Evaluating the impacts of major cyclonic catastrophes in coastal Bangladesh using geospatial techniques

Mashoukur Rahaman¹ · Md. Esraz-UI-Zannat¹

Received: 25 November 2020 / Accepted: 15 June 2021

Published online: 03 July 2021

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Abstract

Cyclonic catastrophes frequently devastate coastal regions of Bangladesh that host around 35 million people which represents two-thirds of the total population. They have caused many problems like agricultural crop loss, forest degradation, damage to built-up areas, river and shoreline changes that are linked to people's livelihood and ecological biodiversity. There is an absence of a comprehensive assessment of the major cyclonic disasters of Bangladesh that integrates geospatial technologies in a single study. This study aims to integrate geospatial technologies with major disasters and compares them, which has not been tried before. This paper tried to identify impacts that occurred in the coastal region by major catastrophic events at a vast level using different geospatial technologies. It focuses to identify the impacts of major catastrophic events on livelihood and food production as well as compare the impacts and intensity of different disasters. Furthermore, it compared the losses among several districts and for that previous and post-satellite images of disasters that occurred in 1988, 1991, 2007, 2009, 2019 were used. Classification technique like machine learning algorithm was done in pre- to post-disaster images. For quantifying change in the indication of different factors, indices including NDVI, NDWI, NDBI were developed. "Change vector analysis" equation was performed in bands of the images of pre- and post-disaster to identify the magnitude of change. Also, crop production variance was analyzed to detect impacts on crop production. Furthermore, the changes in shallow to deep water were analyzed. There is a notable change in shallow to deep water bodies after each disaster in Satkhira and Bhola district but subtle changes in Khulna and Bagerhat districts. Change vector analysis revealed greater intensity in Bhola in 1988 and Satkhira in 1991. Furthermore, over the years 2007 and 2009 it showed medium and deep intense areas all over the region. A sharp decrease in Aus rice production is witnessed in Barishal in 2007 when cyclone "Sidr" was stricken. The declination of potato production is seen in Khulna district after the 1988 cyclone. A huge change in the land-use classes from classified images like water body, Pasture land in 1988 and water body, forest in 1991 is marked out. Besides, a clear variation in the settlement was observed from the classified images. This study explores the necessity of using more geospatial technologies in disastrous impacts assessment around the world in the context of Bangladesh and, also, emphasizes taking effective, proper and sustainable disaster management and mitigation measures to counter future disastrous impacts.

Keywords Remote sensing · Image classification · Landsat · Sentinel · Catastrophe · Cyclone · Indices · Change vector analysis · Crop production variance · Change detection statistics

✉ Mashoukur Rahaman, mashouk.rahaman@gmail.com | ¹Department of Urban and Regional Planning, Khulna University of Engineering & Technology (KUET), Khulna 9203, Bangladesh.

1 Introduction

Bangladesh coasts encounter cyclones frequently. On average, a severe cyclone strikes the country every 3 years [41]. Furthermore, it is heavily impacted by catastrophes because of geographic factors like its location, trivial continental shelf, almost sea-level geography of the coastal land and the high-density population [18]. These disasters cause heavy loss to life, property, biodiversity, livestock and most importantly to agriculture that create social and economic losses to the affected communities. Agricultural and built-up areas are in a more vulnerable zone because of direct contact by cyclonic turbulence [37]. These disasters cause severe distortion socioeconomically by affecting land transactions, livestock damage, destruction of built-up areas and causing debt to the local people for post-disaster recovery [34]. The immeasurable losses of lives due to cyclones in Bangladesh can be stated as follows: 300,000.0 deaths in 1970, 5704.0 deaths in 1988, 138,866.0 deaths in 1991, 4234.0 deaths in 2007, 190.0 deaths in 2009 [52]. Total 1% of the global cyclone hits the Bangladesh coasts, but it experiences 53% of the global fatalities of the cyclone [26].

Throughout the history, tropical cyclones have been considered the worst climate-induced disaster killing at least 1.9 million people over the past two centuries and causing damages worth 26 billion dollars [32]. It is estimated that the number of cyclone will rise in the upcoming years as cyclone is related to sea surface temperature (greater than 27 °C) and which will eventually rise with climate change [40]. So, incorporating different geospatial technologies in measuring cyclonic catastrophic casualties will benefit the people to face this kind of casualties. This study will assist international communities to a better understanding of the impacts of cyclonic catastrophes in more of a technical sense. Furthermore, it will aid them to understand the use of better technical methods and advancing them for evaluating catastrophes. The cyclones in Bangladesh are the ones with the highest casualties in the world in terms of losses of lives and damaging environment, properties. So, these events are taken as they can be represented as the worst cyclonic catastrophes in the world. Also, the techniques and methods used in this study can be replicated to analyze any cyclonic catastrophes of the world.

With the incessant use of technology, geospatial technology has become a very useful method, especially for evaluating catastrophic situations. Remote sensing is an important part of geospatial technology and its recent advances playing a key role in upgrading geospatial technologies. Recently Google Earth Engine

has been used for evaluating the relationship between LST with remotely sensed LULC-derived vegetation indices (NDVI, EVI, LAI, DSI, NDWI, albedo, NDSI, NDBI) [48]. Also, thermal sharpening (TsHARP) downscaling algorithm has been used with a separate combination of four remote sensing indices (NDBI), (NDVI) (NDWI), (NMDI) to evaluate the seasonal variation of estimated error in downscaled land surface temperatures (LST) in Raipur, India [25]. Furthermore, to detect Urban region function recognition two neural network-based methods CNN and LSTM network have been developed to automatically extract discriminative time-dependent social sensing signature features, which are fused with remote sensing image features [13]. Recently, it is found that LCZNet a deep convolutional neural network composed of residual learning and the Squeeze-and-Excitation block is nearly 20% higher than standard WUDAPT method for classifying Local climate zone (LCZ) [39]. Also, to locate land suitability for agricultural land, suitability coding system was used to produce the suitability maps [8]. Integration of GIS, RS, and analytical hierarchy process was done to map potential areas of groundwater in the Waddai region, eastern Chad [45]. Furthermore, a raster GIS-based model Land Susceptibility to Coastal Erosion (LSCE) was applied for the entire coastal area of Bangladesh [4]. Change vector analysis (CVA) was used on the satellite images to identify ecological changes in Fujian Province which is located in South-Eastern China [58]. In addition, recently a unique tri-temporal logic-verified change vector analysis (TLCVA) approach was developed that can identify the errors in CVA [19]. Geospatial technology like remote sensing has been used in detecting land-use land-cover change (LULC) in coastal areas of Bangladesh for the past 20 years [43]. In other studies, it is proposed how the use of SAR satellite images is more effective in evaluating the flood range and crop impairment in the southwestern region of Bangladesh [17]. Also, the geostatistical IDW model of GIS technology was used for assessing the spatial vulnerability of disasters like lightning in Bangladesh [11]. Models like two-dimensional bay and river-coupled numerical model were established to analyze the effect of river associated with storms in an area between Haiderganj and Moishadi (Chadpur) [5]. Besides models like CA-ANN were used for detecting temporal dynamics of land-use and land-cover change and its prediction for southwestern coastal districts in Bangladesh [47]. To estimate the degree of coastline vulnerability to sea-level rise in the Ganges deltaic coast, the coastal vulnerability index was developed using seven physical parameters [9]. To enhance the accuracy of classification combined classification like integration of unsupervised classifications with integrated data-assisted labeling approach

was used [38]. Also, classification with higher accuracy in land-cover classification like Xtreme Gradient Boosting (XGBoost)-based informative feature selection and Random Forest classification was used to detect Spatio-temporal patterns of LULC across coastal areas of Bangladesh over 28 years (1990–2017) [1]. Association among LULC change, flood risk, and poverty data was performed for detecting their impacts on coastal Bangladesh [2]. To incorporate natural disasters and land-use/land-cover change in the Shyamnagar subdistrict, which is situated in the southwest of Bangladesh, satellite images were analyzed to detect changes in land cover in the study period of 13 years (1999–2012) [36]. Moreover, 14 parameters were analyzed through the use of analytic hierarchy process (AHP) and geographic information system (GIS) to investigate the cyclone risk situation of Cox's Bazar district and Rohingya refugee camps in southeast Bangladesh [6]. To map the cyclonic impacts of the 2007 cyclone "SIDR" an object-based approach was used in pre- and post-cyclone satellite images of Sarankhola Upazilla [31]. Furthermore, the disaster crunch model (DCM) which is built on pressure and release (PAR) model of vulnerability was used to explore the variability of risk from the consequence of cyclone Aila in 2009 [51].

There have been few studies that incorporate disasters with geospatial technologies. Most of the studies showed only a trend like for 20- or 30-year evaluation. The investigation of catastrophic events by taking satellite images of the previous and aftermath of major disasters has not been done yet. This study incorporates geospatial technology with major disasters. Most of the studies used a portion or comparatively small area of the coastal districts to evaluate the impacts of catastrophes with integration of geospatial technologies. Specifically, there have been no studies done to evaluate the impact of catastrophes taking major disaster in Bangladesh considering vast areas like coastal regions in a single study.

This research aims to evaluate the impacts of catastrophic events in the coastal areas of Bangladesh using different geospatial techniques. Specific objectives are: to find out the impacts at a broad regional level by the major catastrophic events; to find out the impacts of major catastrophic events on livelihood and food production; to compare the impacts and intensity of different disasters; to compare the losses among several districts. A study related to identifying impacts in the coastal part of Bangladesh would be effective for future implications of policies and frameworks for further Disaster Risk Reduction Strategy and Disaster Management in the disaster-stricken countries over the world and also to assess the livelihood of the people with the same vulnerable condition to disasters. Furthermore, to form better community planning for the area, this study may be viable in this regard. The remotely

sensed processed data for change detection should be an important aspect of identifying the change in catastrophic events that occurred in past years around the world. This study can be replicated to perform analysis in areas having similar disastrous situations. The crop area and production variance analysis would help in biocapacity estimation and stockpiling of crops for disaster-stricken regions. This study is based on the context of Bangladesh, but the techniques and methods can be performed in any severe prone disastrous areas around the world.

2 Study area

Bangladesh consists of an area of 47, 211 km² which is considered a vast coastal zone. There are 19 coastal districts that are divided into three coastal zones south-western, central and south-eastern. The 19 coastal districts are Bagerhat, Barguna, Barishal, Bhola, Chandpur, Chittagong, Cox's Bazar, Feni, Gopalganj, Jessore, Jhalkati, Lakshmipur, Narail, Noakhali, Patuakhali, Pirojpur, Satkhira and Shariatpur.

This study considered southwestern and central parts of the coastal region which covers 10 districts for the analysis. Specifically, this study focuses on the exposed coastal districts of Bangladesh. To clarify, exposed coastal districts mean the districts that face the sea directly. However, this study did not take three exterior coastal districts from the southeastern coast because of the limitation of working with a vast area. These 10 districts are vulnerable to disasters that happened for the past couple of decades. In the early years, the southwestern region is affected by catastrophe, but in recent years it is observed that the central region is mostly affected. So, central and southwestern regions are considered for the research to determine the possible changes in the landscape for a catastrophe. The districts are Khulna, Bagerhat, Barguna, Barishal, Satkhira, Jhalokati, Lakshmipur, Pirojpur, Bhola, Patuakhali.

The topography of the study area varies in different places. The regions have a low- to medium-range category of elevation compared to other regions in Bangladesh. Areas of lower topography are the hosting ground of flood and inundation. The study hosts many cities and important built-up areas like Khulna, Barishal and Mongla port, which is one of the most important ports in the country. It also hosts the largest mangrove forest "Sundarbans" which contains vast biodiversity. There are many dense settlements dispersed in the study area. The densest settlements contribute to the vulnerability of this region. Main rivers like the Padma, Meghna pass through this region. Also, some rivers like *Rupsha*, *Bhairab*, *Pasur*, *Mayur*, *Kirtankhola*, *Dhanshiri* pass through the region. The study area hosts major water bodies like "Beel Dakatia" and "Boalia Khal" (Fig. 1).

Fig. 1 **a** Southwestern and central coastal districts of Bangladesh; **b** elevation-level distribution at district level; **c** population density of the southwestern and central coastal districts; **d** river and stagnant water bodies distribution of southwestern and central coastal districts

Table 1 Satellite images with acquisition dates, spatial resolution and source

Name	Date	Source	Spatial resolution	Satellite acquisition date	
				Pre-disaster	Post-disaster
Bangladesh Cyclone	November 30, 1988	Landsat TM	30 × 30 m	2 January 1988; 9 January 1988; 25 January 1988	27 January 1989; 28 January 1989
Bangladesh Cyclone	April 29, 1991	Landsat TM	30 × 30 m	14 November 1990; 11, 27 February 1991	12 December 1991; 9, 25 April 1992
Sidr	November 15, 2007	Landsat TM	30 × 30 m	22 January 2007; 23 February 2007; 18 March 2007	6 November 2008; 8 November 2008; 24 November 2008; 17 February 2008
Ayla	May 25, 2009	Landsat TM	30 × 30 m	10 December 2008; 26 December 2008; 28 February 2008; 24 April 2008	26 October 2009; 6 February 2010
Fani	April 2019	Sentinel MSI	10 × 10 m	1 February 2019; 6 February 2019; 14 February 2019; 24 February 2019	12 November 2019; 23 November 2019; 18 November 2019; 28 November 2019, 31 December 2019

3 Materials and methods

3.1 Data collection

This research is mainly based on secondary data. Satellite images were collected from USGS for the years 1988, 1991, 1997, 2007, 2009, 2019. All satellite images were taken one to two months before and after the catastrophic events. However, few years like 1988, 2019 images were collected as a gap more than that. Maximum accuracy level was considered to acquire the satellite images. Also, information like crop production and area variance data was collected from secondary source “45 years Agriculture Statistics of Major Crops (Aus, Amon, Boro, Jute, Potato & Wheat)” [10] (Table 1).

3.2 Image processing and correction

This research applied Landsat and Sentinel images to perform spatial analysis. The variation of cell size or change in spatial resolution does not affect pre- to post-analysis. To clarify, this study kept cell size same for pre- and post-images for a single event. For instance, the cell size is fixed to 10 m for pre- and post-disaster images for Cyclone “Fani,” but it varies with Cyclone “Ayla” where the cell size is kept 30 m for pre- and post-disaster images, although for the settlement change analysis the spatial resolution kept same for all the images as it was a time series analysis.

In pre-processing, atmospheric and radiometric errors were removed. Since single satellite images do not cover the entire study area. Hence, the authors performed layer stacking on the bands of the images in Erdas imagine 2015. Then, the mosaic of the images was performed in Erdas imagine 2015 according to their cell size, number of bands and pixels

depth. For extraction, study area AOI was imported in the mosaic tool in Erdas Imagine 2015. Thus, the study area is extracted from several scenes.

3.3 Development of indices

3.3.1 Normalized difference vegetation index

NDVI is the normalized ratio of NIR and RED reflectance. This is an index that represents absorptive and reflective changes in vegetation. It indicates changes in vegetation condition proportion to absorption in active radiation [16].

NDVI value has a limit “+ 1 to − 1.” Close to “+ 1” regarded healthy vegetation and close to “0” regarded as not healthy vegetation. Furthermore, “0” regarded bare land and “0 to − 1” corresponds to other land-cover types [29]. For example, when we have negative values, it may be water. On the other hand, if you have an NDVI value close to + 1, there is a high possibility that it is dense green leaves. However, when NDVI is close to zero, there are not green leaves and it could even be an urbanized area [55].

Normalized difference vegetation index (NDVI) quantifies vegetation by measuring the difference between near-infrared (which vegetation strongly reflects) and red light (which vegetation absorbs). NDVI is calculated pixel by pixel as the normalized difference between the red and near-infrared bands from an image. For Landsat TM sensors band 4 is regarded as NIR and Band 3 is regarded as RED, and for Sentinel MSI sensors Red is Band 4 and NIR is Band 8. The equation of NDVI follows:

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (1)$$

3.3.2 Normalized difference water index

The water body has strong absorbability and low radiation in the range from visible to infrared wavelengths. The index uses the green and near-infra-red bands of remote sensing images based on this phenomenon [20]. The NDWI can enhance the water information effectively in most cases and sensitive to image resolution [57]. If the NDVI equation is reversed and the green band used instead of the red, then the outcome would also be reversed, the vegetation suppressed and the open water features enhanced. For Landsat TM sensors band 2 is regarded as Green and Band 4 is regarded as NIR, and for Sentinel MSI sensors Red is Band 3 and NIR is Band 8. The equation of NDWI is as follows:

$$NDWI = \frac{GREEN - NIR}{GREEN + NIR} \quad (2)$$

Its value ranges from -1 to $+1$. -1 to 0 represents a surface with no vegetation or water content. $+1$ represents water content.

3.3.3 Normalized difference built-up index

Built-up areas and Pasture land can be seen changes in reflectance at a range band 4 to band 5 where vegetation shows little variation from band 5 than on band 4 [59]. The corresponding NDBI images will represent built-up and barren land by positive values, and other values represent other land covers [56]. The equation of NDBI is as follows:

$$NDBI = \frac{SWIR1 - NIR}{SWIR1 + NIR} \quad (3)$$

For Landsat TM sensors band 5 is regarded as SWIR1 and Band 4 regarded as NIR, and for Sentinel MSI sensors SWIR1 is Band 11 and NIR is Band 8.

3.3.4 Image change workflow

Image change workflow is a process done by taking early and afterward disastrous images of indices (NDVI, NDWI, NDBI). The input early and afterward images were taken to have the output of the area where value has increased or decreased. The main output indicates increase or decrease of area of the region with a particular index. Each index is represented by the band of images. From the results, charts and graphs are generated to reveal the change in area for five disastrous years. The overall output of the three indices would be the overall change in the image change workflow. Finally, to carry out this analysis "Image change workflow" tool in ENVI 5.3 was used.

3.4 Changes of waterbody pattern

This analysis is useful in evaluating waterbody dynamics concerning the disaster. NDWI was performed in the bands of pre- and post-disaster images. Then from the pre- and post-disaster images of NDWI, a similar threshold was given to all the images in the ArcGIS platform. Finally, from the threshold, a comparison was made. It showed the changes between shallow and deep water concerning the disaster.

3.5 Change vector analysis

It deals with digital numbers in the images. It represents the total gray-level difference between the two dates. It calculates magnitudes for each pixel which is the Euclidean distance between the spectral values of 2 images [46]. The greater the change magnitude (CM) the higher the possibility of change. A decision on change is made based on whether the change magnitude exceeds a specific threshold [15].

It was used to identify changes in pixels between images of two different dates or times [19, 29]. This study took 2 bands for each year to use in the equation for five years (1988, 1991, 2007, 2009, 2019). RED and NIR bands for each year would be taken for the analysis. For two dates magnitude of change is calculated as follows:

$$CM = \sqrt{(DN_{11} - DN_{21})^2 + (DN_{12} - DN_{22})^2} \quad (4)$$

where DN_{ij} is the digital number corresponding to band j for the date i .

Once a pixel is identified as a change, the direction of CM can be examined further to determine the type of change. The type of change is often identified using the angle of the vector in the two spectral dimensions involved. The geometric concept of CVA does not depend on the band number. It can be applied to any number of bands and measurement of the scale of radiance [14]. Also, to mark the direction in the magnitudes we have used the vector layer in ArcGIS. Now the magnitudes can be represented by the direction.

3.6 Crop production and variance analysis

In this study, a crop production and variance analysis was performed using the data from "45 years Agriculture Statistics of Major Crops (Aus, Amon, Boro, Jute, Potato & Wheat)" [10]. The "Crop Field Area" and "Quantity of Production" were taken for the analysis. Simple statistical operations were performed, and charts and graphs were generated from it. Major crops were taken for the analysis of the districts that produce crops. The districts with available data

were taken and used for the analysis. Crop year data of before and after the disaster were taken and then compared between two consecutive years. The reduction in crop production for certain years was identified. From that, a relation between crop area and production concerning catastrophic events was established.

3.7 Supervised classification

This study used supervised classification to identify the full range of variability in the pixels. Its process is perpetrated with a neural and statistical algorithm [23]. The images were classified according to several classes. By this, the number of classes, their area, the percentage of land cover were determined and pre- and post-disastrous images were compared. This study also performed statistical operations to analyze how the area changes both statistically and thematically. Four classes including vegetation, waterbody, forests and Pasture land were taken for conducting the analysis (Table 2).

To carry out the analysis, satellite images for the years 1988, 1991, 2007, 2009, 2019 were acquired. Spatial analyses were carried out in ArcGIS 10.5, Erdas Imagine 2015 and ENVI 5.3 platform. “Signature Sets” were defined by a thorough investigation of the area. Furthermore, knowledge of that particular area was required to finalize the “Signature Sets.” The number of “Signature Sets” should be enough to estimate the conditional mean vector and covariance matrix of the classes [49]. Some of the more common classification algorithms used for supervised classification include the Minimum-Distance, Parallelepiped, Gaussian Maximum Likelihood, K Nearest Neighbor, Support Vector Machine, Decision Tree, Random Forest and Artificial Neural Network [49].

In this study, the Maximum Likelihood Classifier was used. Other classifiers like Random Forest, ANN can also be used, but they can overly fit data and produce inferior results as compared to Maximum Likelihood classification [30]. The classified images were used in Change Detection Statistics, Thematic Change Dynamics and settlement change analysis. In Change Detection Statistics and Thematic Change Dynamics we only took classified images from ENVI 5.3. Moreover, for a big area and macro-level analysis Maximum likelihood classifier is used. This classifier assumed that each class in each band was normally

distributed and worked based on the multivariate probability density function of classes [7]. Also, it calculates the probability that a given pixel belongs to a specific class based on the Bayes theorem which is viable in this study [3].

3.8 Thematic change dynamics

We need results where we can compare two images thematically. For this thematic change would help to predict change thematically. The output is the maps that showed changes between two images. The changes in pixels were determined by their thematic change. The image that is collected after the catastrophe would give a different combination of spectra than the images that are acquired before the events. We have used the “Thematic Change Workflow” tool of ENVI 5.3 that gave the changes in classes and measured the transition dynamics. This tool would give the idea of land-cover change dynamics from one class to another at a given extent [29]. This study would only focus on classes that are applicable to change.

3.9 Change detection statistics

For analyzing the changes statistically, we used the “Change Detection Statistics” tool in ENVI 5.3. This helped statistically identifying the lands—like water bodies, settlement that changes with time. We generated a transition matrix that gave a better understanding of the dynamics of changes. By doing this, the authors developed and relate the number of changes with the events. Also, different relations were established among numbers that helped to quantify the results. Furthermore, numbers helped to give an exact result of the change. It is a statistical technique for detailed and in-depth changes of pixels. It gives results quantitatively.

3.10 Combined classification

In combined classification initially, we generated land-use classes using Unsupervised Classification algorithm. Unsupervised classification is based on clustering. We are using Iso data clustering here. It is based on K means approach. It establishes checks on clusters which are formed throughout or by the end of iterative allocation process and requires definition of the number of clusters and their initial mean positions [49]. Sometimes the availability of ground truth points is not available; in this scenario, it would be effective to build a classification technique where no training site is needed [12]. It is also known as data clustering and is used to find the same criteria of points in multidimensional data sets [22]. It would help us in accurately determining the classes and their changes. We would use ArcGIS 10.5, ERDAS IMAGINE 2015 and ENVI

Table 2 Defined classes for land-use classification

Class number	Class name
01	Waterbody
02	Forest
03	Vegetation
04	Pasture land

5.3. In this operation computer automatically defines random cluster and iteratively compares the pixels with the clusters. It calculates the mean value and defines certain pixels in certain classes.

These satellite images for the years 1988, 1991, 2007, 2009, 2019 were taken before and after the event. Then two classified images are compared and analyzed. The combined image classification technique was performed using ERDAS IMAGINE 2015 [38]. The first step was to generate 200 to 300 classes by Unsupervised Classification. Then the classes were distributed to 5 classes from the generated classes of Unsupervised Classification. Hence, the five classes were verified by the integration of ERDAS IMAGINE 2015 and Google Earth historical images. Finally, they were recoded into five classes.

In this study both ERDAS IMAGINE 2015 and ENVI 5.3 were used to classify the images. Accordingly, to assess the accuracy of classified images of ERDAS IMAGINE 2015, a stratified random sampling was performed to create the random points in ERDAS IMAGINE 2015 software [44]. A total number of 304 random points were sampled for the four LULC classes [50]. Then, the random points are compared with high-resolution historical imagery of Google Earth. Finally, a confusion matrix was developed from the comparison. Also, to assess the accuracy for the classified images in ENVI 5.3, the “Confusion Matrix using Ground Truth ROIs” tool was used. To clarify, the ROIs were created

based on the actual land-use class on Google Earth. Then the ROIs are compared with land-use classes of the classified images. Hence an error matrix was developed from the comparison which was the final output of the tool. The overall accuracy and the Kappa statistics are stated in the table (Fig. 2).

Year		Overall accuracy (%)	Kappa statistics
1988	Pre-disaster	82.4853	0.7401
	Post-disaster	70.4092	0.5784
1991	Pre-disaster	90.9102	0.8577
	Post-disaster	90.5719	0.8524
2007	Pre-disaster	97.0175	0.9516
	Post-disaster	87.2319	0.8077
2009	Pre-disaster	95.9789	0.9173
	Post-disaster	99.6624	0.9931
2019	Pre-disaster	94.7024	0.9132
	Post-disaster	98.5874	0.9768

Year	Overall accuracy	Kappa statistics
1991	88.49%	0.8205
2009	89.14%	0.8302
2019	90.79%	0.8554

Fig. 2 Overall methodological framework

4 Results

4.1 Changes in water, vegetation and built-up areas

The NDVI, NDWI and NDBI were performed on the bands of pre- and post-disaster images. Then the Image Change Workflow tool was used in ENVI 5.3 to measure the variation of indices concerning disasters. To illustrate, this study considered pre- and post-disaster satellite images for the given years of cyclone incidence. Indices measured the extent and magnitude of vegetation, waterbody and built-up areas. NDVI indicates the changes in vegetation, while NDWI and NDBI represent variance in the waterbody and built-up areas. NDVI closer to positive means healthy, greener vegetation and the same criteria for NDWI and NDBI in measuring water and built-up area. However, the threshold for classifying each of the indices is different. Several classes were generated to classify the areas that are generated from indices. The statistical output is meant to express the amount of changed land. Correspondingly, the change in areas represents respective indices from pre- to post-disastrous scenarios and it is represented in percentages. The chart shows the result of how indices changed between pre- to post-disastrous periods. The chart shows an increase and decreases in indices for each consecutive event that follows (Table 3).

4.2 Changes from shallow water to deep water

The NDWI images were generated by a certain normalized equation of two rays. Then the images were classified according to the suitable threshold for analysis. The study generated three classes to show the thematic difference in waterbody from pre- to post-disastrous period. The NDWI images show the changes in shallow to deep water between the early and post-disaster periods. Also, they show where the deep water body changes to shallow water for example in 1991. It may happen because the effects of water that surge from the 1991 cyclone were mainly on southeastern coastal districts, which did not cover the taken study area [28, 35]. It gives the idea of how

waterbody pattern changes in areas. For each consecutive year, 1988, 1991, 2007, 2009, 2019, it shows the transformation of shallow to deep water, and in some cases, the opposite occurs.

The Satkhira district shows a great variation in shallow to deep water bodies. Subtle changes in Khulna and Bagerhat district were noticed. But noticeable changes can be seen in the Bhola district. Other districts like Pirojpur, Jhalokati, Patuakhali, Barguna, Barishal do not show changes in waterbody patterns (Fig. 3).

4.3 Intensity and direction of change

The output of Change vector analysis represents changes in intensity in a particular area. The magnitude of change is represented by color intensity. The intense color represents the high intensity of change, and the much lighter color represents the low intensity of change. So, the areas which have the darkest and deep color have had the most changes. The direction of change is represented by the arrows. The areas where arrows are perpendicular to the surface have not changed. Also, areas with arrows bending or showing an angle with the surface have the most changes. Ultimately, the arrows direct toward where changes occurred.

In the 1988 cyclone, it shows massive intensity toward Bhola district and arrows directing toward Barishal, Lakhimpur and Bhola. In 1991, greater intensity can be seen in the Satkhira district. In 2007 it shows medium intensified areas all over the study area and some deeply intense regions like Barishal, Satkhira, Khulna. In 2009 it shows deeply stricken areas in some parts of Bhola, Khulna and Barishal. In 2009 there was a mixed and medium severity in Barishal, Bhola, Patuakhali and Barguna Districts (Fig. 4).

4.4 Change of area and production of crops

Crop production variance analysis shows a direct link with catastrophic events. The crop year data were taken from "45 years Agriculture Statistics of Major Crops" by the Bangladesh Bureau of Statistics [10]. There we have

Table 3 Variance of indices

Year	NDVI		NDWI		NDBI	
	Area increase (%)	Area decrease (%)	Area increase (%)	Area decrease (%)	Area increase (%)	Area decrease (%)
1988	51	49	74	16	82	18
1991	50	50	41	59	78	22
2007	70	30	32	68	84	16
2009	65	35	30	70	13	87
2019	60	40	40	60	22	78

Fig. 3 Changes from shallow water to deep water 1988, 1991, 2007, 2009, 2019

used crop year data of pre- and post-disaster. It shows that much of the crop production have changed after the disaster. In some year's crop field areas increased, but crop production did not increase.

"Aus" rice is direct or broadcast seeded during March, April (after the pre-monsoon shower) and harvested between July and August [54]. The data for "Aus" rice were taken from the crop year data of 1989–1990 and 1990–1991 to analyze pre- and post-disaster crop yield. After that, a comparison was made in evaluating the variation of yield in those years. For "Aus" rice, there is a marked decrease in the year 2007 when cyclone "SIDR" stroke. A sharp decrease occurred in the Barishal district. In the year 1988, the production decreased in Barishal and Patuakhali. But for years 1991, no changes occurred as that time the cyclone track was in southeastern coastal districts. Also, for 2009, production remains the same and no changes were found in early to post-disastrous periods. Also, for the years 1988 and 2007 a sharp decrease can be seen (Fig. 5).

"Aman" is planted in two ways: direct seeding with "Aus" in March, April and transplantation between July and August. Both types are harvested from November through

December [54]. In 2007 a sharp decrease in production for three districts Barishal, Khulna and Patuakhali can be seen. Also, the declination in the area is observed in 2007. In 1988, 1991 the area increases for Aman rice, but the production did not increase in proportion to area. Following 2009 the crop area and production were not impacted by disasters (Fig. 6).

The potato production was impacted severely in the year 1988 and Khulna district observed the most decline in potato production. In 2009, potato production was found with little impact. Except for these, there is no proportionate damage concerning disasters. In 1991 and 2007 there was a steadiness in potato production. As the demand for potatoes increased with time there is a rapid increase in potatoes in the host yielding districts. The graph for 2009 shows both increases in crop area and production (Fig. 7).

For wheat production, there was a rapid decrease in production and area in 1988. In the year 1991, a decline in the crop area was observed. But no impact on wheat production was found in this instance. In other years like 2007 and 2009, there was an upward movement in wheat production and shows no decline or link between disasters (Fig. 8).

Fig. 4 Intensity and direction of change 1988, 1991, 2007, 2009, 2019

Fig. 5 Production and area variance of Aus Rice. Source: "45 years Agriculture Statistics of Major Crops"

4.5 Changes in land cover

The thematic changes in the area are results of Thematic Change Dynamics tool. As there are four land-cover types, it shows how one land-cover type frequently changes to other. Only areas that changed are displayed here. Different combinations of colors are used to represent the changes. The transition between before and after the disaster showed changes between early and post-disaster. Each color represents changes in classes from one

land-cover type to another. The early and post-classified images of 1988, 1991, 2007, 2009, 2019 were the inputs, and they gave the concrete idea of the changes of early and post-disaster periods (Fig. 9).

4.6 Land-use change scenario

In this analysis, the results of class change between early and post-disaster are represented statistically. A transition matrix of class change was developed where

Fig. 6 Production and area variance of Aman Rice. Source: “45 years Agriculture Statistics of Major Crops”

Fig. 7 **a** Production and area variance of potato for years 1988, 1991, 2007; **b** production and area variance of potato for years 2009. Source: “45 years Agriculture Statistics of Major Crops”

it shows how much area changes to another and how much remains the same. The results shown are in percentage change between classes. In the end, we found class change between two images in percentage and also the difference between two images. A negative value represents the decrease in value, and a positive value represents the increase in the value class.

In 1988 a huge change in the water body and Pasture land was detected. In 1991 it represents a change in water body and forest and vegetation. In 2009 it shows a change in water bodies and vegetation. In 2019, changes can be seen in waterbody and forest (Tables 4, 5, 6, 7, 8).

Fig. 8 **a** Production and area variance of wheat for years 1988, 1991, 2007; **b** production and area variance of wheat for years 2009. Source: “45 years Agriculture Statistics of Major Crops”

Fig. 9 Thematic change dynamics of 1988, 1991, 2007, 2009, 2019

Table 4 Change detection statistics 1988

	Waterbody (%)	Forest (%)	Vegetation (%)	Pasture land (%)	Row total (%)	Class total (%)
Unclassified (%)	0.014	0.001	0.007	0.011	0.019	100
Waterbody (%)	87.99	0.043	0.419	1.384	99.998	100
Forest (%)	6.415	83.708	7.954	6.92	99.995	100
Vegetation (%)	0.095	15.98	79.863	10.529	99.986	100
Pasture land (%)	5.485	0.268	11.758	81.156	99.998	100
Class total (%)	100	100	100	100	0	0
Class changes (%)	12.01	16.292	20.137	18.844	0	0
Image difference (%)	− 7.09	21.006	33.611	− 13.713	0	0

Table 5 Change detection statistics 1991

	Waterbody (%)	Forest (%)	Vegetation (%)	Pasture land (%)	Row total (%)	Class total (%)
Unclassified (%)	0	0	0	0	0	100
Waterbody (%)	89.031	0	0.016	1.185	100	100
Forest (%)	0	86.321	1.754	0.199	100	100
Vegetation (%)	0.002	7.256	63.48	12.433	100	100
Pasture land (%)	10.967	6.423	34.75	86.183	100	100
Class Total (%)	100	100	100	100	0	0
Class Changes (%)	10.969	13.679	36.52	13.817	0	0
Image Difference (%)	− 7.819	− 9.728	− 16.439	19.218	0	0

Table 6 Change detection statistics 2007

	Pasture land (%)	Vegetation (%)	Forest (%)	Waterbody (%)	Row total (%)	Class total (%)
Unclassified (%)	0.006	0.011	0.001	0.004	0.014	100
Waterbody (%)	7.206	0.315	0.025	93.341	99.993	100
Pasture land (%)	71.622	30.704	1.644	6.65	99.991	100
Vegetation (%)	20.235	66.601	3.968	0.004	99.991	100
Forest (%)	0.931	2.369	94.362	0.002	99.998	100
Class Total (%)	100	100	100	100	0	0
Class Changes (%)	28.378	33.399	5.638	6.659	0	0
Image Difference (%)	− 2.941	− 4.062	1.787	16.396	0	0

Table 7 Change detection statistics 2009

	Waterbody (%)	Forest (%)	Vegetation (%)	Pasture land (%)	Row total (%)	Class total (%)
Unclassified (%)	0.007	0.001	0.015	0.004	0.02	100
Waterbody (%)	80.502	0.015	0.263	1.481	100	100
Forest (%)	0.021	89.999	5.761	0.521	99.999	100
Vegetation (%)	0.001	5.623	62.295	44.842	99.995	100
Pasture land (%)	19.47	4.361	31.667	53.152	99.989	100
Class total (%)	100	100	100	100	0	0
Class changes (%)	19.498	10.001	37.705	46.848	0	0
Image difference (%)	− 16.792	4.694	− 4.047	14.565	0	0

Table 8 Change detection statistics 2019

	Waterbody (%)	Forest (%)	Vegetation (%)	Pasture land (%)	Row total (%)	Class total (%)
Unclassified (%)	0.067	0.006	0.032	0.015	0.068	100
Waterbody (%)	86.425	0.248	1.184	1.449	99.937	100
Forest (%)	0.39	42.534	14.89	0.09	99.995	100
Vegetation (%)	2.265	55.723	55.509	24.491	99.977	100
Pasture land (%)	10.854	1.489	28.385	73.956	99.975	100
Class total (%)	100	100	100	100	0	0
Class changes (%)	13.575	57.466	44.491	26.044	0	0
Image difference (%)	− 7.692	− 10.957	7.31	0.358	0	0

4.7 Changes in settlement

The combined classification was conducted on the images of the years 1991, 2009 and 2009. The result from the classified images clearly showed the variation of settlement. Specifically, settlement grows with the years. It gives clear evidence that areas that are taken for the research have become more vulnerable. The areas needed a disaster risk management strategy as it hosts a growing population over the years. It indicates that over the years more settlements would grow and would become more prone and vulnerable to disasters. This suggests that efficient disaster risk management, resilience and strategies should be taken to conduct efficient disaster planning and management (Fig. 10; Table 9).

5 Discussion

The coastal region of Bangladesh is prone to disasters, especially cyclones. Severe changes occurred due to these types of catastrophic events. There were losses of livelihood and ecological impacts over the years. The land cover has severely changed with the disasters. The people and environment faced a dynamic of change concerning the catastrophe. There is a change in food production, waterbody and vegetation pattern over the years. Also, problems like salinity intrusion, erosion, inundation took place. Both nature and man are greatly impacted by it. Hence, a comprehensive evaluation of these kinds of impacts was needed. Geospatial techniques needed to be integrated with this evaluation for precise measurements. Furthermore, it was essential to perform a long total evaluation of major disasters in a single study and this study justifies it. Since automated techniques have few errors concerning conventional techniques, there is little chance of error with other measurements like statistical or socioeconomic evaluation. Also, a proper evaluation of the vulnerable districts

needed to be evaluated, but for a huge area, it was never done. But this study took the most vulnerable ten districts and showed a comparative analysis among them. In summary, the result section clearly shows that there is a significant change in the livelihood, food production, water resource and land cover by the disasters. The Satkhira district shows a great variation in shallow to deep water bodies, but subtle changes in Khulna and Bagerhat district and noticeable changes can be seen in the Bhola district. There is a mixed intensity of disasters from several districts like Bhola, Satkhira, Khulna, Barishal in different years. The declination of crop production can be seen in crops like Aus, Aman, Potato. Severe changes can be traced in land-use classes like waterbody and forests. The results showed an inclination of settlement over the years. Most of the selected districts showed a significant change concerning catastrophic events. Settlements are growing up making the districts more vulnerable to catastrophes. So, community planning and disaster risk reduction mechanisms should be implemented in the vulnerable districts and an efficient disaster management policy should be implemented to tackle the changes as it impacting the community. Stockpiling of the crop is needed, and more emphasis should be given to building infrastructure in this context. The settlement is vulnerable to disasters; thus, efficient planning should be taken to place the settlement in a convoluted area that is safer from the high magnitude of disasters.

From the Image Change Workflow, the highest decrease is observed in NDVI in 1991. NDVI is scaled to measure vegetation, so it can be assumed that the 1991 cyclone may have a huge impact on vegetation. Also, the 2007 cyclone might have a huge impact on the water body as there is a decrease value of 50% NDWI in 2007. Furthermore, an 87% decrease of NDBI in 2019 can be elucidated as a huge impact on the built-up areas in that year. There is a clear picture of some districts showing a variation and the depth of water rises after every disaster. It indicates that the disasters may have contributed to the rising of water depth

Fig. 10 Changes in land use from classified images of 1991, 2009, 2019

Table 9 Changes in land uses from classified land use

Year	1991	2009	2019
Land-cover types	Area (sq. km)	Area (sq. km)	Area (sq. km)
Pasture land	12,301.1802	10,738.4166	13,188.0422
Vegetation	8438.31	10,573.6023	7098.7264
Waterbody	4677.0372	3743.3511	4113.5278
Settlement	277.6536	610.9416	1131.1436

to some areas like Khulna, Satkhira, Bagerhat. The results show that areas with low elevation have the worst impacts because the water level rises there easily and may cause floods. It may suggest that the disasters may contribute to the rise of water level in waterbody because cyclone is accompanied by heavy rain. The results are evidenced that “the intensity of disasters is unique to time, events and place.” As in the result generation process, different years

represent different types of impacts in different places like Bhola in 1988, Satkhira in 1991; Barishal in 2007; Bhola, Khulna and Barishal in 2009. The results revealed that the impacts of a disaster might not be fixed to a certain region or place but change with time. This statement can also be backed up by the analysis of crop production variance. There is a difference in crop yields with disasters. The “Aus” productive areas are severely impacted by “Sidr” that may result in a severe decline in Aus production in 2009. However, the production of Aus rice declines with other events, but the production got severely impacted that year in Barishal. Severe declination of potato yield can be seen at 1988 in Khulna. It suggests that the declination of crop yields might be related to cyclonic catastrophes in those areas. The changes in land-use classes after every disaster also evident that several districts of the region are severely impacted by disasters. From all disasters, the common land-use class is “waterbody” which marks

a significant relation with waterbody to disasters. It may occur because cyclones form in the sea and the districts are located in coastal areas. Severe impacts can be seen in forest class in 2009 and 2019. As the region hosts the largest mangrove forest in the world, the study revealed how the biodiversity of the area is impacted as massive impacts occur in forests. The biodiversity may be affected by disasters because forest usually resists the cyclone and absorb a portion of the intensity of it before hitting the places with dense settlements. It is evident that the places with the highest settlement have the highest risks for casualties and can be assigned with the highest vulnerabilities. The combined classified images of 1991 to 2019 revealed the inclination of the number of settlements. Also, the number would rise in the following years as revealed from the trend analysis. So, it might create risks of severe casualties in the upcoming years.

In the Land-Use Change Scenario, there is a decrease in Pasture land of 2.94 percent in 2007. A similar study showed that the land in the affected areas reduces drastically and the farmers living on it suffered worst [33]. So, these results indicate that the 2007 cyclone “Sidr” impacted the built-up areas drastically. It can be assumed lack of infrastructural support and early evacuation system at that time, “Sidr” severely impacted people in the built-up areas. In addition, the impacted areas can be seen as the NDBI decrease in the year 2007. These results make a correlation with the results that reported that 2.3 million households were affected to some extent and around 1 million had a severe impact in 2007 cyclone “Sidr” [24]. According to change detection statistics of 2019, a clear decrease in vegetation is found. Similar studies suggest that after “FANI” the agricultural land and vegetation were mostly affected than the built-up areas [37]. These results gave proof that with the advancement of disaster management impacts on the community are less compared to the other four catastrophes. In each catastrophe sheer amount of forest changes to Pasture land, but the value is highest in 1988. From the analysis of changes from shallow water to deep water in NDWI images, a clear transformation from shallow water to deep water can be seen. The northern part of Satkhira and some parts of Khulna have the most change in it because major impacts have gone through those districts. Also, from the Land-Use Change Scenario decrease in vegetation was highest in 1991. In similar studies showed 1991 cyclone flooded low-lying areas marking a 6 m depth [27, 28]. This similarity with other studies suggests that the 1991 cyclone impacted crops and vegetation severely. In the results, there is a sharp decline in Aus and Boro rice, particularly in the Barishal district. Also, other crops like potato and wheat showed clear declination. It can be happened due to the 1991 cyclone that destroyed Boro, Aus and other crops

statistically 210,000 tones, 36,000 tones, 35,000 tones according to FAO/WFO [35]. From the analysis of settlement change, a sharp increase in the settlement is seen. Similar studies showed population would increase and the growth rate eventually decreases with time [21]. It can be assumed from the results that the vulnerability of the region would increase with time. It would happen even if the growth rate declines because so far the region hosts a large number of populations. This would occur because the number of people living in low-elevation coastal zone like Asia. China, India, Bangladesh, Indonesia and Vietnam are estimated to have the highest total coastal population exposure in the following years, and this would remain unchanged in near future [42].

Major cyclones in Bangladesh are needed to be evaluated in a single study. As a result, this would help us identify the impacts of major cyclones that occurred around the world. Also, different geospatial tools needed to be integrated with major cyclones that occurred around the globe. This study used different geospatial techniques and tools to evaluate and compare among major cyclones. Since these events can be represented as the worst cyclones around the world. Furthermore, to evaluate the overall disastrous impact a vast area should be taken as disasters impacts a huge region when hit any part of the world. This study has taken vast regions like the coastal region of Bangladesh consisting of ten districts. So, these techniques can be manipulated in any huge region to measure the impacts of any cyclonic catastrophes in any part of the world. Also, it compares among districts concerning cyclonic impacts. Factors like settlement and crop production needed to be integrated with disasters which are done in this study. How much a cyclonic catastrophe impacts any coastal area of the world should be conducted in a study. It can be learned through this research that cyclonic catastrophes hit the coastal community and natural environment significantly.

This study gives a scope of future research on integrating socioeconomic variables to geospatial analysis. Several other analyses like questionnaire surveys or statistical regression analysis can be integrated with future analysis. Also, for a vast area, the study uses a maximum likelihood classifier because of the technical limitations of analyzing such vast dimensions. In the future, anyone can perform a more accurate classifier like a random forest algorithm with extreme Gradient Boosting (XGBoost) that yields a higher accuracy. Also, Google Earth Engine can be used which provides pre-classified images based on indices such as NDVI and NDWI, but this study was unable to do so because of a vast landscape-level analysis of ten districts. One may explore these technical limitations. Furthermore, more accurate and sophisticated analyses can

be performed in the future for evaluating the impacts of catastrophes. This research helps in advancement in the current edge of knowledge in fields like Disaster Management, Geography, Urban Planning, Coastal management and Agriculture. This study recommends a change to the current best technical tools of GIS and Remote Sensing in the application of measuring disastrous impacts.

The main limitation of the study was the resolution of the image. The 30 m-by-30 m Landsat 4–5 images have a resolution that makes it difficult for precise remote sensing analysis for change detection. Further research is needed by using better-resolution images from modern satellites like MODIS, ASTER, SPOT, IKONOS and OrbView 3. As different scenes were acquired at different times, we face the problem of color balancing. There was a shortage of data for some analysis and most of the data were for a single year. Also, as we are working pre- to post-disaster period we need both year's data for the analysis. Therefore, studies should be conducted on areas or regions with the availability of data of every major disaster. As Landsat and Sentinel have low resolution, we cannot perform micro-level analysis with them. Hence, future studies should take into account micro-level perspectives that this research has limitations to address. Moreover, a huge region containing ten districts creates inconveniences to work with primary data and difficult for conducting the survey. For this reason, statistical techniques that can be applied to the socio-economic variable of a huge area like this should be introduced in future researches. Though the accuracy of images of Landsat and Sentinel-2 was not quite good but yet for a large area like that the output of the change detection is noteworthy. It was a landscape-based vast analysis, so micro-level perspectives were not taken to concern, so image quality did not come to an issue in this regard.

This research inspects the impacts of cyclonic catastrophes around the world using geospatial technologies in the context of Bangladesh. It follows that Cyclonic catastrophe significantly impacts the coastal regions. Accordingly, the results suggest severe impacts in forest, vegetation, waterbody, settlement and agricultural production. Moreover, the impacts vary with time and place. These results should be interpreted with circumspection because each of the analyses revealed huge impacts on the coastal region. So, community planning and Disaster risk reduction mechanisms should be implemented in vulnerable districts. Also, an efficient Disaster Management policy should be implemented to tackle the changes as it impacting the community. Furthermore, stockpiling of crops needed and more emphasis should be given to building infrastructure in the context of early evacuation. Hence, settlement is vulnerable to disasters so efficient planning should be taken to replace

the settlement that is convoluted on the path of the high magnitude of disasters. Finally, more researches should be conducted with the integration of geospatial technologies and disasters to minimize the casualties caused by disasters.

6 Conclusions

This research explored the impacts of cyclones on the coastal communities in Bangladesh. As the coast of the country faces cyclones every year, it confronts severe casualties in both social and economic aspects in many cases. Besides, the natural environment and ecological biodiversity are significantly impacted by the cyclones in vast areas. It becomes difficult to measure the impacts at the landscape level. This paper showed how cyclonic catastrophes caused immense damage to the people and the environment at different periods with the help of geospatial technology.

This research identified the crop production change, in variation to disasters and has taken major crops for the research. Moreover, it tried to identify the change dynamics of the 10 districts concerning disasters by remote sensing approaches. Also, it developed different indices to find the change using the image change workflow. Furthermore, it used a machine learning algorithm and automated change detection technique for marking the change of each class of land use and, through the simulation process, identified the change in each class to another. Though the study found moderate results for the quality of the images, yet it gives a clear result of the changes.

Specifically, this research has implications in the use of more technical tools to assist in advancing the science of evaluating the impacts of cyclonic catastrophes in the world. Furthermore, this study exactly brings better use of geospatial technologies like advanced tools in GIS and Remote Sensing to the fields like Disaster Management, Geography, Urban Planning, Coastal management and Agriculture. In addition, it helps in advancing the proper evaluation of catastrophes and comparison of casualties in any disaster-stricken coastal part of the world. More advance technical tools can be used based on this research as it considers the most vulnerable coasts and most powerful cyclones. International scientists in the field of GIS and Remote Sensing would find this study relevant in terms of using these technologies to evaluate the impacts of any cyclones. Moreover, it may help any non-scientists or casual readers in identifying the disastrous impacts in any region and how to minimize casualties.

This study gives the scope for future research on integrating socioeconomic variables. Also, other analyses like questionnaire surveys or statistical regression analysis can

be integrated with future analyses. It can be expanded by using sophisticated tools like Google Earth Engine and a more accurate classifier like a random forest algorithm with extreme Gradient Boosting (XGBoost) that yields a higher accuracy. Furthermore, the methods can be replicated in evaluating other catastrophes like Tsunami, Earthquakes, Tidal surges, Flood. This research may be expanded upon to multiple integrations with other disaster management tools and techniques.

It can be concluded that researchers are continuing their research to assess the impacts of cyclonic catastrophes that occurred around the world. In particular, they are persistently searching for methods to tackle or even mitigate the impacts of the cyclone on the community and nature. In the future, this research is expected to lead to an advancement in discerning the impacts of any cyclonic catastrophes in the world and ways to mitigate them. If the effects occurred by Cyclonic catastrophes cannot be minimized, the coastal region will face more problems in the community and nature. Finally, more research and advancement are required to keep the world safe from the minacious impacts of natural catastrophes like cyclones.

Declarations

Conflicts of interest The authors declare that they have no conflict of interest.

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