Spatio-temporal changes of mangrove cover and its impact on bio-carbon flux along the West Bengal coast, Northeast coast of India

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ABSTRACT
The present study assesses spatio-temporal variability of the greenness index of Indian mangroves of the Sundarban forest with bio-carbon flux during 1990-2020. The analysis of NDVI derived using Landsat data reveals the mangrove stress level was very high during the years 1990, 2006, 2007, 2009 and 2011, with 2011 km² mangroves were severely affected out of a total 2215 km². The improved and healthy condition prevailed during 1999, 2000, 2001, 2015, 2016 and 2019 and normal condition during 2002, 2005, 2008 and 2010. The net change in mangrove cover during 1990-2020 shows distinct loss and gain regions across the study region. The shoreline change analysis shows that nearly 90 km² of mangroves were lost on the seaward side due to coastal erosion. Whereas, 50 km² of newly developed mangroves were observed in western parts of Southern Parganas due to accretion and no loss/gain was recorded in the rest of the areas. A significant positive correlation (coefficients 0.76 at p=0.01) was recorded between the increase in the extent of the mangrove region and bio-carbon fluxes for the years of normal and high-stress level condition as the dominant classes. Conversely, correlation is insignificant for the years dominated by healthy conditions.

Introduction
Mangroves are an integral part of coastal ecosystem, enriched with diverse flora and fauna. They form some of the most productive and diverse wetlands of this planet, and are found in tropical and subtropical regions. These are highly sensitive to the environment condition associated with climate change and extremes, as the mangroves grow at specific temperature and brackish water conditions. The Sundarban is one of the richest ecosystems and is the largest continuous mangrove forest in the world. It shares the wetland between India and Bangladesh and located on the delta of Ganges, Hooghly, Padma and Brahmaputra rivers. United Nations Educational, Scientific and Cultural Organization (UNESCO) classified this region as a world heritage site in the year 1987 and subsequently this was designated as the Ramsar site on 1 February 2019. The mangrove forests are facing threats in recent years due to anthropogenic activities and climate impacts. According to the Forest Survey of India, Dehradun, mangrove extent of the Indian Sundarban declined from 2076 km² in 1987 and 2112 km² in 2019 (ISFR, 2019). However, it has shown a marginal increasing trend during past three decades (at a rate of 0.061% per year) with distinct spatio-temporal variability due to sea level rise (Rahman et al., 2011) and changes in the fresh water flows from Himalayan Rivers. Variation in precipitation impacts significantly on the mangrove density and stress levels associated with health condition of the ecosystem. It was demonstrated in the earlier studies that increased precipitation has helped in expanding mangrove cover (Buckney, 1987; Eslami-Andargoli et al., 2009) and improves species richness, and diversity due to decreased salinity (Buckney, 1987; Hong & Hong, 1993). On the other hand, the fluvial processes, sea level rise, changes in circulation patterns and associated impacts on the coastal environment in terms of erosion and accretion, and climate change and its variability could have significant impact on the mangrove cover of the Sundarbans (Salam et al., 2007; Thomas et al., 2014).

Carbon dioxide (CO₂) is a major greenhouse gas in the atmosphere and various scientific researchers have shown that increase in the concentration of CO₂ leads to climate change. A 40% increase in CO₂ concentration has been reported since pre-industrial times, from 280 ppm to 404.01 ppm in 2016 (Trends in Carbon Dioxide-NOAA/ESRL). Primarily this increase is due to emissions by anthropogenic activities, fossil fuel combustion, land use land cover changes and changes in the net ecosystem exchanges and air-sea fluxes driven by climatic variability (Knorr & Heimann, 1995; Nayak et al., 2010). Therefore, it’s necessary to
study inter-annual variability of bio-carbon fluxes (source/sink) due to variability of mangrove cover and density during the study period. At the global scale, terrestrial ecosystem and oceans are two major sinks of atmospheric CO2. However, at regional and local scales, they behave as variable role, either as a source or a sink of the atmospheric CO2. The forest uptakes CO2 and emits oxygen during the photosynthesis, and releases CO2 during the respiration. The net carbon fixation by the un-disturbed ecosystem during these processes is known as net ecosystem productivity. The carbon uptake from atmosphere is being consumed by forest vegetation and fixed into various parts of plants and soil. Numerous studies have shown that mangrove forest has been responsible for the uptake of 956 Mg C per hectare within their biomass and sediment which is 3–5 times higher than any other terrestrial forest (Donato et al., 2011; McLeod et al., 2011). It has been described that the net primary production of regulatory mangrove forest ecosystem led to reduce the amount of CO2 in the atmosphere and control the adverse impact of climate change (Castillo et al., 2018; David et al., 1989; Gilmanov et al., 2005; Xu et al., 2017, 2020).

Understanding of spatio-temporal dynamics of mangrove vegetation conditions and its areal extent is an essential component of the global carbon cycle and future climate change studies. Satellite measured Normalized Difference Vegetation Index (NDVI) has been used to estimate the green biomass of the forest (Gamon et al., 1995; Gitelson, 2004; Penuelas et al., 2011; Yoder & Waring, 1994), which helps in quantifying potential photosynthetic activity at the canopy level, and associated net primary productivity, net CO2 exchange etc. at regional and global scales (Boelman et al., 2003; Chladil & Numez, 1995; Gower et al., 1999; Penuelas et al., 2011; Seen et al., 1995; Wylie et al., 2002). Spectral reflectance at Red and NIR bands are used for the calculation of NDVI and to extract the vegetation classes. Healthy vegetation, with higher NDVI level will absorb most of the lights at red spectrum and reflect a large portion of the near-infrared light. Contrary to this, unhealthy or sparse vegetation reflect more in red light and less in near-infrared spectrum (Guha, 2016). There are very few studies such as (Mukhopadhyay et al., 2018; Ray & Jana, 2017; Das et al., 2017; Chellamani et al., 2014; Chanda et al., 2013; Ray et al., 2011; Selvam, 2003; Mukhopadhya et al., 2002) on the spatio-temporal dynamics of Sundarban mangrove forest and associated bio-carbon fluxes. Therefore, current study is an attempt to use the remote sensing technique to assess long-term spatio-temporal NDVI changes to decipher the health condition of the ecosystem and further inter-relate with bio-carbon flux in the Sundarban mangrove forest. Thus, we used NDVI imagery from the Landsat series of satellites during 1990 to 2020 and studied variability of mangrove cover and density associated with extreme climatic events (such as El Nino/Drought Years) results into variability of bio-carbon fluxes. In addition to this, increase and decrease of mangrove cover due to shoreline change was also estimated in the current study.

Study area

The study region, Sundarban mangrove under Indian Territory bounded between 21° 33’ and 22° 12’ N latitude and 88° 16’ and 89° 05’ E longitude, is located on the Gangetic delta in northern part of Bay of Bengal along the coast of West Bengal (Figure 1). The Sundarbans mangrove with its areal extension in both India and Bangladesh is the largest among all the wetlands in the globe (Kathiresan, 2018; Zafar & Khan, 2018). It experiences strong fluvial processes, and sedimentations from Hooghly, Padma and Brahmaputra rivers and their tributaries, and frequent cyclonic storms from the north-western Bay of Bengal. This area falls under a subtropical monsoonal climate and receives an annual rainfall of about 1,600–1,800 mm.

Data and methods

Multi-dated Landsat images were downloaded from United States Geological Survey (USGS) website. It includes data from Landsat-5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+) and Landsat-8 Operation Land Imager (OLI) during the months of January, February and March as per availability stated in Table 1. The data used in this study were selected such a way that, all are nearly at same months with approximately same tidal condition to avoid the seasonal and tidal variations. In addition, these datasets are mostly pertaining to January-march (spring) period in order to pick up the impact of drought on mangrove in the preceding year and availability of cloud free images. The Mangrove area was extracted using contrasting tone/color using visual interpretation key based on False Color Composite (FCC) image with the band combinations of 5, 4, 3.

The atmospheric correction (AC) is a necessary pre-processing step to be followed while comparing the multi-temporal satellite data. AC was applied on all the data set using ACOLITE software tool. This algorithm was based on “Dark Spectrum Fitting” (DSF) procedure as proposed by Vanhellemont and Ruddick (2018) to estimate atmospheric path reflectance (\( \rho_{\text{path}} \)). It has assumed homogenous atmosphere, intervening between sensor and target, for which satellite scene must comprise of at least one pixel with zero surface reflectance (\( \rho_s=0 \)). The lowest value corresponding to the reflectance (\( \rho_l \)) at the top of the
atmosphere in each band is being used to calculate representative dark spectrum ($\rho_{\text{dark}}$) and following which path radiance is estimated from this $\rho_{\text{dark}}$ (Kotchenova et al., 2006; Vanhellemont & Ruddick, 2018; Vermote et al., 2006). This DSF approach was being adopted by Vanhellemont (2019) for the processing of Landsat and Sentinel-2 data. After atmospheric correction of all temporal Landsat data, the surface reflectance ($\rho_s$) of the red (660 nm Landsat 5 TM and 655 nm for Landsat-8 LOI) and NIR bands (839 nm for Landsat 5 TM and 865 nm for Landsat-8 LOI) were used to calculate NDVI. A sample images of Landsat OLI depicting surface reflectance, atmospherically corrected surface reflectance and dark spectrum fitting curve comprise of path radiance and dark radiance are shown in Figure 2.

The surface reflectance of Red & Infra-Red bands was used to estimate NDVI defined as (IR-R)/(IR+R) for each image during the study period. It is noteworthy to mention that these NDVI data vary in the range between −1 and 1 with positive values represent mangroves at different density levels and negative values, approaching −1, represent water (rivers and oceanic region). The values close to zero (−0.1 to 0.1) generally correspond to barren areas of rock, sand or snow. Therefore, negative values of NDVI were not considered here. Positive values of NDVI (time series) are used further to characterize health condition and stress levels of the mangrove of the study region. There are 7 classes of the mangrove/vegetation were created for each dataset based on NDVI pixel value with respect to its temporal mean and standard deviation for entire study period. The criterion with NDVI value within the range of Mean±SD*0.25 (25% of SD) has been considered as the normal. The weighted mean of the pixels satisfying above condition for all the years has been estimated as the climatological normal for the study period. The pixel of a given year with negative deviation from its climatological normal has been classified as the stressful and the pixel with positive deviation considered as the healthier vegetation. Further the stress levels and healthy conditions were subdivided into multiple

Table 1. Date of acquisition of Landsat series datasets with tidal level used in the present study.

| Landsat Data Acquisition Date | Tide level (m) | Landsat Data Acquisition Date | Tide level (m) |
|------------------------------|---------------|------------------------------|---------------|
| 30–01–1990                   | −0.34         | 26–01–2006                   | −0.22         |
| 14–01–1990                   | −0.48         | 27–02–2006                   | −1.57         |
| 18–02–1991                   | −0.39         | 13–01–2007                   | 0.55          |
| 19–12–1991                   | −0.76         | 18–03–2007                   | −1.59         |
| 08–03–1992                   | −0.38         | 16–01–2008                   | 0.91          |
| 22–01–1993                   | −1.25         | 17–02–2008                   | −0.09         |
| 23–02–1993                   | −1.00         | 18–01–2009                   | 0.90          |
| 11–03–1993                   | −0.65         | 15–02–2009                   | 0.26          |
| 25–01–1994                   | −0.80         | 21–01–2010                   | 0.43          |
| 28–01–1995                   | −0.69         | 06–02–2010                   | 0.86          |
| 17–03–1995                   | −1.58         | 24–01–2011                   | 0.29          |
| 16–02–1996                   | −0.72         | 25–02–2011                   | 1.00          |
| 01–01–1997                   | 0.68          | 01–02–2014                   | −1.41         |
| 18–02–1997                   | −0.34         | 04–02–2015                   | −1.22         |
| 05–09–1998                   | 0.82          | 08–03–2015                   | −0.82         |
| 09–03–1998                   | −0.46         | 22–01–2016                   | −1.17         |
| 08–02–1999                   | 0.68          | 07–02–2016                   | −1.28         |
| 12–03–1999                   | 0.38          | 09–01–2017                   | 0.30          |
| 26–01–2000                   | 0.54          | 09–02–2017                   | −1.26         |
| 11–02–2000                   | 0.75          | 25–02–2017                   | −1.26         |
| 12–01–2001                   | −0.64         | 11–01–2018                   | 0.39          |
| 13–02–2001                   | 0.61          | 28–02–2018                   | −1.31         |
| 17–03–2001                   | 0.71          | 30–01–2019                   | 0.41          |
| 08–02–2002                   | −0.25         | 15–02–2019                   | 0.27          |
| 20–12–2003                   | −0.33         | 03–03–2019                   | −0.67         |
| 07–01–2005                   | −0.22         | 01–01–2020                   | 0.44          |
| 24–02–2005                   | −1.23         | 02–02–2020                   | 0.74          |
classes. The pixel value of a given image within Mean-SD*0.25 and Mean-SD*0.5 represents marginally stress; between Mean-SD*0.5 and Mean-SD*0.75 represent moderately stress; less than Mean-SD*0.75 represent highly stress condition. Similarly, the NDVI value between Mean+SD*0.25 and Mean+SD*0.5 shows marginally improve or healthy vegetation; between Mean+SD*0.5 and Mean+SD*0.75 represent moderately improve, higher than Mean+SD*0.75 represent highly improve condition of the mangrove vegetation. The detailed classification of different mangrove classes used in the present study has shown in Figure 3 and that have been used for the generation of maps (Figures 5 & 6) and statistics (Tables 2&3) for every year during the study period.

Data of bio-carbon fluxes for the study region were taken from latest release of NOAA Carbon Tracker analysis, CT2019B version, as published in

Figure 2. (a) Colour composite of reflectance image without the atmospheric correction (b) the same as, but with atmospheric correction and (c) dark spectrum fitting curve algorithm applied to a Landsat-8 LOI scene over the study region (Sundarban Mangrove) on 30 January 2019.

Figure 3. The flow of the data processing and classification of different health condition of the mangrove ecosystem used in present study.
Table 2. Percentage of the area under different classes of mangrove vegetation and NDVI Mean ± SD during the study period.

|                | Year | Highly Stress | Moderately Stress | Marginal Stress | Normal Mangrove | Marginal Improve | Moderately Improve | Highly Improve | NDVI Mean ± SD |
|----------------|------|---------------|-------------------|-----------------|-----------------|------------------|-------------------|---------------|----------------|
| 1990           | 86   | 4             | 2                 | 3               | 1               | 1                | 3                 | 0.41 ± 0.08   |
| 1991           | 22   | 8             | 9                 | 31              | 16              | 7                | 8                 | 0.51 ± 0.13   |
| 1992           | 22   | 8             | 9                 | 31              | 16              | 7                | 8                 | 0.56 ± 0.12   |
| 1993           | 3    | 2             | 4                 | 22              | 26              | 25               | 17                | 0.57 ± 0.12   |
| 1994           | 2    | 2             | 2                 | 16              | 25              | 28               | 25                | 0.50 ± 0.11   |
| 1995           | 10   | 13            | 25                | 43              | 3               | 2                | 5                 | 0.57 ± 0.12   |
| 1996           | 2    | 2             | 3                 | 15              | 24              | 28               | 26                | 0.53 ± 0.13   |
| 1997           | 8    | 7             | 8                 | 29              | 20              | 17               | 14                | 0.53 ± 0.12   |
| 1998           | 3    | 5             | 10                | 39              | 21              | 14               | 10                | 0.60 ± 0.14   |
| 1999           | 1    | 1             | 2                 | 6               | 6               | 11               | 76                | 0.60 ± 0.14   |
| 2000           | 1    | 1             | 2                 | 6               | 6               | 12               | 73                | 0.60 ± 0.12   |
| 2001           | 2    | 1             | 1                 | 6               | 9               | 18               | 64                | 0.48 ± 0.13   |
| 2002           | 19   | 7             | 12                | 50              | 6               | 2                | 4                 | 0.47 ± 0.09   |
| 2004           | 27   | 29            | 22                | 16              | 2               | 1                | 3                 | 0.53 ± 0.11   |
| 2005           | 2    | 3             | 7                 | 60              | 19              | 5                | 5                 | 0.35 ± 0.07   |
| 2006           | 93   | 2             | 2                 | 2               | 1               | 1                | 1                 | 0.36 ± 0.07   |
| 2007           | 91   | 2             | 2                 | 4               | 1               | 1                | 2                 | 0.52 ± 0.11   |
| 2008           | 4    | 4             | 9                 | 63              | 13              | 4                | 5                 | 0.35 ± 0.07   |
| 2009           | 92   | 2             | 2                 | 3               | 1               | 1                | 1                 | 0.54 ± 0.11   |
| 2010           | 3    | 2             | 6                 | 52              | 23              | 10               | 6                 | 0.44 ± 0.09   |
| 2011           | 81   | 9             | 4                 | 4               | 1               | 1                | 2                 | 0.58 ± 0.11   |
| 2012           | 1    | 1             | 2                 | 14              | 26              | 27               | 29                | 0.64 ± 0.13   |
| 2013           | 1    | 1             | 1                 | 2               | 1               | 2                | 92                | 0.65 ± 0.12   |
| 2016           | 1    | 0             | 1                 | 1               | 1               | 2                | 92                | 0.52 ± 0.10   |
| 2017           | 3    | 5             | 23                | 44              | 11              | 6                | 8                 | 0.54 ± 0.11   |
| 2018           | 2    | 1             | 4                 | 43              | 27              | 11               | 12                | 0.63 ± 0.13   |
| 2019           | 2    | 1             | 1                 | 2               | 2               | 4                | 87                | 0.57 ± 0.12   |
| 2020           | 2    | 2             | 4                 | 28              | 17              | 13               | 35                | 0.41 ± 0.08   |

Table 3. Years having specific dominant mangrove vegetation classes based on criterion of more than 50% area fall under a given class.

| Dominated Health of Mangrove Classes | Year          | Average Area (sq.km) |
|-------------------------------------|---------------|----------------------|
| Highly Stress                        | 1990, 2006, 2007, 2009, 2011 | 2011                 |
| Normal Mangrove                      | 2002, 2005, 2008, 2010          | 1279                 |
| Highly Improve                       | 1999, 2000, 2001, 2015, 2016, 2019 | 1831                 |

Jacobson et al. (2020). These data are available at monthly scale in a spatial grid of one degree (at the public domain http://carbontracker.noaa.gov) for the period of 2000 to 2018. The main goal of the Carbon Tracker program is to produce quantitative estimates of atmospheric carbon uptake and release at the Earth’s surface using an inverse model of atmospheric CO₂, which means that it attempts to model atmospheric CO₂ measurements by adjusting inputs and removals of CO₂ at the Earth surface until they best agree with those observational constraints. Generation of carbon flux and validation made by the long-term monitoring of atmospheric CO₂ conducted by many academic and governmental programs around the world which improve the understanding of how the land and ocean are responding to Earth’s changing climate. The negative value of carbon flux indicates the sink of carbon by biosphere due to increase in the vegetation (mangrove) density. In contrast, positive value of carbon flux indicates decrease of mangrove density. The current study is an effort to establish a relation between NDVI classes and carbon flux to understand the role (source/sink) mangrove density on biocarbon flux.

The shoreline change rate during the study period was calculated using Landsat temporal images pertaining to study area as input into the Digital Shoreline Analysis System (DSAS) originally developed by USGS and later implemented by Mohanty et al. (2017) for the Indian region. Shoreline of each data was digitized by using on-screen digitization technique. These individual shorelines were assigned with corresponding date in the attribute table. Then all the shorelines were merged into single spatial feature. The base line was generated by using parallel to one of these shorelines. The shoreline and baseline shape files were fed into DSAS tool to calculate shoreline change rate. With respect to the reference baseline, the rate of shoreline was calculated by casting transects at every 100 meters interval along the study area. The rate of shoreline change was calculated using End point Rate (EPR) statistical method employed (Kumar et al., 2010; Mahendra et al., 2011; Thieler & Danforth, 1994). The representation of baseline, shoreline and transects overlay on satellite data is
shown in Figure 4. In the figure, erosion is represented as negative values and accretion as positive in the study region.

Results and discussions

Figure 5 depicts spatial patterns of different statistical parameters used to characterize the health condition of the mangrove vegetation in the study region. These include climatologically mean NDVI for the spring season (Figure 5(a)), NDVI normal i.e. mean of the NDVI corresponding to the years with NDVI varies in the range of mean± 0.25*standard deviation (Figure 5(b)), standard deviation (Figure 5(c)), distribution of frequency of the NDVI data that satisfy (used to calculate) NDVI normal (Figure 5(d)), net loss or gain of the mangrove vegetation pixel (Figure 5(e)), and shore-line change rate estimated in this study using the procedure described earlier (Figure 5(f)). As shown the simple climatological mean and NDVI normal, in Figure 5(a) and Figure 5(b), respectively, do not show any significant differences except very small values for the mangrove fringes along the sea side (towards south) in the climatological mean NDVI in contrast to the relatively higher values in NDVI normal. However, they together exhibit high (with saturation) values, above 0.4, for most of the pixels in the interior of the mangrove forest which are associated with high temporal frequency, more than 20 out of 30 data points as shown in Figure 5(d). These regions are considered as stable, undisturbed and healthy mangroves. On the other hand, the regions with low values for mean NDVI located along the seaward fringes having low temporal frequency, less than 10 from 30 data points, (in Figure 5(d)) has been considered as stressful and disturbed regions. Therefore, in the following analysis we considered the pixel with NDVI value less than the NDVI normal in a given year has been considered as the mangrove vegetation with stress condition and the pixel that has NDVI value more than the normal value considered as improved mangrove vegetation. There are seven different classes of the mangrove density level have been proposed in the earlier section. The net change of mangrove cover in between 1990 and 2020 datasets, as shown in Figure 5(e), exhibits distinct regions of loss, gain and no change of the mangrove density levels. The gain (loss) means, the region was water or mud flat (vegetation) with significant negative (positive) NDVI in 1990 image, but found to be a vegetated or mangrove (water or mud) pixel in 2020 image with a significant positive (negative) NDVI value within the study region. It was found that 90.1 km² area mangrove has been lost whereas 50.1 km² newly mangrove grown-up from 1990 to 2020 period. As shown the shore line change rate in Figure 5(f) suggests that the most of seaward facing islands pixels are under erosion (rate of 30 to 80 m/y), which leads to the loss of mangrove, whereas some patches of western side of southern Parganas were classified under accretion (20 to 40 m/y) which leads to newly developed mangrove along the coast and creek. The similar conclusions were reported earlier by a national survey of coast line change (Kankara et al., 2018) being conducted for the period 1990 to 2016. The report has stated that West Bengal saw the biggest
coastal erosion (99 km$^2$) during the study period mostly due to waves and tidal dynamics, tropical cyclones and storm surges. On the other hand, the newly developed mangrove patches mostly in south Parganas are coming under the accretion zone.

The percentage area of different health condition of the mangrove forest of the study region during different years is depicted in Table 2 and the summary of the dominant classes, in terms of extreme health status of the mangrove vegetation, during different years were listed in the Table 3. The spatial distributions of mangrove vegetation for some of the selected years during the study period are shown in Figure 6. As shown in Table 3, the years 1990, 2006, 2007, 2009 and 2011 were identified as the stress condition for the mangrove forest of the Indian sector with more than 50% area comes under highly stress, whereas the years 1999, 2000, 2001, 2015, 2016 and 2019 were under highly improved vegetation condition with respect to NDVI normal. Moreover, the major portion of the mangrove during the years 2002, 2005, 2008 and 2010 are classified under normal vegetation condition. However, overall health of the mangrove vegetation is in improved trend during the study period and the similar observation was made earlier by Chellamani et al. (2014). It has been described in earlier studies that the South parganas and north-western part of north parganas having more stress on mangrove vegetation due to neo-tectonic movement of the Bengal Basin which slowly tilting towards the east with raising of the western region (Indian sector) of the Sundarbans and causing separation of tributary-branches of the river Ganges (Morgan & McIntire, 1959; Spalding et al., 1997). This leads to restricted freshwater run-off on the elevated region (western part of Indian Sundarban) from Ganga and Brahmaputra tributary during drought years (Jian et al., 2009). This also causes ecological stress on a large population of less saline-tolerant and freshwater-loving spices in the north western part of the study region (Selvam, 2003). In this region, there is substantial decline of net primary production.

Figure 5. Spatial patterns of (a) NDVI mean climatology for spring season, (b) NDVI mean of the climatological normal (c) NDVI Standard Deviation and (d) number-frequency of data used to calculate NDVI normal as in b (e) change of mangrove cover area between 1990 to 2020 (f) shoreline change rate along the coast of the study region.
associated to growth of the mangrove vegetation have been occurred to maintain the water balance and ion concentration (Clough, 1984; Spalding et al., 1997).

A whisker (box) plot of NDVI along with spread of the data points is shown in Figure 7(a). The measures of spread include the inter quartile range and the mean of the NDVI and difference between the preceding and succeeding NDVI values of a given year. The whiskers chart shows the health condition of the mangrove with five pieces of information: the minimum (down line), first quartile, second quartile, third quartile (inside the box) and the maximum (line at the top of the figure). The outline dot point shows the beyond the range between the minimum and maximum line. As shown in the figure, the average NDVI has increasing trend during 1990 to 1999 (with $R^2$ value 0.01), and following which there is a decreasing trend until 2006 (with $R^2$ value 0.031) and increasing trend till 2020 (with $R^2$ value is 0.015) (Figure 7(b)). The El Nino condition with substantial reduction of precipitation over India were noticed during the years 1991–1992, 1992–1993, 1994–1995, 1997–1998, 2002–03, 2004–05, 2006–07, 2009–10, 2015–16, 2018–19 (Meyers et al., 2006, https://en.wikipedia.org/; Pandey et al., 2019). This leads to relatively moderate to high stress on the vegetation growth of the Sundarban mangrove forest during succeeding years i.e. 1992, 1993, 1995, 1997, 1998, 2002, 2006, 2009, 2011, 2017, 2018 and 2020. Additionally, increase in saline owing to reduction of freshwater flux to river and estuarine system may case relatively stress with respect to the climatic normal.

Figure 8 shows the relationship between the increase of areas (in percentage) under stress condition and bio-carbon fluxes for the years with dominant class being either stressful (more than 50%) and normal for the entire study region. It is observed that with the increase of the area of mangrove on stress leads enhancement in release of carbon from biosphere to the atmosphere (source) and vice versa (sink). The estimated coefficient of determination is 0.53 at a significance level 0.02 p-value. The biosphere flux over the mangrove forest in the 2006 and 2011 years were low net uptake due to photosynthesis (primary productivity) or relatively higher release through
heterotrophic respiration. This results into a net positive bio-flux of about 0.12 and 0.2 Pg C/year for the respective years. During rest of the years, bio-carbon fluxes are negative which describes the region behaves as net sink of atmospheric CO$_2$, however the sink strength is declining as increase of percentage of mangrove area under the stress condition. For example, increase of stress area by 25% in the year 2003 and by 63% in 2008 results into a decrease of sink strength from −0.47 Pg C/year in 2003 to −0.15 Pg C/year in 2008. Therefore, the negative relationship between NDVI anomaly and bio-carbon flux is indicating the carbon uptake by mangrove from atmosphere (sinking) and vice versa. It is noteworthy that the carbon uptake falls with increasing mangrove vegetation stress period mostly during the drought years due to restricted freshwater river run-off. Which results into large population of less saline-tolerant and freshwater-loving spices are under stress (Selvam, 2003; Jian et al., 2009). The Peters et al. (2007) also observed that the uptake of carbon by terrestrial biosphere were decreases during large-scale drought period. We have also analyzed bio-carbon flux for the years of enhanced heath condition of the mangrove, but could not find statistically significant relationship between them and hence not discussed further.
Figure 8. Relationships between Bio-carbon flux and increase in area (in percentage) being classified under ecological-stress for the years with dominant class being either normal or stress mangrove condition.

Conclusions

The current study aims at estimating the spatio-temporal changes in the mangrove cover in Indian part of the Sundarbans. Delineation of stress level and health condition of mangrove vegetation has been carried out with seven classes based on NDVI value with reference to their climatological normal for the study period. It was found that the mangrove is accounting to 2011 km$^2$, out of total study region 2200 Km$^2$ has been classified under highly stressed vegetation during the years 1990, 2006, 2007, 2009 and 2011. Whereas, majority of mangrove vegetation were classified as healthier during 1999, 2000, 2001, 2015, 2016, 2019 (average 1831 km$^2$) and normal during 2002, 2005, 2008, 2010 (average 1279 km$^2$). Significant net change of mangrove cover between 1990 and 2020 were observed with distinct regions of loss and gain. It was found that the loss was mainly found along the seaward side, which accounts for ~90 km$^2$. This loss is mainly due to coastal erosion (with negative shore line change rate of -30 to ~80 m/ y). The gain of mangrove regions, accounting ~50 km$^2$, mainly located as patches along the western side of Southern Parganas, which comes under the zone of coastal accretion (with positive shore line change rate 20 to 40 m/y), which leads to newly developed mangrove along the coast and creek. These spatial-temporal variability and changes of the mangrove patterns were analyzed with respect to the finding of earlier studies in association with regional knowledge on tectonic and geometrical settings and meteorological conditions. The Sundarban mangrove as a whole had undergone through extremely stress condition for the years succeeding to the large-scale drought prevailed on the country due to reduction of availability of fresh-water input to the region. The mangrove patches belong to South parganas and north-western provinces had experienced more stress which can be associated with neo-tectonic movement of the Bengal Basin and changes in the freshwater fluxes in the tributaries of gangs and Brahmaputra system. Overall trend of average NDVI value of the study region increasing from 1990 to 1999, then slightly decreases up to 2006 and then again started increasing until 2020. There is a significant positive correlation (coefficients 0.76) found between the increases of areal extent of mangrove stress region and bio-carbon fluxes for the years of normal and below-normal health condition while the relationship was non-significant but negative correlation for the years dominated by healthier vegetations.

Knowledge and findings of this study may provide baseline inputs for future research in understanding health status and sustainable management of the mangrove ecosystem in relation to environment and climatic issues.

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No potential conflict of interest was reported by the author(s).

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Data availability statement
The data that support the findings of this study are available on request from the corresponding author.

References
Boelman, N. T., Stiegitz, M., Rueth, H. M., Sommerkorn, M., Griffin, K. L., Shaver, G. R., & Gamon, J. A. (2003). Response of NDVI, biomass, and ecosystem gas exchange to long-term warming and fertilization in wet sedge tundra. Oecologia, 135(3), 414–421. https://doi.org/10.1007/s00442-003-1198-3

Buckney, R. (1987). Three decades of habitat change: Kooragang Island, New South Wales. In D.A. Saunders, G.W. Arnold, A.A. Burbridge, & A.J.M. Hopkins (Eds.), Nature conservation, the role of remnants of native vegetation (pp. 227–232). Surrey, Beatty and Sons, Chipping Norton NSW. Chapter 19.

Castillo, E. G. D., Sanchez-Azofeifa, A., Paw, K. T. U., Gamon, J. A., & Quesada, M. (2018). Integrating proximal broad-band vegetation indices and carbon fluxes to model gross primary productivity in a tropical dry forest. Environmental Research Letter, 13(6), 065017. https://doi.org/10.1088/1748-9326/aac3f0

Chanda, A., Akhand, A., Manna, S., Dutta, S., Hazra, S., Das, I., & Dadhwal, V. K. (2013). Characterizing spatial and seasonal variability of carbon biomass and water vapour fluxes above a tropical mixed mangrove forest canopy. Indian Journal of Earth System Science, 122(2), 503–513. https://doi.org/10.1007/s12040-013-0288-9

Chellamani, P., Singh, C. P., & Panigrahy, S. (2014). Assessment of the health status of Indian mangrove ecosystems using multi temporal remote sensing data. Tropical Ecology, 55(2), 245–253. https://tropocel.com/pdf/open/PDF_55_2/09-Chellamani,%20Singh&20%20Panigrahy.pdf

Chladil, M. A., & Núñez, M. (1995). Assessing grassland moisture and biomass in Tansmania The application of remote sensing and empirical models for cloudy environment. International Journal of Wildland Fire, 5(3), 165–171. https://doi.org/10.1071/WF9950165

Clough, B. F. (1984). Growth and salt balance of the mangroves Avicennia marina (Forsk.) Vierh. and Rhizophora stylosa Griff. in relation to salinity. Australian Journal of Plant Physiology, 11(5), 419–430.

Das, S., Ganguy, D., Ray, R., Jana, T. K., & De, T. K. (2017). Microbial activity determining soil CO2 emission in the Sundarban mangrove forest, India. Tropical Ecology, 58 (3), 525–537.

David, S., Bartlett-Gary, J. W., & Hartman, M. (1989). Use of vegetation indices to estimate indices to estimate intercepted solar radiation and net carbon dioxide exchange of a grass canopy. Remote Sensing of Environment, 30(2), 115–128. https://doi.org/10.1016/0303-4257(89)90054-0

Donato, D., Kaufman, J., & Murdiyarso, D. (2011). Mangroves among the most carbon-rich forests in the tropics. Nature Geoscience, 4(5), 293–297. https://doi.org/10.1038/NGEO1123

Eslami-Andargoli, L., Dale, P., Sipe, N., & Chaseling, J. (2009). Mangrove expansion and rainfall patterns in Moreton Bay, Southeast Queensland, Australia. Estuarine, Coastal and Shelf Science, 85(2), 292–298. https://doi.org/10.1016/j.ecss.2009.08.011

Gamon, J. A., Field, C. B., Goulden, M., Griffin, K., Hartley, A., Joel, G., Penuelas, J., & Valentini, R. (1995). Relationship between NDVI, canopy structure and photosynthetic activity in the three Californian types. Ecological Application, 5(1), 28–41.

Gilmanov, T. G., Tieszen, L. L., Wylie, B. K., Flanagan, L. B., Frank, A. B., Haferkamp, M. R., Meyers, T. P., & Morgan, J. A. (2005). Integration of CO2 flux and remotely-sensed data for primary production and ecosystem respiration analyses in the Northern Great Plains: Potential for quantitative spatial extrapolation. Global Ecology and Biogeography, 14(3), 271–292. https://doi.org/10.1111/j.1466-822X.2005.00151.x

Gitelson, A. A. (2004). Wide dynamic range vegetation index for remote quantification of biophysical characteristics of vegetation. Journal of Plant Physiology, 161(2), 165–173. https://doi.org/10.1016/j.jplph.2004.07.039

Gower, S. T., Kucharik, C. J., & Norman, J. (1999). Direct and indirect estimation of leaf area index FAPAR, and net primary production of terrestrial ecosystems. Remote Sensing of Environment, 70(1), 29–51. https://doi.org/10.1016/S0034-4257(99)00056-5

Guha, S. (2016). - Capability of NDVI technique in detecting mangrove vegetation. International Journal of Advanced Biological Research, 6(2), 253–258.

Hong, P. N., & Hong, T. S. (1993). Mangroves of Vietnam. International Union for Conservation of Nature and Natural Resources (IUCN).

ISFR. (2019). Indian state forest report 2019. Retrieved January 21, 2021, from https://fis.nic.in/isfr19/vol1/chapt3.pdf

A. R. Jacobson, K. N. Schuldt, J. B. Miller, T. Oda, P. Tans, A. Andrews, J. Mund, L. Ott, G. J. Collatz, T. Aalto, S. Aeshar, K. Aikin, S. Aoki, F. Apadula, B. Baier, P. Bergamaschi, A. Beyersdorf, S. C. Biraud, A. Bollenbacher, D. Bowling, G. Brailsford, J. B. Abshire, et al. (2020). Carbon tracker documentation. CT2019.

Jian, J., Webster, P. J., & Hoyos, C. D. (2009). Large-scale controls on ganges and brahmaputra river discharge on intraseasonal and seasonal times-scales. Quarterly Journal of the Royal Meteorological Society, 135(639), 353–370. https://doi.org/10.1002/qj.384

Kankara, R. S., Murthy, M. V. R., & Rajeevan, M. (2018). National assessment of shoreline changes along India coast-Status report for 26 years 1990-2016. NCCR publication. http://www.nccr.gov.in

Kathiresan, K. (2018). Mangrove Forests of India. Current Science, 114(5), 976–981. https://doi.org/10.18520/cs/v114/i05/976-981

Knorr, W., & Heimann, M. (1995). Impact of drought stress and other factors on seasonal land biosphere CO2 exchange studied through an atmospheric tracer transport model. Tellus, 47B(4), 471–489. https://doi.org/10.3402/tellusb.v47i4.16062
Kotchenova, S. Y., Vermote, E. F., Matarrese, R., & Klemm, J. F. J. (2006). Validation of a vector version of the 6S radiative transfer code for atmospheric correction of satellite data. Part I: Path Radiance. Applied optics, 45(26), 6762–6774. https://doi.org/10.1364/AO.45.006762

Kumar, S. T., Mahendra, R. S., Nayak, S., Radhakrishnan, K., & Sahu, K. C. (2010). Coastal vulnerability assessment for Orissa state east coast of India. Journal of Coast Res, 26(3), 523–534. https://doi.org/10.2112/09-1186.1

Mahendra, R. S., Mohanty, P. C., Bisoyi, H., Srinivasa, K. T., & Nayak, S. (2011). Assessment and management of coastal multi-hazard vulnerability along the Cuddalore-Villupuram, East Coast of India using geospatial techniques. Ocean & Coastal Management, 54(4), 302–311. https://doi.org/10.1016/j.ocecoaman.2010.12.008

McLeod, E., Chmura, G. L., Bouillon, S., Salm, R., Bjork, M., Duarte, C. M., & Silliman, B. R. (2011). A blueprint for blue carbon: Toward an improved understanding of the role of vegetated coastal habitats in sequestering CO2. Frontiers in Ecology and the Environment, 9(10), 552–560. https://doi.org/10.1890/110004

Meyers, G., McIntosh, P., Pigot, L., & Pook, M. (2006). The years of El Niño, La Niña, and interactions with the tropical Indian Ocean. Journal of Climate, 20(13), 2872–2880. https://doi.org/10.1175/JCLI4152.1

Mohanty, P. C., Mahendra, R. S., Nayak, R. K., & Kumar, S. T. (2017). Impact of sea level rise and coastal slope on shoreline change along the Indian coast. Natural Hazards, 89(3), 1227–1238. https://doi.org/10.1007/s11069-017-3018-9

Mongillo, F., & McIntire, W. G. (1959). Quaternary geology of the Bengal Basin, East Pakistan and India. Geological Society of America Bulletin, 70(3), 319–342. https://doi.org/10.1130/0016-7606(1959)70(319:QGOTBB)2.0.CO;2

Mukhopadhyay, A., Payo, A., Chanda, A., Ghosh, T., Chowdhury, S. M., & Hazra, S. (2018). Dynamics of the Sundarbans Mangroves in Bangladesh under climate change. In R. Nicholls, C. Hutton, W. Adger, S. Hanson, M. Rahman, & M. Salehin (Eds.), Ecosystem services for well-being in deltas. Palgrave Macmillan. 489-503. https://doi.org/10.1007/978-3-319-71093-8_26

Mukhopadhyya, S. K., Biswas, H., De, T. K., Sen, B. K., Sen, S., & Jana, T. K. (2002). Impact of Sundarban mangrove biosphere on the carbon dioxide and mixing ratios at the NE coast of Bay of Bengal, India. Atmospheric Environment, 36(4), 629–638. https://doi.org/10.1016/S1352-2310(01)00521-0

Nayak, R. K., Patel, N. R., & Dadhwal, V. K. (2010). Estimation and analysis of terrestrial net primary productivity over India by remote-sensing-driven terrestrial biosphere model. Environ Monitoring and Assessment, 170, 195–213. https://doi.org/10.1007/s10661-009-1226-9

Pandey, V., Misra, A. K., & Yadav, S. B. (2019). Impact of El-Nino and La-Nina on Indian climate and crop production. In Climate change and agriculture in India: Impact and adaptation. Springer International Publishing AG, part of Springer Nature. Chapter-2. 11-20. https://doi.org/10.1007/978-3-319-90866-5_2

Penuelas, J., Garbulsky, M. F., & Filella, I. (2011). Photosynthetic reflectance index (PRI) and remote sensing of plant CO2 uptake. New Phytologist, 191(3), 596–599. https://doi.org/10.1111/j.1469-8137.2011.03791.x

Peters, W., Jacobson, A. R., Sweeney, C., Andrews, A. E., Conway, T. J., & Masarie, K. (2007). An atmospheric perspective on North American carbon dioxide exchange: Carbon tracker. Proceedings of the National Academy of Sciences, 104(48), 18925–18930. http://dx.doi.org/10.1073/pnas.0708986104

Rahman, A. F., Dragoni, D., & El-Masri, B. (2011). Response of the Sundarban coastline to sea level rise and decreases sediment flow: A remote sensing assessment. Remote Sensing of Environment, 115(12), 3121–3128. https://doi.org/10.1016/j.rse.2011.06.019

Ray, R., Ganguly, D., Chowdhury, C., Dey, M., Das, S., Dutta, M. K., Mandal, S. K., Majumder, N., De, T. K., & Mukhopadhyay, S. K. (2011). Carbon sequestration and annual increase of carbon stock in a mangrove forest. Atmospheric Environment, 45(28), 5016–5024. https://doi.org/10.1016/j.atmosenv.2011.04.074

Ray, R., & Jana, T. K. (2017). Carbon sequestration by mangrove forest: One approach for managing carbon dioxide emission from coal-based power plant. Atmospheric Environment, 171, 149–154. https://doi.org/10.1016/j.atmosenv.2017.10.019

Salam, M., Lindsay, R. G., & Beveridge, C. (2007). The use of GIS and remote sensing techniques to classify the Sundarbans Mangrove vegetation. Bangladesh Journal of Agro Forestry Environment, 1(1), 7–15.

Seen, D. L., Mougin, E., Rambal, S., Gaston, A., & Hiernaux, P. (1995). A regional Sahelian grassland model to be coupled with multispectral satellite data. II: Toward the control of its simulations by remote sensing indices. Remote Sensing of Environment, 52(3), 194–206. https://doi.org/10.1016/0034-4257(94)00127-9

Selvam, V. (2003). Environmental classification of mangrove wetlands of India. Current Science, 84(6), 757–765.

Spalding, M., Blasco, F., & Field, C. (Eds.). (1997). - In World Mangrove Atlas. International Society for Mangrove Ecosystems, WCMC, National Council for Scientific Research. ISBN: 4-906584-03-9.

Thieler, E. R., & Danforth, W. W. (1994). Historical shoreline mapping, Improving techniques and reducing positioning errors. Journal of Coastal Research, 10(3), 549–563. https://www.jstor.org/stable/4298252

Thomas, J. V., Arunachalam, A., Jaiswal, R. K., Diwakar, P. G., & Kiran, B. (2014). Dynamic land use and coastline changes in active Estuarine Regions – A study of Sundarban delta. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XL-8, 133–139. https://doi.org/10.5194/isprsarchives-XL-8-133-2014

Vanhellemont, Q. (2019). Adaptation of the dark spectrum fitting atmospheric correction for aquatic applications of the Landsat and Sentinel-2 archives. Remote Sensing of Environment, 225, 175–192. https://doi.org/10.1016/j.rse.2019.03.010

Vanhellemont, Q., & Ruddick, K. (2018). Atmospheric correction of metre-scale optical satellite data for inland and coastal water applications. Remote Sensing of Environment, 216, 586–597. https://doi.org/10.1016/j.rse.2018.07.015

Vermote, E., Tanré, D., Deuzé, J. L., Herman, M., Morcrette, J. J., & Kotchenova, S. Y. (2006). Second simulation of a satellite signal in the solar spectrum-vector (6SV) 6S User Guide, Version, 3, 1–55. https://salsa.umd.edu/files/6S/6S_Manual_Part_3.pdf

Wylie, B. K., Meyer, D. J., Tieszen, L. L., & Mannel, S. (2002). Satellite mapping of surface biophysical parameters at the biome scale over the North American grasslands. A case study. Remote Sensing of Environment, 79(2–3), 266–278. https://doi.org/10.1016/S0034-4257(01)00278-4
Xu, H., Wang, X., & Yang, T. (2017). Trend shifts in satellite-derived vegetation growth in Central Eurasia, 1982–2013. Science of the Total Environment, 579, 1658–1674. https://doi.org/10.1016/j.scitotenv.2016.11.182

Xu, H., Wang, X., Zhao, C., & Yang, X. (2020). Assessing the response of vegetation photosynthesis to meteorological drought across northern China. Land Degradation & Development, 32(1), 20–34. https://doi.org/10.1002/ldr.3701

Yoder, B. J., & Waring, R. H. (1994). The normalized difference vegetation index of small douglas-fir canopies with varying chlorophyll concentrations. Remote Sensing Environment, 49(1), 81–91. https://doi.org/10.1016/0034-4257(94)90061-2

Zafar, T. B., & Khan, M. G. (2018). A geographical overview of Sundarban: The Largest Mangrove forest of Bangladesh. International Journal of Geology, Agriculture and Environmental Sciences, 6(2), 9–10. http://www.woarjournals.org/admin/vol_issue1/upload%20Image/IJGAES061202.pdf