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Research Article

Detection of vegetation cover change in the Southern region of Bangladesh using the Normalized Difference Vegetation Index (NDVI) and Climate Smart Agriculture (CSA) practices

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Abstract
Bangladesh is extremely vulnerable to climate change, and vegetation indices serve as sensitive indicators. Due to the impacts of climate change, the cropping intensity of Southern region of Bangladesh is very low. So, this study aimed to analyze the changes in vegetation cover over time using the Normalized Difference Vegetation Index (NDVI) and identify the use of Climate Smart Agriculture (CSA) technologies and the benefits of using such technologies. A questionnaire survey was carried out by purposive random sampling method to detect 120 farmers' socioeconomic status, hazards faced by climate change, adopted climate smart agricultural practices and its benefits for assessing Adaptive Strategy Index (ASI) in Amtali upazila of Barguna district and Kalapara upazila of Patuakhali district. NDVI analysis of multi-spectral remote sensing data from 2012 and 2022 indicated the extent of sparse vegetation of Kalapara has increased. Western part of Amtali upazila, fallow areas have become lessened in 2022 (354.55 km^2) compared to 2012 (368.78 km2) due to adopting different CSA practices. Saline-tolerant crop varieties, sunflowers, and watermelon cultivation were the highest ranked among the CSA practices, with 301, 300, and 296 ASI, respectively. Calculated weighted average of CSA practices indicated the reduction of production cost, increased family income (49.19%) and cropping intensity (51.67%), which impacts developed social bonding.

Keywords: Adaptation Strategy Index (ASI), Climate Change, Climate Smart Agricultural Practices, Normalized Difference Vegetation Index (NDVI), Satellite imagery, Sparse Vegetation

INTRODUCTION

Bangladesh is one of the world's most climate change-vulnerable countries, ranking seventh on the 2021 World Climate Risk Index due to its geographical location and climatic conditions (Asian Development Bank, 2023; Chowdhury *et al.,* 2022). The coastal zone of Bangladesh covers an area of 47,201 km^2, 32% of the country with the landmass of 19 districts, and is the home to over 43.8 million people as per Bangladesh Bureau of Statistics (2022). Around 13.3 million people worldwide are at risk of becoming climate refugees in the upcoming 30 years (World Bank, 2022).The climate has an inescapable impact on vegetation and the growing environment (Gao *et al.*, 2014). Due to the growing demand for fuel, timber, agricultural land and food, remaining forests throughout the globe are under threat; 2.5 billion people out of 3 billion people living in rural areas are largely dependent on agriculture (Potapov *et al.*, 2017).

Communities prone to several hazards show a poverty reduction, or sometimes poverty rises. An approach recognizing the regional differences in climate impacts and forms on a rich history of Bangladesh's locally-led action is critical. Crop divergence and climate-smart technology are the cue to advanced agriculture productivity, climate resilience, and income rise in rural areas (World Bank, 2022). Geographical location and socio-economic dynamics play roles in increasing the vulnerabilities of climate change that can be reduced by different adaptation practices in the coastal areas of Bangladesh (Chowdhury *et al.*, 2022). Climate Smart Agriculture (CSA) is an approach to agricultural development that addresses the intertwined challenges of food security and climate change (Lipper *et al.*, 2014). According to Mizik (2021), overpopulation and climate change are among the world's greatest challenges. The CSA practices are identified based on agricultural practices disseminated by DAE (Department of Agricultural Extension) through CFS (Climate Field Schools) (Ajij *et al.*, 2014). Climate Smart agriculture (CSA) provides an adequate answer by aiming for higher productivity, resilience, and reduction of greenhouse gas emissions. Whether a technology is CSA is based on its impact on these outcomes and agricultural interventions that meet these goals are considered "climate-smart" (FAO, 2013).

Ali and Hossain (2019) stated that the worldwide development of climate-smart agriculture is mainly based on food security, adaptation and mitigation measures and facing a big problem due to rise in climatic variability. Certainly, the country is slowly moving towards new and more effective approaches to adaptation using indigenous knowledge and nature-based solutions. Hasan and Kumar (2020) surmised that coastal farmers are the first group of people who suffer severely from climate-related calamities, such as sea-level rise, salinity intrusion, coastal flooding, tidal surges and tropical cyclones. Bangladesh is facing severe difficulties linked to changing vegetation cover and other environmental concerns. Patuakhali and Barguna districts of Bangladesh are suffering from various climatic hazards as an effect of climate change. These coastal areas are highly vulnerable to cyclone risks because of various crucial factors (Kabir *et al.*, 2016). The responses of people are mostly unsatisfactory in terms of climate resiliency and sometimes vague due to lack of knowledge, skill, adaptation technology and monetary instrumental support (Hasan, 2017). So, the climate-smart adaptation practices should concentrate on the issues of climate education, sustainable livelihoods and climate compatible health support for the vulnerable people. Remote sensing and GIS technologies have been used extensively to analyze land-use changes through time and get useful perceptions into their causes and effects. The Normalized Difference Vegetation Index (NDVI) is generally used to monitor the changes in vegetation cover in various spatio-temporal scales (Liu *et al.*, 2015). It identifies the responses of vegetation to climate changes which have significant benefits (Leprieur *et al.*, 1994: Piao *et al.*, 2011). Pantho *et al.* (2022) found a significant decrease (32%) in the dense vegetation in Barisal, Bangladesh, from 2002 to 2020. On the other hand, sparse vegetation has increased drastically throughout the study period. A study conducted by Rahman (2013) in the Patuakhali district showed continuous deforestation from 1989 to 2010, which increased soil erosion and biodiversity loss in the Southern part of Bangladesh. Islam *et al.* (2023) revealed noteworthy variations in barren areas as well as sparse moderate and dense vegetation types of Barguna district of Bangladesh. They also found that 412.90 square kilometers of land have been deforested from 1989-2020. So, the study aimed to analyze the changes in vegetation cover over time using the GIS and remote sensing techniques and present the state of use of CSA technology and the benefits of using such technology in the Southern part of Bangladesh.

MATERIALS AND METHODS

Study area

The study was conducted in two areas: Amtali upazila of Barguna district and Kalapara upazila of Patuakhali district in Barisal division of Bangladesh. The geographical co-ordinates of Kalapara upazila are 21° 59' 9.96" North latitude and 90° 14' 31.92" East longitude. The latitude and longitude of Amtali upazila are 22° 07' 45.84" North and 90° 13' 44.04" East, respectively (Fig. 1). The questionnaire was used for survey in the Barabagi and Karaibaria union of Amtali upazila and Nilganj and Tiakhali union of Kalapara upazila (Fig.2).

Image collection and pre-processing

Landsat data were used to show the vegetation coverage and to identify the change detection over time. The Landsat satellite images were collected from the United States Geological Survey (USGS) Earth Explorer website (https://earthexplorer.usgs.gov/) open-source data. Landsat thematic mapper (TM) of 2012 and Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) of 2022 were used in the analysis. Image acquisition date and its characteristics are shown in Table 1.

Landsat TM images have seven spectral bands and the spatial resolution is 30 meters for Bands 1 to 5 and 7, whereas Band 6 is thermal infrared having 120 meters spatial resolution. Landsat 8 OLI-TIRS consists of nine spectral bands with 30 meters spatial resolution for Band 1 to 7 and 9. Band 8 is panchromatic with resolution of 15 meters. Collected images were pre-processed to extract data from remotely sensed images. Image radiometric and atmospheric corrections were completed using Erdas Imagine 2014 software. The Spatial Analyst tool (Mask) of ArcMap 10.8 was used to extract the study area. Landsat 8 data were adjusted to Top of Atmosphere (TOA) radiance by reflectance rescaling coefficients. Here, thermal infra-red digital numbers (DN) have been converted to TOA spectral radiance using Landsat's metadata (MTL) file. The following equation derived from USGS has been used to estimate TOA radiance:

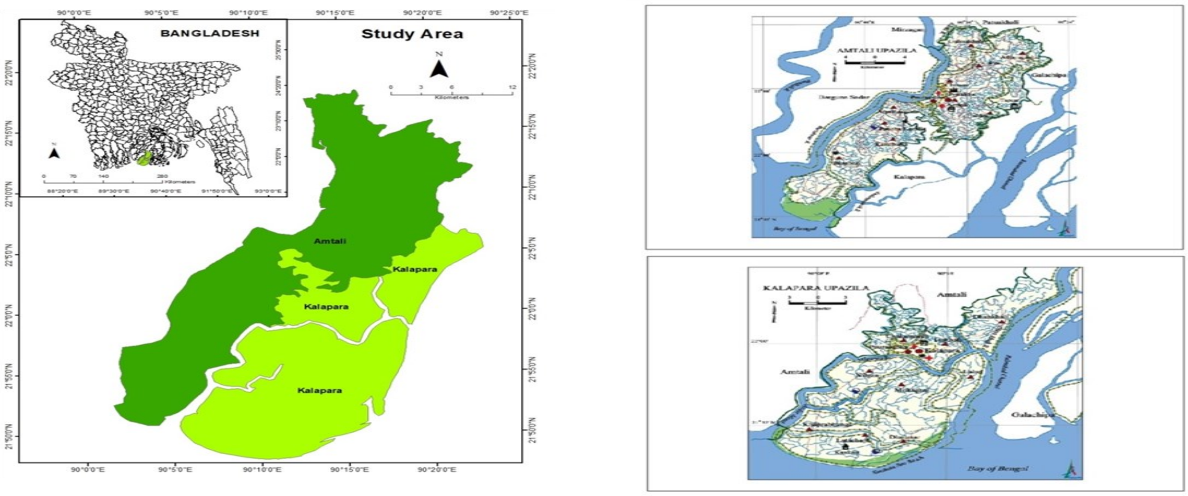

Fig. 1. *Map of the study area Amtali upazila of Barguna district and Kalapara upazila of Patuakhali district of Bangladesh*

Fig. 2. *Map showing the survey locations in the study areas Amtali and Kalapara upazilas*

Table 1. Image acquisition date and characteristics

Image Acquisition Date	Satellite	Data Type	Path/ Row	Projection, Datum, UTM Zone	Spatial Resolution (meter)	Cloud Cover
01.04.2012	Landsat 5	TM	137/45	UTM, WGS1984, 46N UTM	30	0%
20.03.2022	Landsat 8	OLI-TIRS	137/45	UTM, WGS1984, 46N UTM	30	0%

$$L_\lambda = M_L \times Q_{cal} + A_L \qquad \text{Eq. 1}$$

where, L_λ is TOA spectral radiance, without correction for the solar angle, ML is band-specific multiplicative rescaling factor from the metadata file, Qcal denotes Quantized and calibrated standard product pixel values (DN) and AL means band-specific additive rescaling factor from the metadata file.

Normalized Vegetation Index mathematically compares the amount of absorbed visible red light (650-700 nm) and the reflected near-infrared (780-2500 nm) light. In healthy plants, chlorophyll pigment absorbs most of the visible red light and a plant's cell structure reflects most of the near-infrared (NIR) light. It means that high photosynthetic activity, commonly associated with dense vegetation, will have less reflectance in the red band and higher reflectance in the near-infrared one (NASA). By analyzing the values compared to each other, vegetation cover can be detected separately from other land cover types. So, to calculate NDVI, the reflectance value in two bands: the visible red band and near-infrared band are needed.

Band 3 and 4 of Landsat 5 TM are visible red and near-infrared, respectively. On the other hand, Band 4 and 5 of Landsat 8 OLI-TIRS are visible red and near-infrared. These bands were used to calculate Normalized Difference Vegetation Index (NDVI) for study areas. The formula for calculating NDVI is (Huyen et al., 2017)

$$NDVI = \frac{NIR-RED}{NIR+RED} \qquad \text{Eq. 2}$$

Here, NIR indicates near infra-red reflectance (Band 4 of Landsat 5 TM and Band 5 of Landsat 8 OLI-TIRS) and RED indicates the reflectance of visible red (Band 3 of Landsat 5 TM and Band 4 of Landsat 8 OLI-TIRS).
For Landsat 5 TM and Landsat 8 OLI-TIRS, NDVI was estimated following the equation:

$$NDVI_{\text{Landsat } 5} = \frac{\text{Band 4-Band 3}}{\text{Band 4+Band 3}} \quad \text{Eq. 3}$$

$$NDVI_{\text{Landsat } 8} = \frac{\text{Band 5-Band 4}}{\text{Band 5+Band 4}} \quad \text{Eq. 4}$$

In this study, NDVI was calculated using Arc Toolbox-Spatial Analyst Tools-Map Algebra-Raster calculator of ArcGIS 10.8 version.

Sample size determination for the questionnaire survey

This study used a purposive random sampling process for questionnaire survey (Supplementary Table S1). A total number of 175 farmers were listed. From According to Yamane (1967) formula, Margin of error was assumed to be 5%.

$$n = \frac{N}{1+Ne^2} \quad \text{Eq. 5}$$

Where, N= Population Size, n= Sample Size, e= margin of error

Then 120 farmers were selected from the population following a proportionate random sampling technique. Pretested semi-structured interview schedule has been used to collect data through face-to-face personal interview. The independent variables and climate-smart agricultural practices were defined based on Hasan *et al.* (2018). Information of socioeconomic status, climate change and climate change hazards, climate smart agricultural practices and benefits data were collected from primary and secondary sources. Adaptation strategy index was calculated by the following formula (Uddin *et al.*, 2014)

Adaptation Strategy Index (ASI) = ASn×0+ ASl×1+ASm×2+ASh×3 Eq. 6

Where,
ASI= Adaptation Strategy Index
ASn= Frequency of farmers rating adaptation Strategy as having no importance
ASl= Frequency of farmers rating adaptation Strategy as having low importance
ASm= Frequency of farmers rating adaptation Strategy as having moderate importance
ASh = Frequency of farmers rating adaptation Strategy as having high importance

To compare different dimensions of benefits obtained from CSA practices weighted average of benefit has been calculated using the following formula (Ali, 2008)

$$\textit{Weighted average of benefit} = \frac{Flr*0+Fmd*1+Flo*2+Fna*3}{6} \quad \text{Eq. 7}$$

Where,
Flr= Frequency (in %) of respondents claiming to be benefitted largely.
Fmd= Frequency (in %) of respondents claiming to be benefitted moderately.
Flo= Frequency (in %) of respondents claiming to experience low benefit.
Fna= Frequency (in %) of respondents claiming experience no benefit.
Climate Smart Agriculture Technology Index (CSAT)
A dependent variable based on Climate Smart Agriculture Technology use named CSAT Index has been defined for this study. CSAT Index is calculated for each responded. CSAT represents the summation of the extent of use of each of 21 CSA technologies.

CSAT=CSTn×0+CSTr×1+CSTo×2+CSTf×3 Eq. 8

Where,
CSAT = CSA technology use Index
CSTn = Number of technologies rated as never used by the farmer
CSTr =Number of technologies rated as rarely used by the farmer
CSTo = Number of technologies rated as occasionally used by the farmer
CSTf = Number of technologies rated as frequently used by the farmer
The primary and secondary data were processed and analyzed with the help of Microsoft Office 365 and the statistical package SPSS-23.

RESULTS AND DISCUSSION

Spatial distribution of Normalized Difference Vegetation Index (NDVI)

NDVI is a significant variable for agronomical and climate applications (Islam and Mamun, 2015) and is applied to identify mainly vegetation patterns (Orimoloye *et al.*, 2019; Jia *et al.*, 2014). NDVI values generally range from +1.0 to -1.0. Snow, sand and barren rocks show low NDVI values, such as 0.1 or less (USGS, 2018; Alex *et al.*, 2017; Laksono *et al.*, 2020). Negative values usually indicate water bodies. Sparse vegetation, such as shrubs and grasslands, have moderate NDVI values from 0.2 to 0.5. High NDVI values (approximately 0.6 to 0.9) resemble dense vegetation found in temperate and tropical forests or crops at their peak growth stage (Gaznayee *et al.*, 2022). In this study, two specific years, 2012 and 2022 were considered for detecting vegetation cover change in Amtali and Kalapara upazilas. The collected imageries of these years were then classified through NDVI formula. The NDVI analysis of an area over the years can aid in identifying the vegetation that is thriving or under stress, and vegetation changes because of anthropogenic activities, for example, deforestation and natural interferences. The NDVI threshold values for this study are shown in Table 2.

From the NDVI map of 2022 of the study area, it can be seen that the Rabnabad Channel of the Kalapara upazila has eventually dried up due to human influences than it was back in 2012 (Fig.3). But, the area of Andar Manik River has increased in 2022 rather than 2012. Similar result was also found by Rashid *et al.* (2023). They reported that based on NDVI values, the water body in the Southern coast of Bangladesh was 220.08 km^2 in 1989, increased to 534.3 km^2 in 2000, decreased to 529.07 km^2 in 2014, and further decreased to 389.54 km^2 in 2020. In Kalapara Paurasabha, people are cultivating crops around homesteads. As a result, the extent of sparse vegetation in this part of Kalapara has increased in 2022. Again, in the Western part of Amtali upazila, Barabagi in the place where fallow areas lessened in 2022 (354.55 km^2) compared from 2012 (369.20 km^2) NDVI map due to farmers of that area adopting different types of CSA practices. Similarly, in Chowra, Kukua, and in the north of Amtali, fallow areas decreased in number compared to the NDVI map of 2022 and 2012. In the case of sparse vegetation comprising shrubs and grasses, the area has notably increased from 2012 to 2022 as people have changed their cropping patterns and now tend to leave less land fallow. They are now cultivating saline-tolerant crop varieties on small scales.

On the contrary, the densely forested areas of both Amtali and Kalapara have decreased since 2012. The reasons can be traced back to various natural disasters such as cyclones and storm surges hitting these coastal regions of Bangladesh over time. The dense vegetation areas of Gulishakhali and Atharogasia of Amtali and Dhankhali of Kalapara have declined drastically, which can be identified by observing the NDVI maps of 2012 and 2022. Conversely, in the Southern part of Amtali upazila, the forested areas have increased cause of the application of CSA techniques. Murshed *et al.* (2019) and Sun *et al.* (2022) reported

Table 2. Normalized Difference Vegetation Index (NDVI) threshold values used in this study (Thorat *et al.,* 2015)

NDVI Range	Classes
<0.06	Waterbody
0.06-0.14	Builtup area
0.14-0.21	Fallow land
0.21-0.28	Sparse Vegetation
>0.28	Dense Vegetation

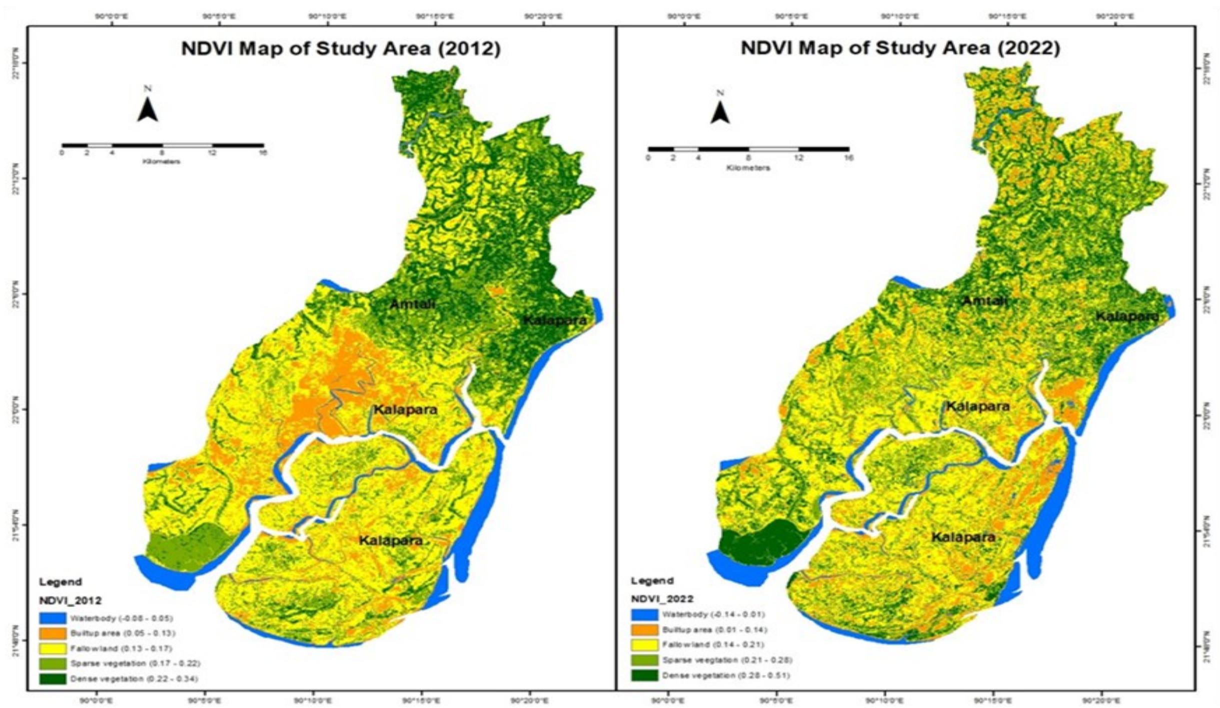

Fig. 3. *Comparison between Normalized Difference Vegetation Index (NDVI) maps of 2012 and 2022 of Amtali and Kalapara upazila*

that the southwestern coast of Bangladesh is more vulnerable than other areas due to the rise in sea level and salinity.
Islam *et al.* (2023) observed that over the last 31 years, the dense vegetation areas of Barguna district have declined due to deforestation, but the sparsely vegetated areas have increased throughout the region. Rashid *et al.* (2023) reported that the Southern part of Bangladesh's water area increased around 5.40 km^2 per year from 1989 to 2020.

Changes in Cropping Pattern

Vegetation indices can assist as a sensitive indicator of climate change and anthropogenic effects of changing climate (*Rousvel et al*., 2013). According to farmers' perceptions, salinity, cyclones with storm surges, unpredictable rainfall and tidal surges are the most adverse climatic hazards in the study area. Rukaia *et al.* (2021) mentioned that salt accumulation in soils affects agricultural productivity, environmental health, and the economy of coastal farmers. Due to the ingression of salinity, erratic rainfall and other climatic factors in the dry season, *Rabi* crops are mostly affected. The scarcity of irrigation water reduces the option of cultivating different types of crops. At *Kharif* I (mid-March to June), most of the land becomes fallow. Farmers mentioned that they now incorporate pulse crops, vegetables, sunflowers, watermelon, and the main Transplanted Aman rice (Table 4). Besides, late monsoon hampers Boro Aus cultivation, whereas high irrigation costs are needed. However, the innovation of high-yielding varieties and modern technology slightly increases crop production and cropping intensity.

Adaptation Strategy Index (ASI)

Farmers were interviewed to know the extent of the use of CSA technologies. The effects of climate change, as observed in different dimensions, were considered as flood, drought, salinity, etc. (Supplementary Table S2). The relative importance of adaptation strategies to climate change was calculated based on the index calculated using the ranking of different adaptation strategies

Table 3. Change detection of vegetation status of Amtali and Kalapara from 2012-2022

NDVI Categories	Area (sq. km) 2012	Area (sq. km) 2022	Change Detection
Waterbody	62.50	70.34	Increased (+)
Builtup area	139.21	137.38	Decreased (-)
Fallow land	368.78	354.55	Decreased (-)
Sparse vegetation	266.33	282.89	Increased (+)
Dense vegetation	154.40	148.14	Decreased (-)

Table 4. Cropping pattern in the study area in 2022

Sl. No.	Rabi (Mid October to mid March)	Kharif I (Mid March to June)	Kharif II (July to mid October)
1.	Mungbean	Fallow	T. Aman
2.	Boro	Fallow	T. Aman
3.	Sunflower	Fallow	T. Aman
4.	Fallow	Aus	T. Aman
5.	Watermelon	Fallow	T. Aman
6.	Khesri	Aus	T. Aman
7.	Maize	Fallow	T. Aman
8.	Mustard	T. Aus	T. Aman

Table 5. Rank order of the adaptation strategies to climate change

Adaptation strategies	Importance for the farm: High (3)	Medium (2)	Low (1)	Not at all (0)	ASI	Rank
Saline Tolerant Crop Varieties	79	29	6	6	301	1
Sunflower Cultivation	80	24	12	4	300	2
Watermelon Cultivation	77	25	15	3	296	3
Sorjan Method	76	20	15	9	283	4
Early variety of rice	72	19	19	10	273	5
Pondside vegetable Cultivation	65	26	20	9	267	6
Flood Tolerant crop Varieties	60	24	22	14	250	7
Drought resistant crop Varieties	59	20	23	18	240	8
Organic fertilizer	55	22	25	18	234	9
Relay Cropping	50	17	31	22	215	10
Used of pheromone traps	48	15	37	20	211	11
Mulching	48	14	28	30	200	12
Rain water Harvesting	30	16	34	40	156	13

Table 6. Benefits obtained from Climate Smart Agriculture (CSA) practices

Benefits	Frequency distribution of response (%)				WA of benefit
	Largely benefitted(3)	Moderatebenefitted(2)	Low benefitted (1)	Not at all (0)	
Social benefits					
Development of organizational participation	30.00	30.83	19.17	20.00	28.47
Increased extension contacts	51.67	29.17	10.83	8.33	37.36
Development of leadership	53.33	28.33	8.33	10.00	37.50
Increased social bonding	38.33	34.17	18.33	9.17	33.61
Economic benefits					
Increased family income	49.17	31.67	8.33	10.83	36.53
Low production cost	30.00	50.00		10.00	33.33
Technical benefits					
Improved capacity on new tech implementation	44.17	38.33	10.00	8.33	36.39
Increased crop production and productivity	49.17	30.83		11.67	36.25
Increased cropping intensity	51.67	32.50	11.67	4.17	38.61
Increased crop yield	50.83	27.50	11.67	10.00	36.53
Psychological benefits					
Positive mental state to adopt new tech	44.17	30.83	10.83	14.17	34.17
Positive attitude towards change in food habit	30.83	35.00	14.17	20.00	29.44

to climate change, as identified by the surveyed farmers are presented in Table 5.

Out of 13 adaptation strategies, Practicing “Saline tolerant crop varieties” (ASI-301) was ranked first (Table 5) and, thus, most important among farmers’ adaptive strategies to climate change. Since salinity is a common problem in the Southern region of Bangladesh like --Amtali and Kalapara Upazila, most of the farmers use salinity tolerant varieties to get more production, like BRRI dhan 47 and BINA dhan 8, which are gaining popularity among the farmers in the coastal areas (Singh *et al.*, 2012) also BRRI dhan 64, BRRI dhan 97 and BRRI dhan 99 are grown by farmers. Sunflower cultivation (ASI-300) was identified as the second-ranked adaptation strategy (Table 5). Continuous monocropping (For example, rice cultivation) has adverse effects, including pest resurgence and soil quality deterioration. Along with rice cultivation, farmers are now cultivating salt-tolerant Sunflower variety “Hysun 33” is most prevalent in these regions. The third most important adaptation strategy was the “Watermelon cultivation” (ASI-296).

In coastal regions, the texture of the soil is mostly sandy. This sandy soil offers a profound scope for watermelon cultivation. Most of the farmers in these regions find watermelon cultivation to be a profitable farming practice in spite of all climatic hazards. Practicing “Sorjan method” (ASI-283) was ranked fourth and it is an important adaptive strategy for changing climate. It enhances production and proper land use. Tidal flooding into the crop land and homestead are common in Amtali upazila of Barguna district and Kalapara upazila of Patuakhali district. Soil salinity more than 20 dS/m is unsuitable for crops. Farmers adapt to tidal water intrusion by digging trenches, raising land, and cultivating different crops and trees on the raised land. High beds, 1-2 m wide, alternated with low beds of similar size (called Sorjan) are constructed.

Disaster and Climate Risk Management in Agriculture (DCRMA) Project suggested an improved method of the Sorjan, supported by Bangladesh Agriculture Research Institute in different farmers’ field and added vegetables, trees, fishes, spices etc. These practices conform to the principles of CSA provided by FAO (2012, 2013, 2014; Mahashin, 2019) ; Sain *et al.* (2017). Kabir *et al.* (2020) identified 28 adaptation strategies implemented by the farmers of the Satkhira and Barguna districts of Bangladesh where crop diversification, stress-resistant varieties and crop rotation were the most common measures. Uddin (2014) mentioned that majority of farmers in the Satkhira district of Bangladesh were engaged in different adaptive strategies. They identified 14 strategies; among them, irrigation ranked first and crop insurance ranked the least used strategy.

Benefits obtained from Climate Smart Agricultural (CSA) practices

Obtaining benefits from any technology is one of the important aspirations of farmers. Farmer aspects are social, economic, technical, and psychological benefits from CSA practices. This study attempted to analyze to what extent farmers obtained benefits from using the CSA approach in different dimensions. Table 6 represents the results obtained from the survey.

As shown in Table 6, CSA practice helps develop farmers' leadership. 51.67% of the respondents claimed to largely benefit from leadership development due to CSA practices. CSA practices also increased extension contacts. 49.17% of the respondents claimed to largely benefit from increased family income due to CSA practices. 51.67% of the respondents claimed to have largely benefitted from increased cropping intensity resulting from CSA practices. CSA practices also reduced production cost. CSA also increased crop yield and productivity. 44.17% of the respondents claimed to largely benefitted from a positive mental state to adopt new tech resulting from CSA practices. However, the respondents do not seem enthusiastic about changes in their eating habits. Hasan *et al.* (2018) reported that adaptation practices were of variable importance for the farmer's beneficial effects on enhancing food production and household income. Appropriate technologies like climate-smart agriculture (CSA) can help resolve smallholder farming systems' constraints (Zerssa *et al.*, 2021).

Conclusion

The level of sparse vegetation in Amtali upazila of Barguna district and Kalapara upazila of Patuakhali district has increased in 2022 comparing to 2012 found from Normalized Difference Vegetation Index (NDVI) maps as most farmers of these areas embraced Climate Smart Agriculture (CSA) technologies.Saline-tolerant crop varieties, sunflowers, and watermelon cultivation were the top-rated adaptation strategies in the study area, followed by other technologies like the Sorjan method, early varieties of rice, etc. These CSA practices positively changed farmers' social, economic and psychological states. Farmers with higher education levels could use CSA technology more effectively. So, increasing education and sufficient funding can help farmers increase the use of various CSA technologies. This research offers suggestions for policymakers to reinforce farmers' adaptation strategies that can minimize the negative impacts of climate change and steer policies correspondingly.

Supplementary Information

The authors are responsible for the content or functionality of any supplementary information. Any queries regarding the same should be directed to the corresponding author. The questionnaire on Climatic Hazards and Climate Smart Agricultural Practices in the Southern Region of Bangladesh and the data of 120 respondents regarding climate hazards and adaptation strategies in the study areas are shown in Supplementary Table S1 and Table S2, respectively. The supplementary information is downloadable from the paper's webpage and will not be printed in the print copy.

Conflict of interest

The authors declare that they have no conflict of interest.

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