affected HHs	1.53	0.71	0.68
Cyclone-affected HHs	4.78	2.36	0.67
Flood-affected HHs	2.20	1.89	0.54
Maximum temperature	5.22	1.62	0.76
Minimum temperature	3.59	1.47	0.71
Precipitation	4.50	1.24	0.78
Hazard class	2.92	0.25	0.92
Tidal flood	3.01	1.18	0.72
Sea-level rise	4.66	0.90	0.84
Cyclone	6.34	0.37	0.95
Salinity intrusion	4.23	0.66	0.86
Flush flood	1.07	0.70	0.60
River flood	1.55	0.79	0.66

Table 8 Calculation of the over KMO of the sample datasets

Statistic	Value
$\sum_{i\neq j} R_{ij}^2$	123.86
$\sum_{i\neq j} U_{ij}^2$	45.15
KMO	0.73

Table 9 Summary of Bartlett's test of sphericity

Statistic	Value
Chi-square	61,742.39514
Degree of freedom	703
p-value	0.0001

Bartlett's test of sphericity:

Bartlett's test of sphericity compares an observed correlation matrix to the identity matrix. Essentially it checks to see if there is a certain redundancy between the variables that we can summarize with a few numbers of factors. The null hypothesis of the test is that the variables are orthogonal, i.e., not correlated. The alternative hypothesis is that the variables are not orthogonal, i.e., they are correlated enough to where the correlation matrix diverges significantly from the identity matrix.

This test is often performed before we use a data reduction technique such as principal component analysis or factor analysis to verify that a data reduction technique can compress the data in a meaningful way. If the *p*-value from Bartlett's test of sphericity is lower than our chosen significance level (common choices are 0.10, 0.05, and 0.01), then our dataset is suitable for a data reduction technique.

To measure the overall relationship between the variables, the determinant of the correlation matrix |R| is calculated. Under H_0, $|R|=1$, if the variables are highly correlated, then $|R| \approx 0$. Bartlett's sphericity is tested by chi-square statistic and level of significance. Equation 6 has been used for chi-square statistics.

$$\chi^2 = -\left(n - 1 - \frac{2p+5}{6}\right) \times \ln|R| \tag{6}$$

where p = number of variables, n = total sample size, and R = correlation matrix.

A summary of Bartlett's test of sphericity has been shown in Table 3. Since Bartlett's test showed a p-value < 0.0001 (Table 9), the datasets have suitability for dimensionality reduction techniques like PCA.

Appendix 5. Test of reliability: Cronbach's alpha

Cronbach's alpha usually ranges from 0.00 to 1.00, and values higher than 0.5 are generally considered indicative of a valid internal relation. Equation 7 has been used for calculating Cronbach's alpha of each PC.

$$\alpha = \frac{k \times \overline{c}}{\overline{v} \times (k-1)\overline{c}} \tag{7}$$

where k = the number of items in the components, $\overline{c}$ = the average of all covariances between items, and $\overline{v}$ = the average variance of each item.

An overview of the calculation of alpha has been given in Table 10.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s11027-022-10013-w.

Acknowledgements The authors are grateful to the following organizations for data: Bangladesh Bureau of Statistics (BBS), Institute of Water and Flood Management (IWFM), Comprehensive Disaster Management

Table 10 Calculation of Cronbach's alpha

PC	k	$\bar{c}$	$\bar{v}$	α
PC1	9	0.017	0.033	0.906
PC2	5	0.022	0.046	0.814
PC3	12	0.007	0.020	0.879
PC4	6	0.009	0.028	0.723
PC5	3	0.019	0.040	0.722
PC6	3	0.008	0.020	0.659

Program (CDMP), Bangladesh Center for Advanced Studies (BCAS), Bangladesh Agricultural Research Council (BARC), Center for Environmental and Geographic Information Services (CEGIS), Soil Resource Development Institute (SRDI), and Bangladesh Water Development Board (BWDB).

The authors are also grateful to the Environmental Science Discipline of Khulna University for giving access to the GIS lab and other resources.

Author contribution Md. Golam Azam: conceptualization, methodology, software, formal analysis and investigation, writing–original draft preparation, visualization, and writing–review and editing.

Md. Mujibor Rahman: supervision.

Data availability Not applicable.

Code availability Not applicable.

Declarations

Conflict of interest The authors declare no competing interests.

References

Abson DJ, Dougill AJ, Stringer LC (2012) Using principal component analysis for information-rich socio-ecological vulnerability mapping in Southern Africa. Appl. Geogrhttps://doi.org/10.1016/j.apgeog.2012.08.004

Adger WN (2006) Vulnerability. Glob. Environ. Changhttps://doi.org/10.1016/j.gloenvcha.2006.02.006

Ahmed N, Occhipinti-Ambrogi A, Muir JF (2013) The impact of climate change on prawn post larvae fishing in coastal Bangladesh: socioeconomic and ecological perspectives. Mar. Policy.https://doi.org/10.1016/j.marpol.2012.10.008

Ahsan MN, Warner J (2014) The socioeconomic vulnerability index: a pragmatic approach for assessing climate change led risks-a case study in the south-western coastal Bangladesh. Int. J. Disaster Risk Reduct. https://doi.org/10.1016/j.ijdrr.2013.12.009

Anderberg M (2014) Cluster analysis for applications: probability and mathematical statistics: a series of monographs and textbooks. Academic Press/Elsevier Science, Burlingtonhttps://doi.org/10.1016/C2013-0-06161-0

Barbier EB (2015) Climate change impacts on rural poverty in low-elevation coastal zones. Estuar. Coast. Shelf Sci. https://doi.org/10.1016/j.ecss.2015.05.035

BARC (2001) Flood risk map of Bangladesh., Bangladesh Agricultural Research Council. Dhaka

BBS (2016) Bangladesh disaster related statistics 2015: climate change and natural disaster perspective. Bangladesh Bureau of statistics. Government of the People Republic of Bangladesh, Dhaka

BBS (2013) District Statistics 2011. Bangladesh Bureau of statistics. Government of the People Republic of Bangladesh, Dhaka

BBS (2012) Bangladesh Population and Housing Census 2011: National Report, Volume-4. Bangladesh Bureau of Statistics. Government of the People's Republic of Bangladesh, Dhaka

BCAS (2008) Climate change: responses. Bangladesh center for advanced studies, Dhaka
Blasius J (2014) Visualization and verbalization of data, visualization and verbalization of data. https://doi.org/10.1201/b16741
Bouroncle C, Imbach P, Rodríguez-Sánchez B et al (2017) Mapping climate change adaptive capacity and vulnerability of smallholder agricultural livelihoods in Central America: ranking and descriptive approaches to support adaptation strategies. Clim Change 141:123–137. https://doi.org/10.1007/s10584-016-1792-0
Bro R, Smilde AK (2014) Principal component analysis. Anal. Methodshttps://doi.org/10.1039/c3ay41907j
Brooks N (2003) Vulnerability, risk and adaptation: a conceptual framework. Tyndall Cent. Clim. Chang. Res. Work. Pap. 38
Bukvic A, Rohat G, Apotsos A, de Sherbinin A (2020) A systematic review of coastal vulnerability mapping. Sustain 12:1–26. https://doi.org/10.3390/su12072822
Burton I, Huq S, Lim B, Pilifosova O, Schipper EL (2002) From impacts assessment to adaptation priorities: the shaping of adaptation policy. Clim. Policy. https://doi.org/10.3763/cpol.2002.0217
BWDB (2010) Annual Flood Report 2010. Bangladesh Water Development Board, Dhaka
Cattell RB (1966) The scree test for the number of factors. Multivariate Behav. Res. https://doi.org/10.1207/s15327906mbr0102_10
CDMP (2006) Component 4B of Comprehensive Disaster Management Programme. Comprehensive Disaster Management Programme (CDMP), Dhaka
CEGIS (2006) Draft final report of impact of sea level rise on land use suitability and adaptation options in southwest region of Bangladesh, Center for Environmental and Geographic Information Services (CEGIS). Dhaka
Chadwick R, Good P, Martin G, Rowell DP (2016) Large rainfall changes consistently projected over substantial areas of tropical land. Nat. Clim. Chang. https://doi.org/10.1038/nclimate2805
Chang LF, Huang SL (2015) Assessing urban flooding vulnerability with an emergy approach. Landsc. Urban Plan. https://doi.org/10.1016/j.landurbplan.2015.06.004
Comer PJ, Young B, Schulz K, Kittel G, Unnasch B, Braun D, Hammerson G, Smart L, Hamilton H, Auer S, Smyth R, Hak J (2012) Climate change vulnerability and adaptation strategies for natural communities: piloting methods in the Mojave and Sonoran Desert, Report to the U.S. Fish and Wildlife Service. Arlington
Coulibaly JY, Mbow C, Sileshi GW, Beedy T, Kundhlande G, Musau J (2015) Mapping vulnerability to climate change in Malawi: spatial and social differentiation in the Shire River Basin. Am. J. Clim. Chang. https://doi.org/10.4236/ajcc.2015.43023
Cronbach LJ (1951) Coefficient alpha and the internal structure of tests. Psychometrika 16:297–324
Das S, Ghosh A, Hazra S et al (2020) Linking IPCC AR4 & AR5 frameworks for assessing vulnerability and risk to climate change in the Indian Bengal Delta. Prog Disaster Sci 7:100110. https://doi.org/10.1016/j.pdisas.2020.100110
Dasgupta S, Huq M, Khan ZH, Ahmed MMZ, Mukherjee N, Khan MF, Pandey K (2014) Cyclones in a changing climate: the case of Bangladesh. Clim. Dev. https://doi.org/10.1080/17565529.2013.868335
Dasgupta S, Huq M, Khan ZH, Ahmed MMZ, Mukherjee N, Khan MF, Pandey K (2010) Vulnerability of Bangladesh to cyclones in a changing climate potential damages and adaptation cost. World-https://doi.org/10.1111/j.1467-7717.1992.tb00400.x
Davies R, Midgeley S (2010) Risk and vulnerability mapping in southern Africa: a hotspot analysis, Regional Climate Change Programme: Southern Africa For the Department for International Development. Cape town
DDM (2017) Disaster Report, 2017. Ministry of Disaster Management & Relief. Government of People's Republic of Bangladesh
de Sherbinin A, Bukvic A, Rohat G et al (2019) Climate vulnerability mapping: a systematic review and future prospects. Wiley Interdiscip Rev Clim Chang 10:1–23. https://doi.org/10.1002/wcc.600
Delaney JT, Bouska KL, Eash JD et al (2021) Mapping climate change vulnerability of aquatic-riparian ecosystems using decision-relevant indicators. Ecol Indic 125:107581. https://doi.org/10.1016/j.ecolind.2021.107581
Deressa T, Hassan R, Ringler C (2008) Measuring Ethiopian farmer's vulnerability to climate change across regional states, International Food Policy Research Institute. Washington D.C.
Dewan A, Yamaguchi Y, Rahman Z (2012) Dynamics of land use/cover changes and the analysis of landscape fragmentation in Dhaka Metropolitan, Bangladesh. GeoJournal 77:315–330. https://doi.org/10.1007/s10708-010-9399-x
DoE, (2012) Environmental outlook. Department of Environment. Government of the People's Republic of Bangladesh, Dhaka

Dore MHI (2005) Climate change and changes in global precipitation patterns: what do we know? Environ. Inthttps://doi.org/10.1016/j.envint.2005.03.004
Duran B, Odell P (2013) Cluster analysis: a survey. Springer Science and Business Media
DW (2018) Weather, Climate Risk Index: 2017 broke records for extreme weather. Environment: Extreme [WWW Document]. Duetche Welle. URL https://www.dw.com/en/climate-risk-index-2017-broke-records-for-extreme-weather/a-46565140 (accessed 3.7.19)
Ericksen PJ, Thornton PK, Notenbaert AMO, Cramer L, Jones PG, Herrero MT (2011) Mapping hotspots of climate change and food insecurity in the global tropics. Climate Change Agriculture and Food Security (CCAFS), Copenhagen
Feng X, Porporato A, Rodriguez-Iturbe I (2013) Changes in rainfall seasonality in the tropics. Nat. Clim. Chang. https://doi.org/10.1038/nclimate1907
Fischer G, Shah M, Tubiello FN, Van Velhuizen H (2005) Socio-economic and climate change impacts on agriculture: an integrated assessment, 1990–2080, in: Philosophical Transactions of the Royal Society B: Biological Sciences. https://doi.org/10.1098/rstb.2005.1744
Fisher B, Ellis AM, Adams DK, Fox HE, Selig ER (2015) Health, wealth, and education: the socioeconomic backdrop for marine conservation in the developing world. Mar. Ecol. Prog. Serhttps://doi.org/10.3354/meps11232
Füssel HM, Klein RJT (2006) Climate change vulnerability assessments: an evolution of conceptual thinking. Clim. Change. https://doi.org/10.1007/s10584-006-0329-3
Gallopín G (2003) A sistemic synthesis of the relations between vulnerability, hazard, exposure and impact at policy identification. Econ. Comm. Lat. Am. Caribb. (ECLAC). Handb. Estim. Socio-Economic Environ- Ment. Eff. Disasters. ECLAC
Gallopín GC (2006) Linkages between vulnerability, resilience, and adaptive capacity. Glob. Environ. Chang https://doi.org/10.1016/j.gloenvcha.2006.02.004
Gerlitz JY, Banerjee S, Brooks N, Hunzai K, Macchi M (2014) An approach to measure vulnerability and adaptation to climate change in the Hindu Kush Himalayas, in: Handbook of Climate Change Adaptation. https://doi.org/10.1007/978-3-642-40455-9_99-1
Germanwatch (2021) GLOBAL CLIMATE RISK INDEX 2021: Who suffers most from extreme weather events? Weather-related loss events in 2019 and 2000 to 2019. Munich. https://germanwatch.org/en/19777
GIZ (2014) Concept and guidelines standardised vulnerability assessments. [WWW Document]. vulnerability Sourceb. URL https://gc21.giz.de/ibt/var/app/wp342deP/1443/wpcontent/uploads/filebase/va/vulnerability-guides-manualsreports/Vulnerability_Sourcebook_-_Guidelines_for_Assessments_-_GIZ_2014.pdf (accessed 3.13.19)
Glibert PM, Icarus Allen J, Artioli Y, Beusen A, Bouwman L, Harle J, Holmes R, Holt J (2014) Vulnerability of coastal ecosystems to changes in harmful algal bloom distribution in response to climate change: projections based on model analysis. Glob. Chang. Biolhttps://doi.org/10.1111/gcb.12662
Guillard-Gonçąlves C, Cutter SL, Emrich CT, Zêzere JL (2015) Application of Social Vulnerability Index (SoVI) and delineation of natural risk zones in Greater Lisbon. J. Risk Res, Portugal. https://doi.org/10.1080/13669877.2014.910689
Gupta AK, Negi M, Nandy S, Kumar M, Singh V, Valente D, Pandey R (2020) Mapping socio-environmental vulnerability to climate change in different altitude zones in the Indian Himalayas. Ecol Ind 109:105787
Hair (2010) Multivariate data analysis. Seventh Edition. Prentice Hall, Exploratory Data Analysis in Business and Economics. https://doi.org/10.1007/978-3-319-01517-0_3
Haque MA, Ahmed N, Pradhan B, Roy S (2019) Assessment of coastal vulnerability to multi-hazardous events using geospatial techniques along the eastern coast of Bangladesh. Ocean and Coastal Management. https://doi.org/10.1016/j.ocecoaman.2019.104898
Heltberg R, Bonch-Osmolovskiy M (2011) Mapping vulnerability to climate change, The World Bank. Washington D.C.
Hossain MS, Arshad M, Qian L et al (2020) Climate change impacts on farmland value in Bangladesh. Ecol Indic 112:106181. https://doi.org/10.1016/j.ecolind.2020.106181
Howden SM, Soussana JF, Tubiello FN, Chhetri N, Dunlop M, Meinke H (2007) Adapting agriculture to climate change. Proc. Natl. Acad. Sci. U. S. A.https://doi.org/10.1073/pnas.0701890104
Howe C, Suich H, van Gardingen P, Rahman A, Mace GM (2013) Elucidating the pathways between climate change, ecosystem services and poverty alleviation. Curr. Opin. Environ. Sustainhttps://doi.org/10.1016/j.cosust.2013.02.004
ICCCAD (2019) Understanding climate change vulnerability in two coastal villages in Bangladesh and exploring options for resilience. HELVELTAS Bangladesh, Dhaka

IPCC (2014) Summary for policymakers, In: Climate Change 2014, Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. https://doi.org/10.1017/CBO9781107415324

IPCC (2013) Climate change 2013: the physical science basis, contribution of working group I, Fifth Assessment Report of the Intergovernmental Panel on Climate Change

IPCC (2007) Climate change 2007: mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Intergovernmental Panel on Climate Change

IPCC (2001) Climate change 2001: impacts, adaptation and vulnerability, contribution of working group II to the third assessment report of the intergovernmental panel on climate change. Cambridge

IPCC (1996) Climate change 1995. Impacts, adaptation and mitigation of climate change: scientific technical analyses. Cambridge University Press, Cambridge

IWFM (2014) Impact of climate change on rainfall intensity in Bangladesh, Institute of Water and Flood Management (IWFM). Bangladesh University of Engineering and Technology (BUET), Dhaka

Iyalomhe F, Rizzi J, Pasini S, Torresan S, Critto A, Marcomini A (2015) Regional risk assessment for climate change impacts on coastal aquifers. Sci. Total Environhttps://doi.org/10.1016/j.scitotenv.2015.06.111

Javid K, Akram MAN, Mumtaz M, Siddiqui R (2019) Modeling and mapping of climatic classification of Pakistan by using remote sensing climate compound index (2000 to 2018). Appl. Water Sci. https://doi.org/10.1007/s13201-019-1028-3

Jenks GF (1967) The data model concept in statistical mapping. Int. Yearb. Cartogr.

Jolliffe IT (2002) Principal component analysis, second edition. Encycl. Stat. Behav. Sci. https://doi.org/10.2307/1270093

Kaiser HF (1960) The application of electronic computers to factor analysis. Educ. Psychol. Meashttps://doi.org/10.1177/001316446002000116

Kang H, Xuxiang L, Jing Z (2015) GIS analysis of changes in ecological vulnerability using a SPCA model in the Loess plateau of Northern Shaanxi. Int. J. Environ. Res. Public Health, China. https://doi.org/10.3390/ijerph120404292

Kelly PM, Adger WN (2000) Theory and practice in assessing vulnerability to climate change and facilitating adaptation. Clim. Changehttps://doi.org/10.1023/A:1005627828199

Kerr RA (2009) Fall meeting of the American geophysical union: galloping glaciers of greenland have reined themselves In. Science (80). https://doi.org/10.1126/science.323.5913.458a

Khan JU, Islam AKMS, Das MK, Mohammed K, Bala SK, Islam GMT (2020) Future changes in meteorological drought characteristics over Bangladesh projected by the CMIP5 multi-model ensemble. Clim Change 162:667–685. https://doi.org/10.1007/s10584-020-02832-0

Kim JE, Park JY, Lee JH, Kim TW (2019) "주성분 분석 및 엔트로피 기법을 적용한 사회·경제적 가뭄 취약성 평가", Journal of Korea Water Resources Association. Korea Water Resources Association 52(6):441–449. https://doi.org/10.3741/JKWRA.2019.52.6.441

Ledesma RD, Valero-Mora P (2007) Determining the number of factors to retain in EFA: an easy-to-use computer program for carrying out Parallel Analysis. Pract. Assessment, Res. Eval.

Liu J, Fritz S, van Wesenbeeck CFA, Fuchs M, You L, Obersteiner M, Yang H (2008) A spatially explicit assessment of current and future hotspots of hunger in Sub-Saharan Africa in the context of global change. Glob. Planet. Changehttps://doi.org/10.1016/j.gloplacha.2008.09.007

Lorentzen T (2014) Statistical analysis of temperature data sampled at Station-M in the Norwegian Sea. J. Mar. Systhttps://doi.org/10.1016/j.jmarsys.2013.09.009

Macharia D, Kaijage E, Kindberg L, et al (2020) Mapping climate vulnerability of river basin communities in Tanzania to inform resilience interventions. Sustain 12https://doi.org/10.3390/su12104102

Mcinnes KL, Macadam I, Hubbert G, O'Grady J (2013) An assessment of current and future vulnerability to coastal inundation due to sea-level extremes in Victoria, southeast Australia. Int. J. Climatolhttps://doi.org/10.1002/joc.3405

Metzger MJ, Schröter D (2006) Towards a spatially explicit and quantitative vulnerability assessment of environmental change in Europe. Reg. Environ. Changhttps://doi.org/10.1007/s10113-006-0020-2

Miller S (2014) Indicators of social vulnerability in fishing communities along the west coast region of the US. Oregon State University, New York

Moser SC, Davidson MA (2016) The third national climate assessment's coastal chapter: the making of an integrated assessment. Clim. Changehttps://doi.org/10.1007/s10584-015-1512-1

Neumann JE, Emanuel KA, Ravela S, Ludwig LC, Verly C (2015) Risks of coastal storm surge and the effect of sea level rise in the Red River delta, Vietnam. Sustain. https://doi.org/10.3390/su7066553

Nick FM, Vieli A, Howat IM, Joughin I (2009) Large-scale changes in Greenland outlet glacier dynamics triggered at the terminus. Nat. Geoscihttps://doi.org/10.1038/ngeo394
Okey TA, Alidina HM, Agbayani S (2015) Mapping ecological vulnerability to recent climate change in Canada's Pacific marine ecosystems. Ocean Coast. Manag. https://doi.org/10.1016/j.ocecoaman.2015.01.009
Piya L, Maharjan K, Joshi N (2012) Vulnerability of rural households to climate change and extremes: analysis of Chepang households in the Mid-Hills of Nepal., in: The International Association of Agricultural Economics (IAAE) Triennial Conference. Brazil
Preston B, Stafford-Smith M (2009) Framing vulnerability and adaptive capacity assessment: discussion paper, CAF Working Paper 2
Quackenbush J (2002) Microarray data normalization and transformation. Nat. Genet.https://doi.org/10.1038/ng1032
Rahman MR, Lateh H (2017) Climate change in Bangladesh: a spatiotemporal analysis and simulation of recent temperature and rainfall data using GIS and time series analysis model. Theor. Appl. Climatolhttps://doi.org/10.1007/s00704-015-1688-3
Rahman MR, Lateh H (2016) Meteorological drought in Bangladesh: assessing, analysing and hazard mapping using SPI, GIS and monthly rainfall data. Environmental Earth Sciences, 75(12). https://doi.org/10.1007/s12665-016-5829-5
Rajesh S, Jain S, Sharma P (2018) Inherent vulnerability assessment of rural households based on socio-economic indicators using categorical principal component analysis: a case study of Kimsar region, Uttarakhand. Ecol Indic 85:93–104. https://doi.org/10.1016/j.ecolind.2017.10.014
Rashid H (1991) Geography of Bangladesh. University Press Ltd, Dhaka
Rencher A (2002) Principal component analysis. Methods of multivariate analysis, 2nd ed. Wiley & Sons, New York
Roy DC, Blaschke T (2015) Spatial vulnerability assessment of floods in the coastal regions of Bangladesh. Geomatics, Nat. Hazards Risk. https://doi.org/10.1080/19475705.2013.816785
Ruane AC, Major DC, Yu WH, Alam M, Hussain SG, Khan AS, Hassan A, Hossain BMT, Goldberg R, Horton RM, Rosenzweig C (2013) Multi-factor impact analysis of agricultural production in Bangladesh with climate change. Glob. Environ. Changhttps://doi.org/10.1016/j.gloenvcha.2012.09.001
Salinger MJ, Sivakumar MVK, Motha R (2005) Reducing vulnerability of agriculture and forestry to climate variability and change: workshop summary and recommendations, in: Climatic Change. https://doi.org/10.1007/s10584-005-5954-8
Schiavinato L, Payne H (2015) Mapping coastal risks and social vulnerability: current tools and legal risks. Springer, North Carolina
Shaw J (2015) Vulnerability to climate change adaptation in rural Bangladesh. Clim Policy 15:410–412. https://doi.org/10.1080/14693062.2015.1007837
Singh SK, Vedwan N (2015) Mapping composite vulnerability to groundwater arsenic contamination: an analytical framework and a case study in India. Nat. Hazardshttps://doi.org/10.1007/s11069-014-1402-2
Stelzenmüller V, Ellis JR, Rogers SI (2010) Towards a spatially explicit risk assessment for marine management: assessing the vulnerability of fish to aggregate extraction. Biol. Conservhttps://doi.org/10.1016/j.biocon.2009.10.007
Tan PN, Steinbach M, Kumar V (2013) Data mining cluster analysis: basic concepts and algorithms, Introduction to Data Mining
The Washington Post (2015) The countries most vulnerable to climate change, in 3 maps. Climate and Environment [WWW Document]. URL https://www.washingtonpost.com/news/energy-environment/wp/2015/02/03/the-countries-most-vulnerable-to-climate-change-in-3-maps/?noredirect=on&utm_term=.3fb7e3aa57b2 (accessed 3.7.19)
Thompson B (2004) Exploratory confirmatory factor analysis: understanding concepts and applications. American Psychological Association (APA), New York
Uddin MN, Saiful Islam AKM, Bala SK, Islam GMT, Adhikary S, Saha D, Haque S, Fahad MGR, Akter R (2019) Mapping of climate vulnerability of the coastal region of Bangladesh using principal component analysis. Appl. Geogrhttps://doi.org/10.1016/j.apgeog.2018.12.011
UNDP (2007) Human development report 2007/2008: Fighting climate change: human solidarity in a divided world. Oxford University Press, London
UNICEF (2016) Learning to live in a changing climate: the impact of climate change on children in Bangladesh, United Nations Children's Fund (UNICEF). Dhaka
Vaske JJ, Beaman J, Sponarski CC (2016) Rethinking internal consistency in Cronbach's alpha. Leis Sci 39(2):163–173. https://doi.org/10.1080/01490400.2015.1127189

Williams B, Onsman A, Brown T (2012) Exploratory factor analysis: a five-step guide for novices EDUCATION exploratory factor analysis: a five-step guide for novices. Australas. J. Paramed

Yohe G, Tol RSJ (2002) Indicators for social and economic coping capacity - moving toward a working definition of adaptive capacity. Glob. Environ. Changhttps://doi.org/10.1016/S0959-3780(01)00026-7

Yusuf A, Francisco H (2009) Climate change vulnerability mapping for Southeast Asia, Economy and Environment Program for Southeast Asia (EEPSEA). Singapore

Zhu Q, Liu T, Lin H, Xiao J, Luo Y, Zeng W, Zeng S, Wei Y, Chu C, Baum S, Du Y, Ma W (2014) The spatial distribution of health vulnerability to heat waves in Guangdong province, China. Glob. Health Action. https://doi.org/10.3402/gha.v7.25051

Zaiontz C (2020) Real statistics using excel. www.real-statistics.com