Journal of Environmental Management 326 (2023) 116800

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Research article

The role of protected areas co-management in enhancing resistance and resilience of deciduous forest ecosystem to extreme climatic events in Bangladesh

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ARTICLE INFO

Keywords:
Deciduous forest
Co-management
Land-use/cover change
Sal forest
Forest health
Biomass
Climate events

ABSTRACT

Due to ongoing and projected climate change as well as increasing anthropogenic disturbances, the tropical deciduous forest has been experiencing a decline in its biomass and productivity. To mitigate this adverse effect, many tropical countries have adopted forest co-management engaging local communities. However, the effects of co-management on the resistance and resilience of forest ecosystems to extreme climatic events have rarely been tested. The present study investigates the effects of co-management on resistance and resilience to extreme climatic events in two major tropical deciduous forest protected areas of Bangladesh, namely Madhupur National Park (MNP) and Bhawal National Park (BNP), through remotely sensed satellite data. We used the Google Earth Engine platform to access the Landsat images from 1990 to 2020 for a comprehensive assessment of the forest cover condition under two major management regimes (i.e., traditional and co-management). We find that co-management slows down the rate of forest destruction, where the rate of forest destruction was 108 ha year^{-1} in MNP and 121 ha year^{-1} in BNP during the year 1990–2008 under traditional forest management system. Under the co-management regime, forest cover increased by 19 ha year^{-1} and 41 ha year^{-1} from 2009 to 2020 respectively in MNP and BNP. Our study finds a highly significant correlation between rainfall ($p < 0.001$) and forest health, although co-management had poor impacts on forest resistance and resilience in case of extreme climatic events, such as drought and heavy rainfall. We find, no significant impacts of co-management on resistance and resilience to drought in MNP, and on resistance and resilience to heavy rainfall in MNP and BNP. In BNP, the impacts of co-management on resistance ($p < 0.05$) and resilience ($p < 0.01$) of forest to drought were highly significant. Forest co-management although have the potentials to reduce the deforestation rate by mitigating anthropogenic disturbances, its capacity to tackle the adverse impact of climate change was limited in our study. An adaptive co-management model, therefore, is crucial for mainstreaming the adverse effect of climate change on the tropical deciduous forest to harness the maximum potential of community participation in forest resources management.

1. Introduction

Tropical forests cover only 7% of the earth's land surface but harbor the greatest biodiversity of any biome on earth (Tarakeswara et al., 2018; Davis et al., 2020). Deciduous forests account for 55.9% of the total area of tropical forests and are considered the most critical biomes due to ongoing climate change (Igarashi et al., 2015). Within the tropical biome, deciduous forests also experience a higher rate of degradation and loss than humid forests (Pérez-Vega et al., 2012). Globally, they are diminishing at an unprecedented rate of 0.8%–2% every year as a

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https://doi.org/10.1016/j.jenvman.2022.116800
Received 26 March 2022; Received in revised form 12 November 2022; Accepted 13 November 2022
0301-4797/

result of increasing anthropogenic disturbances (Tarakeswara et al., 2018). Many co-management projects have been implemented across the tropics to halt forest cover loss as well as to improve forest health resulting from human disturbances (see - Mukul and Quazi, 2009; Rashid et al., 2013). The outcomes of these projects have been assessed in several studies looking at forest cover change, changes in forest dependency of the local community, etc. (see - Mukul et al., 2012; Salam and Pramanik, 2018; Gondwe et al., 2019; Chowdhury et al., 2020). How does the co-management approach may affect the resistance and resilience of forests in terms of climate change, another major driver of forest cover change, however, has not yet been properly studied (Takahashi and Todo, 2012; Chinangwa et al., 2017; Gondwe et al., 2019). Our study attempted to assess this gap with the help of remote sensing techniques through a robust and comprehensive analysis using the Google Earth Engine platform.

Tropical deciduous forests across the globe thrive under varied climatic conditions and overall vegetation health is influenced by climatic factors such as the amount of precipitation and temperature (Butt et al., 2015; Rahman et al., 2015; Tarakeswara et al., 2018). For instance, interannual fluctuation in rainfall regimes is a major determinant of vegetation cover in tropical deciduous forests (Chaturvedi et al., 2011; Igarashi et al., 2015). Moreover, extreme climatic events can affect the health of tropical deciduous forests (Alamgir et al., 2015). Drought and high rainfall can decrease forest diversity by increasing tree mortality (Margrove et al., 2015). It has been reported that the distribution of Sal (*Shorea robusta* L.), a major tropical deciduous species in South Asia, is likely to reduce due to climate change (Deb et al., 2018). Reduction in forest cover in the region due to a combination of factors is posing a serious threat not only to human life but also to the lives of other keystone species (Mukul et al., 2019; Malik et al., 2020).

To combat the continuous deterioration of forest resources, co-management has been introduced as a continual approach to integrating local communities in forest management processes by utilizing the capacities and comparative advantages of various social actors (Rashid et al., 2013; Soliku and Schraml, 2020). This approach seeks to enhance both forest health conservation and local livelihoods by offering local communities the responsibility to manage forest resources and the opportunity to enjoy the benefits derived from them (Mukul et al., 2012; De Pourcq et al., 2016). Co-management approach is considered as a successful forest conservation technique to address the anthropogenic disturbance in many regions of the world, such as Nepal, Honduras, Ethiopia, and Malawi (see -Nagendra et al., 2004; Takahashi and Todo, 2012; Niraula et al., 2013; Chinangwa et al., 2017). However, there is a lack of evidence regarding the beneficial effects of co-management on forest vegetation cover under a rapidly changing climate. There is also a lack of empirical evidence of forest resistance and resilience to extreme climatic conditions under co-management versus traditional management systems (Karim et al., 2020).

In Bangladesh, the tropical moist deciduous forest encompasses only 0.12 million hectares which is 4.7% of the total forest areas of the country (Mukul et al., 2018; Hasan et al., 2020). Two major protected areas (PA) within this forest region are Madhupur National Park (MNP) and Bhawal National Park (BNP), where MNP is in proximity to different ethnic communities and BNP is close to the capital city is under persistent human pressure (Hasan and Bahauddin, 2014). To reduce such pressure and improve the health of the degraded deciduous forest, the government along with donor agencies has undertaken co-management of PAs in Bangladesh which was first introduced in 2004 in 5 PAs under the Nishorgo Support Project (NSP) (Chowdhury and Koike, 2010; Rashid et al., 2017). It was later replicated in 18 PAs through the Integrated Protected Area Co-management (IPAC) project (Rashid et al., 2017), and was also a policy target (under strategy nine) of the National Biodiversity Strategy and Action Plan (NBSAP) (Chowdhury et al., 2020). Nevertheless, in Bangladesh, where human pressure is extremely high, the efficacy of co-management faces major challenges in the case of improving forest cover. A co-management system has mixed outcomes in the protected areas of Bangladesh (Rashid et al., 2013). In certain PAs, studies indicated no substantial improvement in forest cover (Islam et al., 2019), whereas, in others, forest cover has increased (Chowdhury et al., 2020). Still, such studies are limited to tropical evergreen or semi-evergreen forests of Bangladesh (Islam et al., 2019; Chowdhury et al., 2020), and are very limited in the case of country's deciduous forests. Therefore, it is critical to assess the land use and land cover change (LULCC) and forest vegetation health of deciduous forest ecosystem (here MNP and BNP) to understand the efficacy of management practices and to plan for future forest management under a rapidly changing climate. Precise information on forest cover is also crucial for spatial planning of forest activities, investigating forest degradation, inventorying forest resources, formulating policy decisions, and preparing forest management plans (Mukul et al., 2017a; Pirnat and Hladnik, 2018).

As LULCC is a continual process, satellite imageries can generate more precise assessments than do conventional inventory methods and provide an effective and accurate evaluation of the anthropogenic impact on the environment from smaller to larger scales at a particular point in time or over a long period (Islam et al., 2018; Malik et al., 2020). Apart from being relatively low-cost, accurate, less time-consuming and versatile, remote sensing provides a wide range of applications and is considered the most effective monitoring tool for forest change detection in the modern research field (Zaman and Katoh, 2011; Woodcock et al., 2020). Yet studies regarding the changes in forest cover over time and the efficacy of co-management to protect forest dynamics from ongoing climate change are limited. Consequently, our research attempted to fill that gap by using remotely sensed data from 1990 to 2020, firstly by assessing the long-term forest cover change through LULC mapping, secondly by assessing how local climate are co-related with the forest cover change, and thirdly by determining the efficacy of co-management in enhancing resistance and resilience of forest ecosystems in our study protected areas (i.e., MNP and BNP).

2. Methodology

2.1. Study areas

2.1.1. Madhupur National Park (MNP)

Madhupur National Park (MNP) was declared as a protected area in 1982 which is located at 23°30' to 24°50' N latitude and 89°54' to 90°50' E longitude (Mukul et al., 2017b, Fig. 1). The total area of the MNP is 18439.58 ha (Islam and Hyakumura, 2019). Average temperatures were recorded at 25.4 °C and the average total rainfall was estimated at 2366 mm (Salam and Pramanik, 2018). June to September is the monsoon season with the most rainfall (Fig. 2). The forest is dominated by Sal (*Shorea robusta* L.) trees. The topography of the park comprises low and high land, while soil is poor in nutrients, acidic and red to brown in color (Rahman et al., 2010). The park is inhabited both by the ethnic (Garo and Koch) community and mainland Bengali people and all areas of the park have been subjected to some degree of usage (Tuihedur et al., 2014). There are about 176 species of plants recorded from the park, including 73 tree species (Islam and Hyakumura, 2019). An estimated 140 species of birds, 19 mammal species, 19 species of reptiles, and 4 amphibian species have been recorded from the area, although large wildlife species, like tiger (*Panthera tigris*), leopard (*Panthera pardus*), elephant (*Elephas maximus*), sloth bear (*Melursus ursinus*), spotted deer (*Axis axis*) have already been extirpated (Rahman et al., 2019b).

The forest in MNP is administratively under the control of Tangail and Mymensingh Forest Division of Bangladesh Forest Department (FD) (Islam and Sato, 2010). MNP was one of the PAs associated with the IPAC project. The FD has overall responsibility for the management, conservation, and development of MNP through planting, patrolling, and guarding forest resources with the active participation of local communities, and there exists a benefit-sharing agreement between all

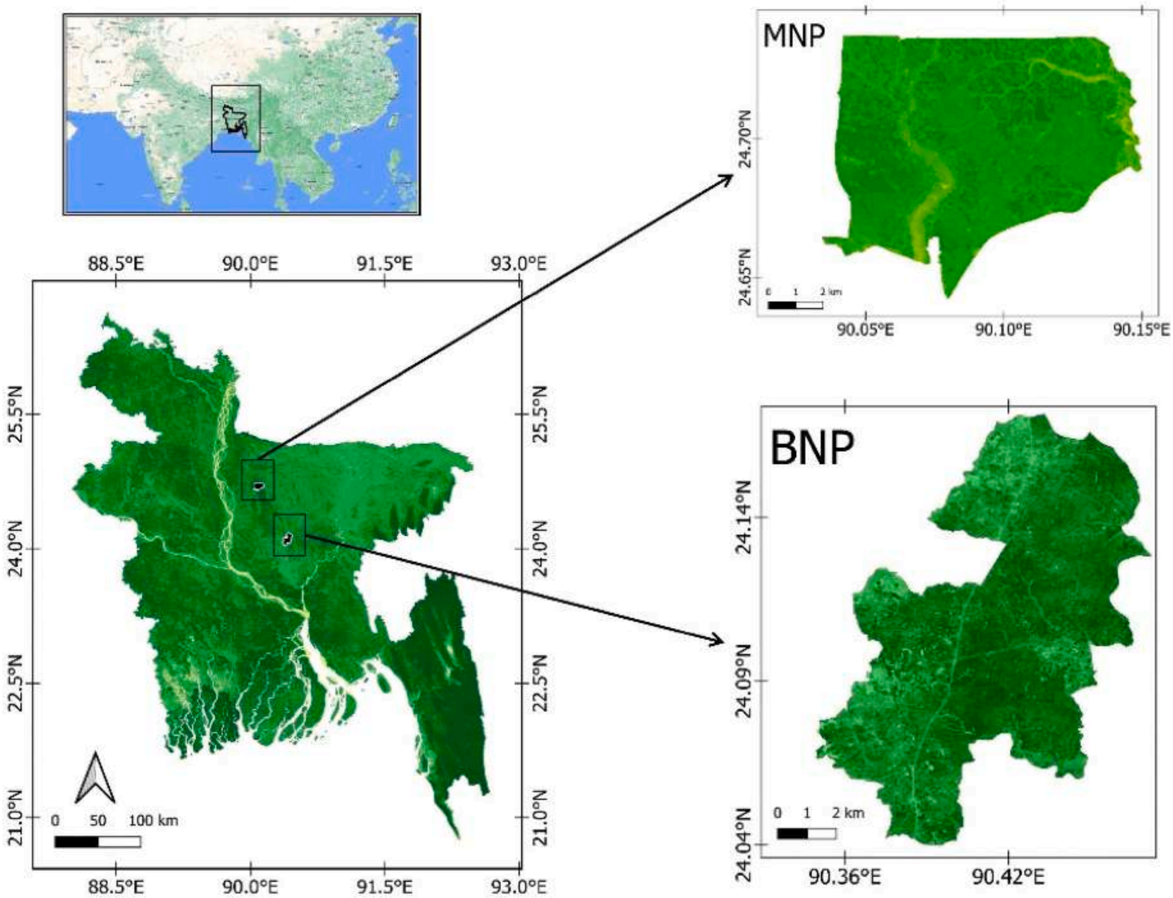

Fig. 1. Location map of the study sites (i.e., Madhupur National Park and Bhawal National Park).

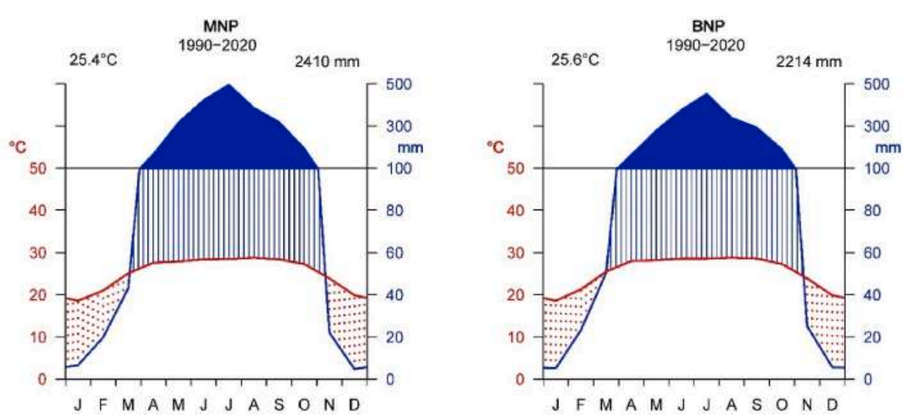

Fig. 2. Walter lieth diagram of the study areas. Based on Climatic Research Unit (CRU) Time-Series (TS) version 4.04 (Zepner et al., 2021).

the stakeholders (Begum, 2011).

2.1.2. Bhawal National Park (BNP)

Bhawal National Park (BNP) was declared as a protected area (IUCN Management Category IV) in 1982 and comprises 5222 ha of forestland (Mohd et al., 2008, Fig. 1). BNP is located between 24°01′–24°12′ N latitude and 90°19′–90°28′ E longitude with two forest ranges, namely Bhawal Forest Range and National Park Forest Range (Masum et al., 2016). This park is amongst the closest forest of the capital city Dhaka, and this proximity renders it vulnerable to several influences that most other forests do not face. Average temperatures were recorded at 25.6 °C and the average total rainfall was estimated at 2214 mm. Like, MNP, June to September is the monsoon season with the most rainfall rate in this region (Fig. 2). The topography is characterized by low hills, which rise 3.0–4.5 m above the surrounding paddy fields and are intersected by numerous depressions or baids.

The dominant forest tree Sal (*Shorea robusta* L.) had been almost completely removed about 40 years ago, and then the protection program planted Sal which now covers 90% of the area. About 221 species of plants (24 species of climber, 27 species of grass, 3 species of palm, 105 species of herb, 19 species of shrubs, and 43 species of tree) have been recorded from BNP. This national park is inhabited by a few mammals such as Bengal fox (*Vulpes bengalensis*), jackal (*Canis aureus*), small Indian civet (*Viverricula indica*), wild boar (*Sus scrofa*), jungle babbler (*Turdoides striatus*), etc. (Kabir and Ahmed, 2005). The forest has been under co-management program under IPAC since 2008. The FD has overall responsibility for the management, conservation, and development of BNP through 17 village conservation forums (VCF) (Hasan and Bahauddin, 2014).

2.2. Satellite data

Surface reflectance (SR) products from Landsat 5 ETM, 7 ETM+, and 8 OLI sensors have been used to create NDVI composites in our study. The Landsat satellites have near-polar orbits with a repeat overpass every 16 days; throughout the Landsat missions; however, two satellites have often operated simultaneously in asynchrony, creating an eight-day return overpass for a given area. Our data processing has three parts. first, we calculated the NDVI for all the Landsat images available in Google Earth Engine (GEE) and determined the annual median NDVI composites. Then, true-color composite images of the growing season from 1990 to 2020 with a 10-year interval have been produced to monitor the different land use and cover (LULC) changes. Finally, the land cover types of changed land were determined by extracting pixel values of respective classification (Fig. 3).

2.2.1. Landsat archive data in the GEE

GEE provides online access to archived Landsat data, which includes Landsat 5 TM from 1985 to 2011, Landsat 7 ETM+ from 1999 to 2014, and Landsat 8 OLI/TIRS from 2013 to 2021 (Gorelick et al., 2017). But original images were obtained from the United States Geological Survey (USGS). GEE ingest the images with an atmospheric correction from USGS when we executed this study, so we used the calibrated Surface reflectance (SR) data from Landsat 5, 7, and 8 which are also radiometrically adjusted. We used a total of 1426 images of three Landsat datasets in our study (Table 1).

2.2.2. Atmospheric and geometric correction

The Landsat SR products (Masek et al., 2006; Vermote et al., 2016) are corrected for atmospheric and illumination geometry effects and are the highest level of image processing available for Landsat data. Although some images are not processed due to missing auxiliary data, the use of SR is generally more appropriate for measuring and monitoring vegetation at the land surface (Song et al., 2001; Feng et al., 2012). Landsat Surface reflectance products also contain useful pixel data quality flag information indicating clear, water, snow, cloud, or shadow conditions, as determined by the CFMask algorithm (Foga et al., 2017) that classifies pixels containing clear land (0), water (1), shadow (2), snow (3) or clouds (4). Pixels containing e.g., clouds can then be masked out and will not be used in NDVI calculations. We employ this information to select the best available data within each composite period.

2.2.3. NDVI composites extraction

1426 scenes Landsat images were acquired from 1990 to 2020 by Landsat 5, 7, and 8. Among these images, the maximum cloud cover in this area is 100%. To minimize the effects of clouds and cloud shadows, we used a cloud score algorithm available in the GEE. This algorithm computes a simple cloud-likelihood score ranging from 0 to 100 using a combination of brightness, temperature, and the Normalized Difference Snow Index (NDSI) (https://developers.google.com/earth-engine/landsat). We masked the images when the score was greater than 20. After applying the cloud mask all available Landsat surface reflectance images (from 5 ETM, 7 ETM+, and 8 OLI) are processed to produce an 8-day composite. Landsat scenes are resampled bilinearly to a Geographic Coordinate System WGS84 grid of approximately 30 m (1/5000°) resolution. NDVI is calculated as,

$$NDVI = \frac{\rho NIR - \rho \mathrm{RED}}{\rho NIR + \rho \mathrm{RED}}$$

where ρNIR is surface reflectance in the near-infrared band (band 4—Landsat 5, 7; band 5—Landsat 8) and ρRED is surface reflectance in the red band (band 3—Landsat 5, 7; band 4—Landsat 8).

To account for sensor differences, we adjusted Landsat NDVI values from Landsat 5 ETM and 7 ETM + to match Landsat 8 OLI using a simple linear transformation (Roy et al., 2016),

$$NDVI_{L8} = 0.0235 + 0.9723 \times NDVI_{L5,7}$$

We produced an annual composite NDVI band from the google earth engine by using the median of all available pixel values of a year of the

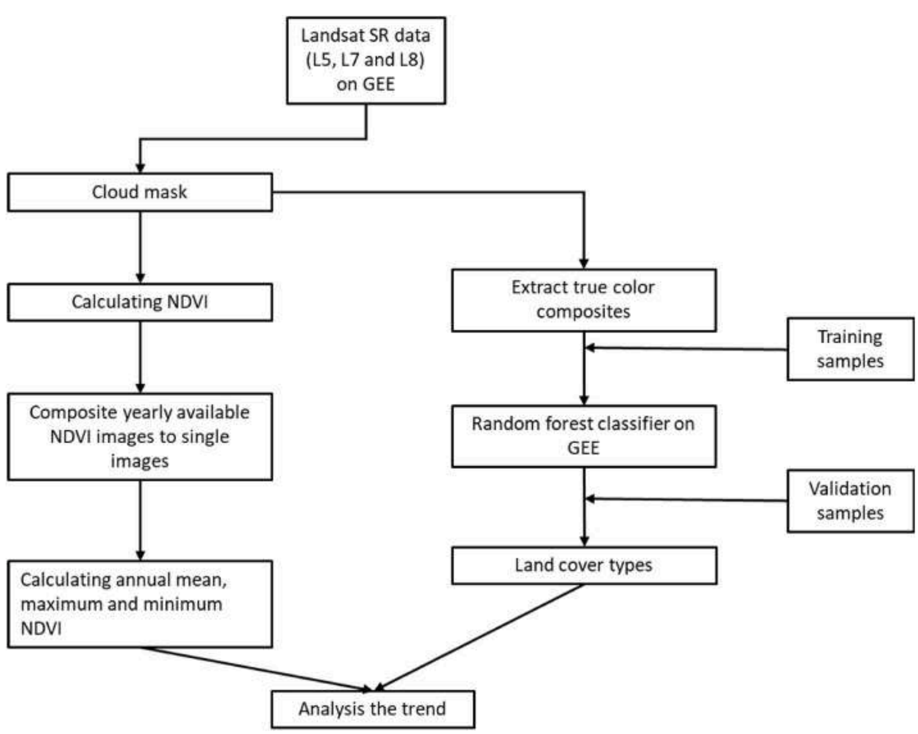

Fig. 3. Flowchart describing the steps followed during this study.

Table 1
Dataset and other information of the images used in the study.

Dataset	Sensor	Level	Collection	Acquisition year	Resolution	Path/ Row	Yearly acquired images	Total acquired images
Landsat 5	Thematic Mapper (TM)	1	1	1990–2011	30 m	137/43	46	1012
Landsat 7	Enhanced Thematic Mapper Plus (ETM+)	2	2	2012	30 m	137/43	46	46
Landsat 8	Operational Land Imager (OLI)	2	2	2013–2020	30 m	137/43	46	368

study areas. This composite scene carried the robustness of annual NDVI variation of the study area, and the median composite contained the growing season nearest pixel values also.

2.3. Classification with random forest in the GEE

We used Landsat 5, 7, and 8 images from 1990 to 2020 to classify land cover in MNP and BNP. These images were orthorectified and calibrated to top-of-atmosphere reflectance, and the image with the least cloud cover was used as the primary input data. Except for the bands used for coastal aerosol and cirrus detection, we used all the bands with a 30-m resolution. Contrast, sum variance, and entropy were extracted as additional textural features for classification. We chose the Random Forest algorithm as a classifier, given the superior performance of its multi-dimensional features. We collected several training samples from Landsat true color images and interpreted various validation samples from higher-resolution images using GE. For each type, the numbers of the samples were determined according to the proportion of their area. Both the training samples and validation samples were uploaded to the GEE via Google Fusion Tables. Finally, we classified the study area into four types: forest, waterbody, agricultural land, and barren land with built-up. The classification system is consistent with the first level of the FROM-GLC classification scheme (Gong et al., 2013).

2.4. Accuracy assessment of LULC

User accuracy and the Kappa coefficient were used for accuracy assessment in our study. Google earth engine was used to conduct statistical assessments of the accuracy of the classified image and calculate the confusion matrix. The classification products were evaluated for mapping accuracy using an independent set of accurate data points. Seventy percent of the points were used for the training process and 30% was used for the verification process of each LULC map. Historical data for training and validation of LULC maps from 1990 to 2020 were obtained from the existing topographic map (prepared by NSP, USAID for 2020) and Google Earth images from 1990 to 2010 using historical image features.

2.5. Climatic data

Data for this study was extracted from the Bangladesh Meteorological Department (BMD). The BMD collects everyday surface data through weather stations situated all over the country. In this study, we used data from two weather stations nearby to our study sites, i.e., Dhaka (for BNP) and Tangail (For MNP). The study period was January 1990 to December 2020. Annual and monsoon average rainfall for different stations is anticipated to analyze the variation and to estimate the trend line for the period 1990 to 2020. The yearly rainfall and temperature were obtained from daily data. Later, the mean of temperature and the sum of annual rainfall were obtained by using a pivot table in Microsoft Excel (version 365). We categorized the year 1990–2020 into three classes, i.e., drought, heavy rainfall, and normal (Table 2). We took the 30 years average annual rainfall data from per study area. Subsequently, we classified the drought and heavy rainfall year which are shown below and upper 200 mm value from average annual rainfall value. The normal year was marked as those years which have the nearest average values (average of total Rainfall ± 200 mm) of the mean annual rainfall of 30 years.

Table 2
Three broad climatic classes (year) based on annual rainfall recorded between 1990 and 2020.

Category	MNP	BNP
Drought (rainfall >1800 mm)	1990, 1992, 1996, 1999, 2001, 2006, 2009, 2012, 2013, 2014, 2016	1992, 1994, 1995, 2001, 2003, 2010, 2012, 2013, 2014, 2016, 2018, 2019
Heavy rainfall (rainfall <2000 mm)	1991, 1993, 1995, 2000, 2002, 2005, 2017, 2020	1991, 1993, 1998, 2000, 2004, 2005, 2007, 2008, 2017
Normal (rainfall = 1800–2000 mm)	1994, 1997, 1998, 003, 2004, 2007, 2008, 2010, 2011, 2015, 2018, 2019	1990, 1996, 1997, 1999, 2002, 2006, 2009, 2011, 2015, 2020

Source: Bangladesh Meteorological Department.

2.5.1. Resistance and resilience assessment

We define measures of resistance and resilience that are dimensionless, symmetric, and thus directly comparable between positive and negative perturbations, such as heavy rainfall and drought climate events; applicable to dynamic systems that exhibit either monotonic recovery or hampered fluctuations after a perturbation.

We define resistance and resiliency as described in (Isbell et al., 2015),

$$\boldsymbol{\Omega} \equiv \frac{\overline{NDVI_n}}{\left|NDVI_e - \overline{NDVI_n}\right|};\ \Delta \equiv \left|\frac{NDVI_e - \overline{NDVI_n}}{NDVI_{e+1} - \overline{NDVI_n}}\right|$$

Where $\overline{NDVI_n}$ = average of the mean NDVI of all normal years, $NDVI_e$ = mean NDVI of the drought/heavy rainfall event year and $NDVI_{e+1}$ = mean NDVI of the normal year after a drought/heavy rainfall event.

2.6. Statistical analysis

Analysis of variance (ANOVA) was used to test for the significant effects of climate (annual total rainfall and annual mean temperature) on NDVI. Pearson's correlation was performed to assess the relationships between dependent variables (NDVI) and independent variables (Climatic factors). At 5% of a significant level, all statistical significances were decided. All data were analyzed using R version 3.6.1 (Pinheiro et al., 2020) and figures were produced using the packages "ggplot2" for trendline, linear regression analysis, bargraph, and boxplot with significant marks and "nlme" for ANOVA. We used the "raster" package for NDVI value extraction from Landsat images. Before statistical analysis, the normality and homogeneity of all data were tested.

3. Results

3.1. Changing NDVI and climate in Sal forest ecosystem

We observed both positive and negative trends of NDVI changes from 1980 to 1990. A positive linear trend was observed in case of MNP whereas a very slight negative linear trend was observed in BNP

(Fig. 4a). A strong mean NDVI drop also found in MNP from 1998 to 2001 interval however from 2001 to 2003 this drop was minimal. A similar drop was observed again for 2007 to 2009 but after the co-management period from 2009, no significant mean NDVI drop was evident in our study. On the other hand, in BNP, from 2001 to 2006 a significant NDVI fall was observed and after the CM from 2009, the value slightly rises with a frequent small drop (Fig. 4a). The annual rainfall trendline also showed a marginally decreasing linear trend for both study sites. We observed an almost similar pattern in rainfall in both of our study protected areas except for the year 1998–2000 (Fig. 4b). From the linear regression trendline it is possible to predict the future decreasing pattern in rainfall events in our study protected areas, especially in MNP. We, however, observed an increasing pattern in the annual mean temperature linear trendline in both of our study protected areas. Here we also observed an almost similar pattern between the trendline of the study areas except from 2000 to 2003. From the linear regression trendline it is clear that global warming effects will be obvious in our study areas in the future (Fig. 4c).

3.2. Changes in LULCC and forest cover

Our analysis reveals significant LULC changes in MNP and BNP during the study period. We prepared 4 LULC maps for each of our study sites with a 10-year time interval (Fig. 5). We classified four major land use/cover types (i.e., forest, agriculture, waterbody, barren + built-up) for our study sites. We found severe forest cover changes in two of our sites, which was very similar in MNP and BNP (Fig. 6a). In MNP from 1990 to 2010, the forest cover decreased by 2165.8 ha. Forest cover was increased by 211.7 ha in MNP after the co-management initiated at the site in 2009 (see Annex 1). From 1990 to 2010, the forest cover of MNP declined from the periphery to the core zone. Co-management halt some of this degradation and improved forest cover in some fragmented portions presumably through community-led afforestation (Fig. 5). The overall accuracy of the classification was 92.9%, 93.6%, 92.1%, and 91.8% respectively, and the Kappa statistics were 0.90, 0.92, 0.89, and 0.88 for the years 1990, 2000, 2010, and 2020, respectively (Annex 2). In BNP, the forest cover was reduced by almost 2430.0 ha from 1990 to 2010. Between 2010 and 2020, after the co-management, the forest area increased by almost 447.0 ha (Annex 1). From 1990 to 2010, the forest cover of BNP was severely fragmented in most of the core zones, which

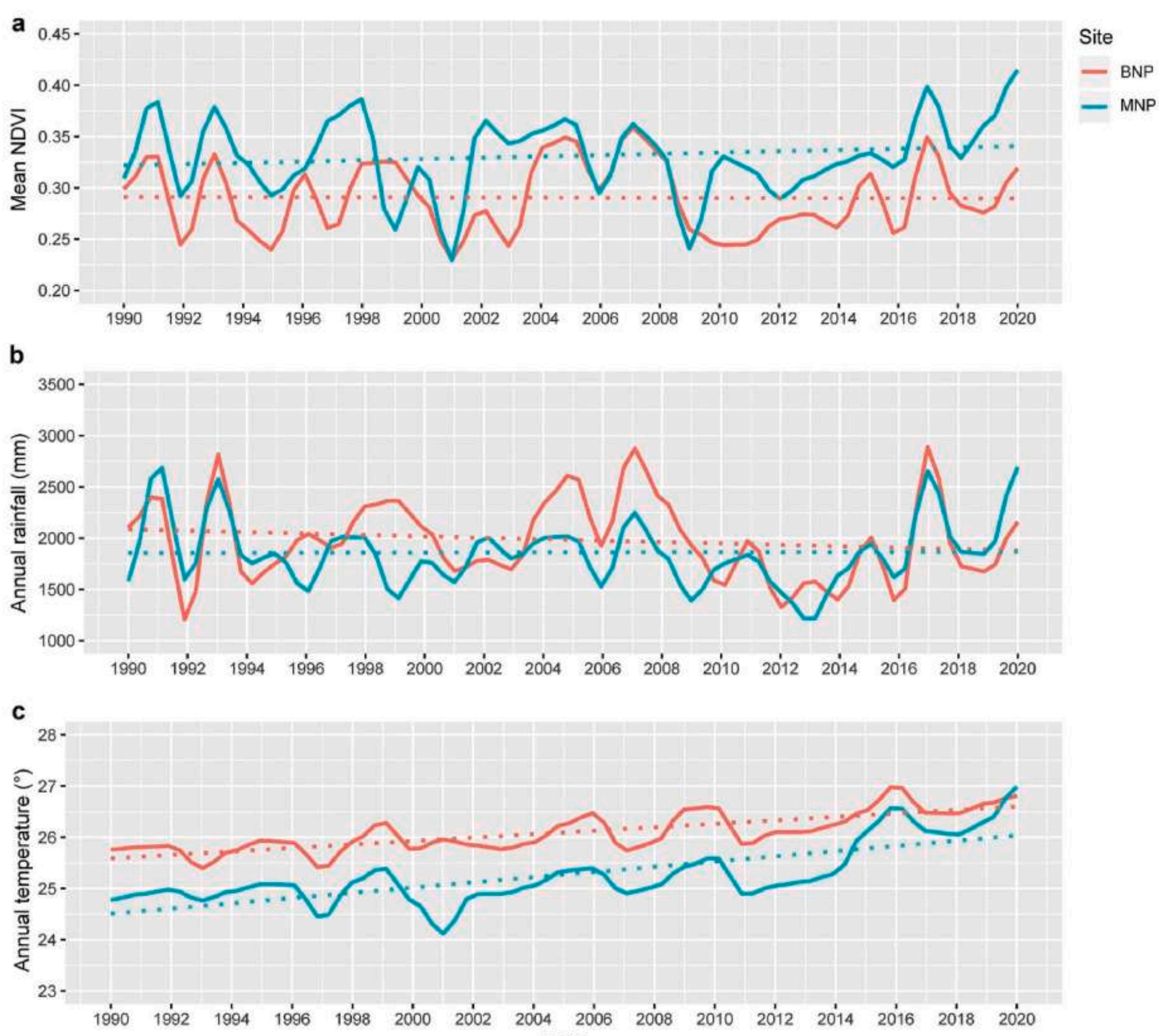

Fig. 4. Trends of (a) mean NDVI, (b) total annual rainfall (mm), and (c) mean annual temperature (^{o}C) across the study period (per year).

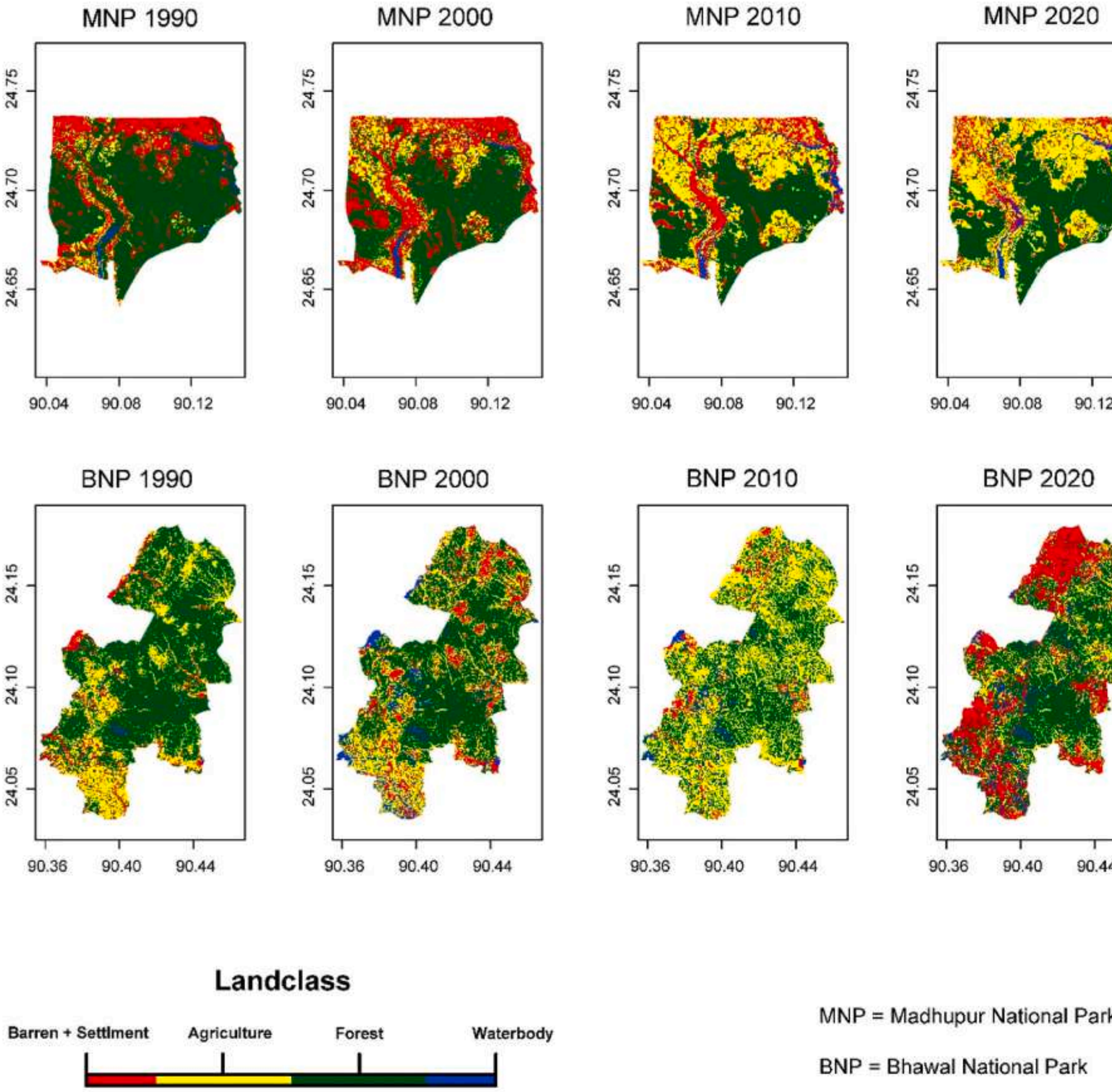

Fig. 5. Land use/land cover change map of our study sites during 1990 and 2020 derived from Landsat 5, 7, and 8.

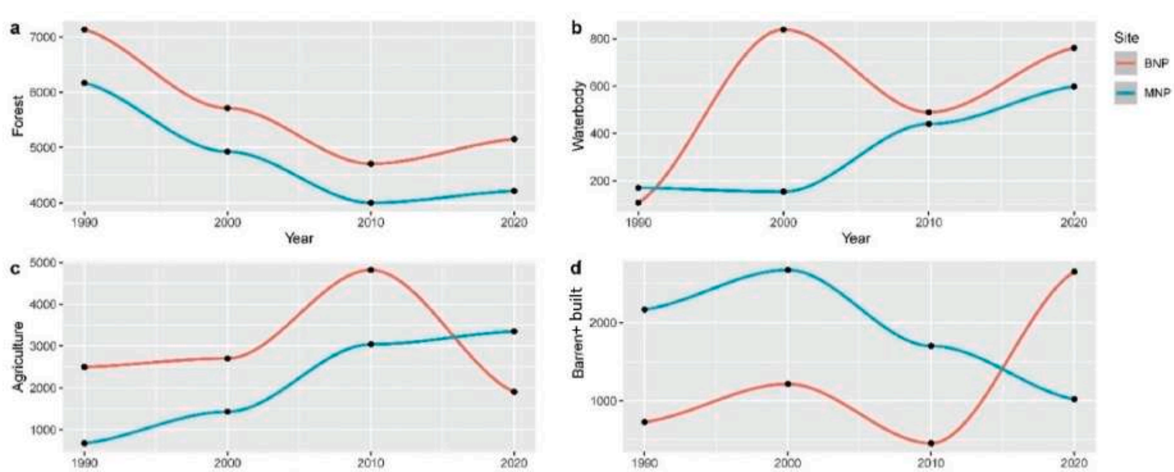

Fig. 6. Change in the extent of a) forest cover, b) waterbody, c) agricultural land, and d) barren + built-up area between 1990 and 2020 in our study sites.

was later enhanced after the introduction of co-management like MNP (Fig. 5). The overall accuracy of the classification was 92.7%, 93.5%, 88.3%, and 90.3% respectively, and the Kappa statistics were 0.89, 0.91, 0.84, and 0.87 respectively for the years 1990, 2000, 2010, and 2020 (see Annex 2). In MNP, waterbody increased by almost 427.0 ha during the study period (1990–2020) (Fig. 6b, Annex 1). However, this trend was irregular in BNP. From 1990 to 2000, the waterbody increased by almost 731.0 ha, which dropped to almost 249.0 ha from 2000 to 2010, and again increased by almost 272.0 ha from 2010 to 2020 (Fig. 6b, Annex 1). The expansion of agricultural land in BNP increased by almost 2322.0 ha from 1990 to 2010. This trend came downward under co-management regime, and the agricultural land significantly decreased by almost 2911.0 ha from 2010 to 2020 (Fig. 6c, Annex 1). The barren and built-up area increased from 1990 to 2000 by almost 487.0 ha. However, due to the higher conversion of barren land to agriculture, this decreasing trend of barren land came to 759.0 ha lower from 2000 to 2010. Furthermore, the barren land and human settlements took a sharp rise from 2010 to 2020, accounting almost 2192.0 ha (Fig. 6d, Annex 1).

3.3. Forest health and climate change

Annual rainfall has a significant ($p < 0.0001$ in MNP and BNP) positive correlation (R = 0.87 in BNP, R = 0.82 in MNP) with the mean NDVI value of both of our study sites (Fig. 7). Increasing mean NDVI values indicate an improvement in vegetation health. However, annual rainfall had no significant ($p = 0.09$ for BNP and p = 0.34 for MNP) correlation (R = 0.32 for BNP and R = 0.18 for MNP) with minimum NDVI indicating the non-forest structure (e.g., barren land, agriculture, built-up area, etc.). Moreover, annual rainfall has a marginally significant correlation ($p < 0.05$, R = 0.4) with a maximum NDVI value of BNP, whereas no significant relation ($p = 0.09$, R = 0.31) was observed in the case of MNP (Fig. 7). The maximum NDVI value indicates the dense vegetation cover represented by a healthy forest.

The annual mean temperature had no significant ($p = 0.8$ for BNP and $p = 0.12$ for MNP) correlation (R = −0.047 for BNP and R = 0.28) with mean NDVI in both of our study sites (Fig. 7). We find a marginally significant correlation ($p < 0.05$, R = 0.41) of annual temperature on minimum NDVI on BNP, but no significant association (p = 0.31, R = 0.19) was observed in the case of MNP. Moreover, no significant (p = 0.55 in BNP and $p = 0.44$ in MNP) correlation (R = 0.11 in BNP and R = 0,14 in MNP) was found between annual temperature and maximum NDVI in our study sites (Fig. 7).

3.4. Does co-management enhance forest vegetation and health?

The mean NDVI under traditional management during a drought year in MNP was 0.29, whereas under co-management this value increased to 0.30 (Fig. 8a). During heavy rainfall, year means NDVI value was recorded at 0.35 under traditional management, whereas under co-management this value increased to 0.41 (Fig. 8a). We observed a lower mean NDVI value under co-management (0.34) than the traditional management (0.36) in the normal climatic year (Fig. 8a). Furthermore, the mean NDVI during co-management (0.265) under drought events was higher than the mean NDVI during traditional management (0.243) in BNP (Fig. 8b). A similar result was observed under heavy rainfall events whereas the mean NDVI under co-management (0.34) is slightly higher than the mean NDVI under traditional management (0.33) (Fig. 8b). Interestingly, during the normal climatic years, the mean NDVI value under co-management (0.28) was lower than the traditional management (0.30) (Fig. 8b).

We observed improvements in forest resistance and resilience before and after the co-management regime in our study of drought events. In MNP, under traditional management, the average resistance to drought value was 7.7 whereas in co-management this value improved to 11.17 (Fig. 9a). Here, a higher resistance value indicates a higher percentage of resistance. For example, if NDVI is reduced during a drought or heavy

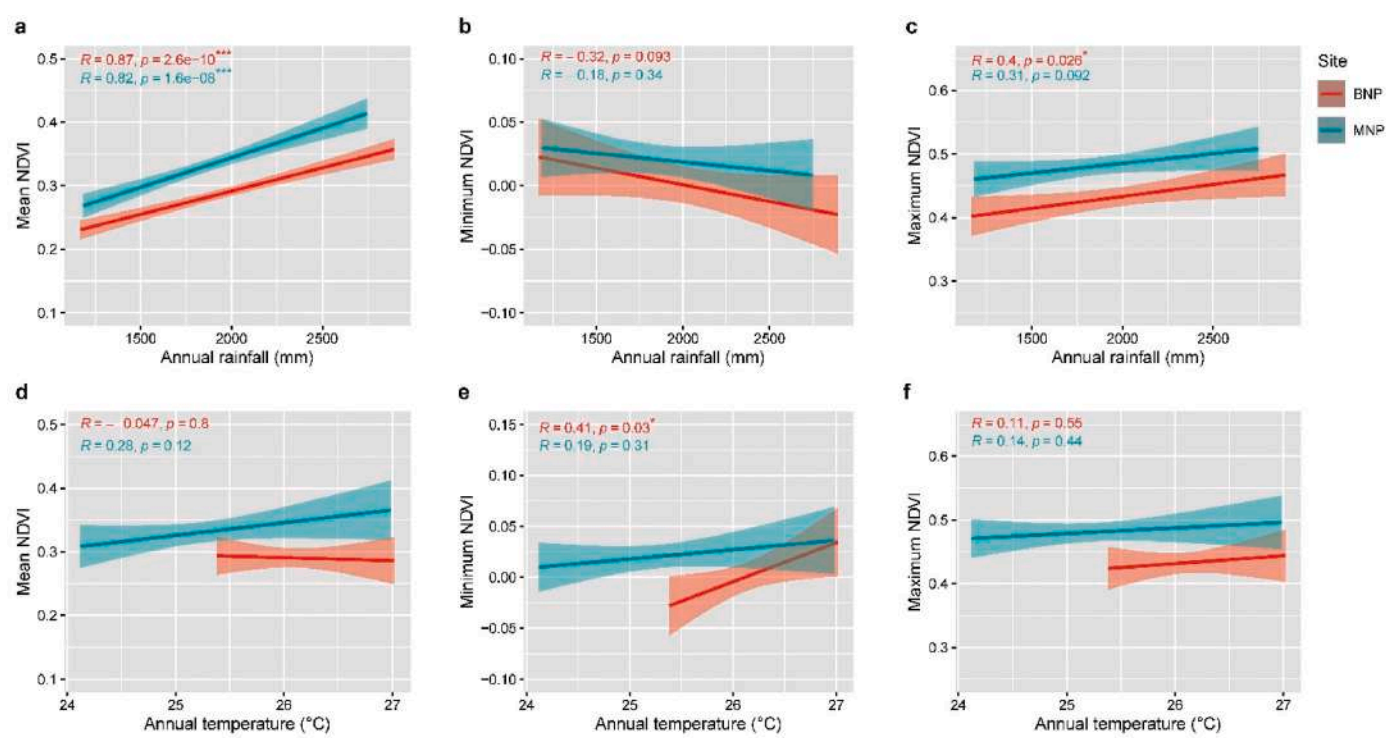

Fig. 7. Linear regression between a) annual rainfall and mean NDVI, b) annual rainfall and minimum NDVI, c) annual rainfall and maximum NDVI, d) annual mean temperature and mean NDVI, e) annual mean temperature and minimum NDVI, and f) annual mean temperature and maximum NDVI.

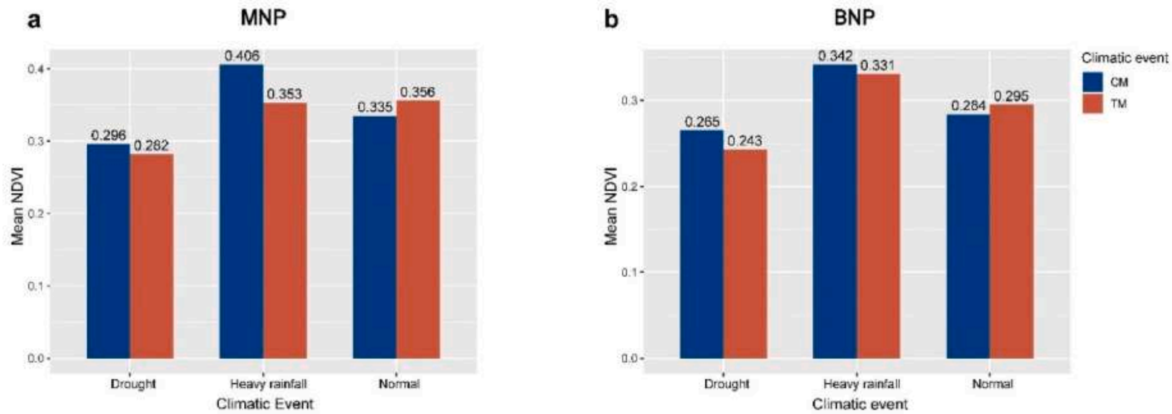

Fig. 8. Mean NDVI in three climatic events under traditional management (TM) and co-management (CM) in Madhupur National Park (MNP) and Bhawal National Park (BNP).

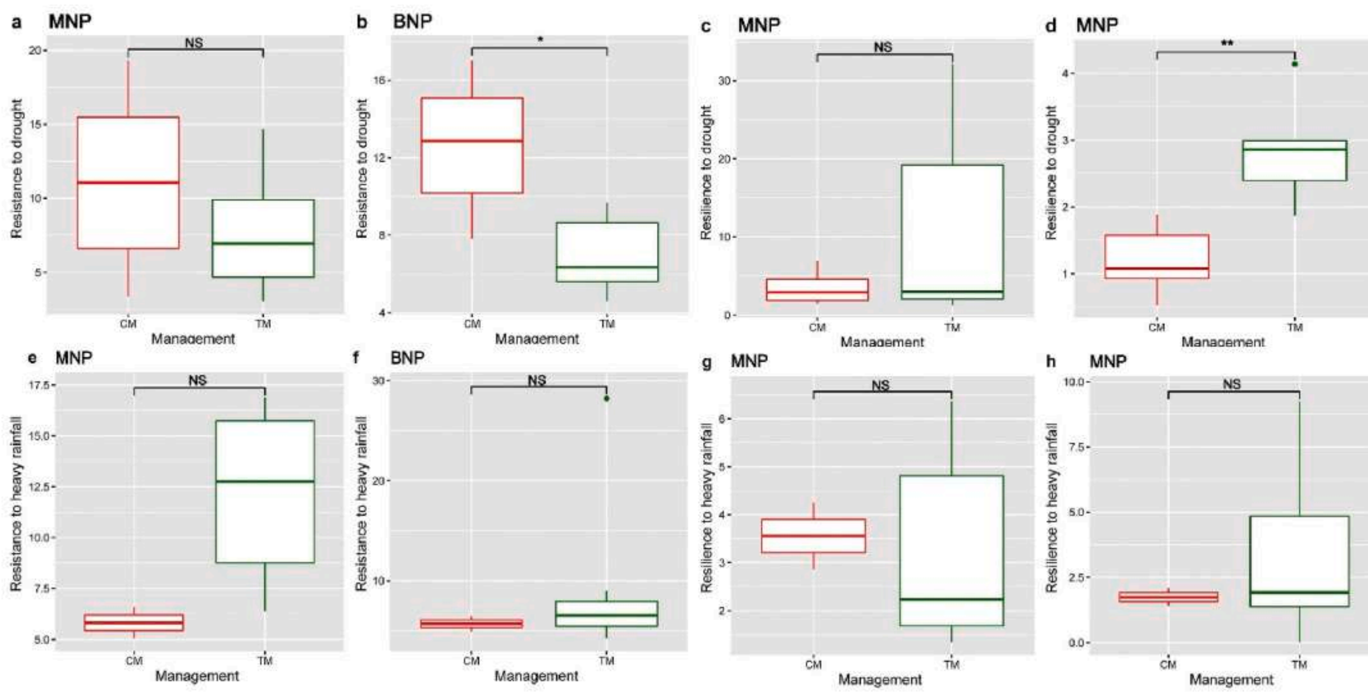

Fig. 9. Boxplot between forest management regime and a) resistance to drought in MNP, b) resistance to drought in BNP, c) resilience to drought in MNP, d) resilience to drought in BNP, e) resistance to heavy rainfall in MNP, f) resistance to heavy rainfall in BNP, g) resilience to heavy rainfall in MNP, and h) resilience to heavy rainfall in BNP.
Here, CM = co-management and TM = traditional management.

rainfall event to half its normal level, then $\Omega = 2$. In BNP, under traditional management, the average resistance to drought during a drought or heavy rainfall event was 6.97, whereas under co-management the resistance to drought improved to 12.60 (Fig. 9b). The resiliency after a drought event also improved under co-management in both of our study sites. The average resiliency after the drought year in MNP was 10.95 under traditional management but under co-management, this value improved to 3.5 (Fig. 9c). Here the lower value of resiliency indicates a higher rate of recovery of forest health. For instance, if during the year after a climate event productivity recovers either from 50 to 75% or 50–125% of normal mean NDVI levels, then mean NDVI will have returned halfway from perturbed to normal levels, and $\Delta = 2$. The same is true for recovery in the opposite direction after a positive deviation: that is, recovery from 150 to 125% or 150 to 75% of normal mean NDVI levels would also give $\Delta = 2$. In, BNP the average resiliency to drought under traditional management was 10.95 but under co-management, it improved to 3.54 (Fig. 9d). Furthermore, resistance and resilience under heavy rainfall events have no significant changes in our study areas. In MNP, the average resistance to heavy rainfall value under traditional management was 12.15 whereas under co-management this value changed to 5.825 (Fig. 9e). In BNP, during traditional management average resistance to heavy rainfall value was 9.44 whereas in co-management this value altered to 5.74 (Fig. 9f). Moreover, the average resiliency to heavy rainfall was recorded 3.22 under traditional management, whereas under co-management the value was 3.55 in MNP (Fig. 9g). Lastly, the mean resiliency to heavy rainfall in BNP was observed 3.37 during traditional management while 1.74 under co-management (Fig. 9h).

4. Discussion

4.1. LULC change detection

Forest cover has drastically reduced in both of our study protected areas from 1990 to 2020, where the reducing pattern was almost similar. The high level of anthropogenic disturbances account for this significant reduction as also mentioned in different studies from across the tropics (see – Romero-Sanchez and Ponce-Hernandez, 2017; Hasanah and Indrawan, 2020). Different land-use change patterns were observed in both MNP and BNP. In MNP, agricultural land has significantly increased from 1990 to 2020 since co-management facilitated agroforestry practices there (Rahman et al., 2014). However, the initial agricultural land increasing pattern altered to a decreasing trend in BNP due to the primary co-management goal was considerable improvement in forest cover (Mohd et al., 2008). Furthermore, waterbody and built-up area have increased steadily in BNP, whereas MNP showed a reducing pattern in barren + built-up area under co-management.

4.2. Changing forest health under climate change

Annual rainfall significantly improved the forest health condition in both of our study sites which is evident from previous studies in other countries (see- Al-Bakri and Suleiman, 2004; Alamgir et al., 2015; Kundu et al., 2018). Our findings indicate that a decreasing pattern in annual rainfall is likely to be a significant future climatic threat to the existing deciduous forest cover in our study protected areas. However, the annual temperature had no significant impact on forest health in our study, although several studies found a significant correlation between them (Revadekar et al., 2012; Muradyan et al., 2019). Species distribution might be responsible for that because most of the species in our study protected areas were drought tolerant (Rahman et al., 2019a).

4.3. Co-management impacts on forest health under varied climatic condition

Our study finds that forest co-management have significantly improved the forest resistance to drought and forest resilience to drought in BNP. However, we did not find any significant effects of co-management on resistance to drought and resilience to drought in MNP, where different agroforestry systems are an integral part of forest co-management. Furthermore, co-management had no significant impacts on resistance to heavy rainfall events and resilience to heavy rainfall events in both of our study areas. Islam et al. (2020) reported that co-management alone is inadequate to improve the biodiversity of the tropical forest protected areas which may be a prime factor for the unchanged resistance and resiliency of the co-managed forest in our study.

Although the impact of co-management on forest health condition under a rapidly changing climate is still understudied, Chinangwa et al. (2017), in Malawi, found that forest condition as measured by tree density and species richness was greater in forest managed under co-management than traditional forest management. The authors, however, suggested that such outcomes may vary by site pre-existing conditions and how communities understand and interpret the co-management program in the locality (Chinangwa et al., 2017). On contrary, Islam et al. (2020), in Lawachara National Park and Teknaf Wildlife Sanctuary in Bangladesh found better tree diversity status in non-co-managed sites than in co-managed sites. Carbon sequestration in forest biomass, however, was slightly elevated in forests managed under co-management compared to the traditionally managed forest (Islam et al., 2020). Ullah et al. (2022), also reported a contrasting outcome, where using a remote sensing approach they found after the implementation of co-management, the rate of deforestation increased inside a protected area in Bangladesh (i.e., Teknaf Wildlife Sanctuary). This may be due to uncontrolled illegal forest activity and the exclusion of a large number of people in co-management program who find themselves deprived (Rashid et al., 2013). The impact of collaborative forest management on community and household resilience is also evident from many studies (Mukul et al., 2012). In tropical forests of Ghana, Akamani and Hall (2019) found that compared to traditional forest management, forest co-management has a positive impact on household resilience, although they recognize the scale of such community outcomes.

5. Conclusion

In tropical regions, co-management has widely been prescribed to better conserve the forest as well as to reduce the anthropogenic pressure on it. The tropical deciduous forest is one of the hardest to be hit by climate change and more specifically changing rainfall. Based on our empirical study in two deciduous forest-protected areas of Bangladesh where the co-management system is in practice since 2008, we investigated the resilience and resistance of forest ecosystems to extreme climatic events. We find that, although co-management has a positive impact on forest cover change in our study, in protected areas through reducing anthropogenic pressure, they are not adequate to tackle the adverse impact of climate change. Moreover, the climatic extreme event has significantly affected vegetation health (NDVI). We suggest mainstreaming climate change effects in forest protected areas management in Bangladesh and elsewhere. Co-management system should also be more dynamic by incorporating activities such as the selection of species that are more tolerant to extreme climatic events, considering and strengthening people's adaptive capacity and resilience to fight against climate change, etc.

Credit author statement

Md. Rezaul Karim: Conceptualization, Methodology, Investigation, Data curation, Formal analysis, Writing – Original Draft. **Sharif A. Mukul:** Conceptualization, Methodology, Formal analysis, Writing – Review and editing; Project administration. **Rokaiya Binte Zahir:** Investigation, Writing – Review and editing, Formal analysis. **Md. Shamim Reza Saimun:** Investigation, Writing – Review and editing, Formal analysis. **Mohammed A.S. Arfin-Khan:** Conceptualization, Methodology, Supervision, Formal analysis, Writing – Review and editing; Project administration.

Annex 1

Major LULC changes in our study sites in Madhupur National Park (MNP) and Bhawal National Park (BNP) between 1990 and 2020.

Study area	Year	Forest (ha)	Waterbody (ha)	Agricultural land (ha)	Barren land + Settlement (ha)
MNP	1990	6166.8	170.91	677.34	2166.3
	2000	4923.6	153.9	1431.7	2672.1
	2010	4001	439.74	3040	1700.55
	2020	4212.7	597.96	3350.3	1020.42
BNP	1990	7134.9	107.91	2498.8	729.18
	2000	5711.9	838.71	2703.5	1216.62
	2010	4704	489.06	4820.1	457.56
	2020	5151.6	761.31	1908.4	2649.51

Annex 2
Accuracy assessment of LULC maps in our study sites in Madhupur National Park (MNP) and Bhawal National Park (BNP).

Study area	Year	Producer accuracy (%)				User accuracy (%)				Overall accuracy (%)	Kappa statistics
		WB*	FL	Ag	Ba + Se	WB	FL	Ag	Ba + Se		
MNP	1990	94.11	90.63	90.90	95.24	96.30	96.67	90.90	86.95	92.92	0.90
	2000	82.35	96.43	93.54	95.45	100	93.10	96.66	84.00	93.69	0.92
	2010	100	100	81.81	88.89	100	100	90.12	80.21	92.11	0.89
	2020	100	88.23	89.80	92.11	100	93.75	93.62	85.71	91.80	0.88
BNP	1990	82.35	96.29	90.90	100	100	96.29	83.33	86.67	92.75	0.89
	2000	94.12	92.59	90.48	100	100	92.59	95.00	86.67	93.51	0.91
	2010	82.35	82.36	100	92.85	93.33	93.33	80.00	86.67	88.33	0.84
	2020	94.12	83.33	100	90.00	91.67	93.75	85.71	90.00	90.38	0.87

Where, WB = water body, FL = forest land, Ag = agricultural land and, Ba + Se = barren land + settlement.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

Alamgir, M., Mukul, S.A., Turton, S.M., 2015. Modelling spatial distribution of critically endangered Asian elephant and Hoolock gibbon in Bangladesh forest ecosystems under a changing climate. Appl. Geogr. 60, 10–19. https://doi.org/10.1016/j.apgeog.2015.03.001.

Al-Bakri, J.T., Suleiman, A.S., 2004. NDVI response to rainfall in different ecological zones in Jordan. Int. J. Rem. Sens. 25, 3897–3912. https://doi.org/10.1080/01431160310001654428.

Akamani, K., Hall, T.E., 2019. Scale and co-management outcomes: assessing the impact of collaborative forest management on community and household resilience in Ghana. Heliyon 5, e01125. https://doi.org/10.1016/j.heliyon.2019.e01125.

Begum, R., 2011. People's livelihoods and involvement in co-management of Madhupur National Park, Bangladesh. In: Sustaining Commons: Sustaining Our Future, the Thirteenth Biennial Conference of the International Association for the Study of the Commons: Digital Library of the Commons. Indiana University, pp. 156–170.

Butt, N., Seabrook, L., Maron, M., Law, B.S., Dawson, T.P., Syktus, J., et al., 2015. Cascading effects of climate extremes on vertebrate fauna through changes to low-latitude tree flowering and fruiting phenology. Global Change Biol. 21, 3267–3277. https://doi.org/10.1111/gcb.12869.

Chaturvedi, R.K., Gopalakrishnan, R., Jayaraman, M., Bala, G., Joshi, N.V., Sukumar, R., et al., 2011. Impact of climate change on Indian forests: a dynamic vegetation modeling approach. Mitig. Adapt. Strategies Glob. Change 16, 119–142. https://doi.org/10.1007/s11027-010-9257-7.

Chinangwa, L.L., Pullin, A.S., Hockley, N., 2017. Impact of forest co-management programs on forest conditions in Malawi. J. Sustain. For. 36, 338–357. https://doi.org/10.1080/10549811.2017.1307764.

Chowdhury, F.I., Islam, K., Faroque, M.A., Islam, K.N., Rahman, M.F., Arif, M.T.A., et al., 2020. Assessing the impacts of co-management on protected area landscape under socio-imagery lens: evidence from Bangladesh. J. Sustain. For. 1–20. https://doi.org/10.1080/10549811.2020.1747497.

Chowdhury, M.S.H., Koike, M., 2010. An overview on the protected area system for forest conservation in Bangladesh. J. For. Res. 21, 111–118. https://doi.org/10.1007/s11676-010-0019-x.

Davis, K.F., Koo, H.I., Dell'Angelo, J., D'Odorico, P., Estes, L., Kehoe, L.J., et al., 2020. Tropical forest loss enhanced by large-scale land acquisitions. Nat. Geosci. 13, 482–488. https://doi.org/10.1038/s41561-020-0592-3.

De Pourcq, K., Thomas, E., Arts, B., Vranckx, A., Léon-Sicard, T., Van Damme, P., 2016. Conflict in protected areas: who says co-management does not work? PLoS One 10, e0144943. https://doi.org/10.1371/journal.pone.0144943.

Deb, J.C., Phinn, S., Butt, N., McAlpine, C.A., 2018. Climate change impacts on tropical forests: identifying risks for tropical Asia. J. Trop. For. Sci. 30, 182–194.

Feng, M., Huang, C., Channan, S., Vermote, E.F., Masek, J.G., Townshend, J.R., 2012. Quality assessment of Landsat surface reflectance products using MODIS data. Comput. Geosci. 38, 9–22. https://doi.org/10.1016/j.cageo.2011.04.011.

Foga, S., Scaramuzza, P.L., Guo, S., Zhu, Z., Dilley, R.D., Beckmann, T., et al., 2017. Cloud detection algorithm comparison and validation for operational Landsat data products. Rem. Sens. Environ. 194, 379–390. https://doi.org/10.1016/j.rse.2017.03.026.

Gondwe, M.F., Cho, M.A., Chirwa, P.W., Geldenhuys, C.J., 2019. Land use land cover change and the comparative impact of co-management and government-management on the forest cover in Malawi (1999-2018). J. Land Use Sci. 14, 281–305. https://doi.org/10.1080/1747423X.2019.1706654.

Gong, P., Wang, J., Yu, L., Zhao, Y., Zhao, Y., Liang, L., et al., 2013. Finer resolution observation and monitoring of global land cover: first mapping results with Landsat TM and ETM+ data. Int. J. Rem. Sens. 34, 2607–2654. https://doi.org/10.1080/01431161.2012.748992.

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R., 2017. Google earth engine: planetary-scale geospatial analysis for everyone. Rem. Sens. Environ. 202, 18–27. https://doi.org/10.1016/j.rse.2017.06.031.

Hasan, E., Bahauddin, K.M., 2014. Community's perception and involvement in co-management of Bhawal National Park, Bangladesh. J. Nat. Sci. Res. 4, 60–67.

Hasan, M., Islam, M.T., Roshni, N., Hemel, S., 2020. Effects of forest encroachment on tree stock parameters and soil nutrient status in the Madhupur Sal (Shorea robusta C. F. Gaertn) forest of Bangladesh. J. Agric. Food Econ. 1, 35–40.

Hasanah, A., Indrawan, M., 2020. Assessment of tropical forest degradation on a small island using the enhanced vegetation index. IOP Conf. Ser. Earth Environ. Sci. 481, 012061 https://doi.org/10.1088/1755-1315/481/1/012061.

Igarashi, Y., Kumagai, T., Yoshifuji, N., Sato, T., Tanaka, N., Tanaka, K., et al., 2015. Environmental control of canopy stomatal conductance in a tropical deciduous forest in northern Thailand. Agric. For. Meteorol. 202, 1–10. https://doi.org/10.1016/j.agrformet.2014.11.013.

Isbell, F., Craven, D., Connolly, J., Loreau, M., Schmid, B., Beierkuhnlein, C., et al., 2015. Biodiversity increases the resistance of ecosystem productivity to climate extremes. Nature 526, 574–577. https://doi.org/10.1038/nature15374.

Islam, K., Jashimuddin, M., Nath, B., Nath, T.K., 2018. Land use classification and change detection by using multi-temporal remotely sensed imagery: the case of Chunati wildlife sanctuary, Bangladesh. Egyptian J. Remote Sens. Space Sci. 21, 37–47. https://doi.org/10.1016/j.ejrs.2016.12.005.

Islam, K.K., Hyakumura, K., 2019. Forestland concession, Land rights, and livelihood changes of ethnic minorities: the case of the Madhupur Sal Forest, Bangladesh. Forests 10, 288. https://doi.org/10.3390/f10030288.

Islam, K.K., Sato, N., 2010. Constraints of participatory agroforestry program to poverty alleviation: the case of the Sal forests, Bangladesh. Am.-Eurasian J. Agric. Environ. Sci. 9, 427–435.

Islam, K.N., Rahman, M.M., Jashimuddin, M., Hossain, M.M., Islam, K., Faroque, M.A., 2019. Analyzing multi-temporal satellite imagery and stakeholders' perceptions to have an insight into how forest co-management is changing the protected area landscapes in Bangladesh. For. Pol. Econ. 101, 70–80. https://doi.org/10.1016/j.forpol.2019.01.011.

Islam, K.N., Rahman, M.M., Jashimuddin, M., Islam, K., Zhang, Y., 2020. Impact of co-management on tree diversity and carbon sequestration in protected areas: experiences from Bangladesh. Trees, Forests People 2, 100033. https://doi.org/10.1016/j.tfp.2020.100033.

Kabir, D., Ahmed, A., 2005. Wildlife biodiversity in Bhawal national park: management techniques and drawbacks of wildlife management and nature conservation. Our Nat. 3, 83–90. https://doi.org/10.3126/on.v3i1.340.

Karim, M.R., Sultana, F., Saimun, M.S.R., Mukul, S.A., Arfin-Khan, M.A.S., 2020. Plant diversity and local rainfall regime mediate soil ecosystem functions in tropical forests of north-east Bangladesh. Environ. Adv. 2, 100022 https://doi.org/10.1016/j.envadv.2020.100022.

Kundu, A., Denis, D.M., Patel, N.R., Dutta, D., 2018. A Geo-spatial study for analysing temporal responses of NDVI to rainfall. Singapore J. Trop. Geogr. 39, 107–116. https://doi.org/10.1111/sjtg.12217.

Malik, S., Pal, S.C., Das, B., Chakrabortty, R., 2020. Intra-annual variations of vegetation status in a sub-tropical deciduous forest-dominated area using geospatial approach: a case study of Sali watershed, Bankura, West Bengal, India. Geol., Ecol., Landscapes 4, 257–268. https://doi.org/10.1080/24749508.2019.1633219.

Margrove, J.A., Burslem, D.F.R.P., Ghazoul, J., Khoo, E., Kettle, C.J., Maycock, C.R., 2015. Impacts of an extreme precipitation event on Dipterocarp mortality and habitat filtering in a Bornean tropical rain forest. Biotropica 47, 66–76. https://doi.org/10.1111/btp.12189.

Masek, J.G., Vermote, E.F., Saleous, N.E., Wolfe, R., Hall, F.G., Huemmrich, K.F., et al., 2006. A Landsat surface reflectance dataset for North America, 1990-2000. Geosci. Rem. Sens. Lett. IEEE 3, 68–72. https://doi.org/10.1109/LGRS.2005.857030.

Masum, K.M., Islam, M.N., Saha, N., Hasan, M.Z., Mansor, A., 2016. Assessment of land grabbing from protected forest areas of Bhawal National Park in Bangladesh. Landsc. Res. 41, 330–343. https://doi.org/10.1080/01426397.2015.1078456.

Mohd, A., Jusoff, K., Sheikh, A.H., Yaman, A.R., 2008. The management of Bhawal National Park, Bangladesh by the local community for resource protection and ecotourism. Asian Soc. Sci. 4, 101–107.

Mukul, S.A., Alamgir, M., Sohel, M.S.I., Pert, P.L., Turton, S.M., Herbohn, J., Khan, M.S.I., Ali Reza, A.H.M., Munim, S.A., Laurance, W.F., 2019. Combined effects of climate change and sea-level rise project dramatic habitat loss of the globally endangered Bengal tiger in the Bangladesh Sundarbans. Sci. Total Environ. 663, 830–840. https://doi.org/10.1016/j.scitotenv.2019.01.383.

Mukul, S.A., Biswas, S.R., Rashid, A.Z.M.M., 2018. Biodiversity in Bangladesh. In: Pullaiah, T. (Ed.), Global Biodiversity (Vol. 1: Selected Countries in Asia). Apple Academic Press/CRC Press, Canada, pp. 93–107.

Mukul, S.A., Sohel, M.S.I., Herbohn, J., Inostroza, L., König, H., 2017a. Integrating ecosystem services supply potential from future land-use in protected area management: a Bangladesh case study. Ecosyst. Serv. 26, 355–364. https://doi.org/10.1016/j.ecoser.2017.04.001.

Mukul, S.A., Rashid, A.Z.M.M., Khan, N.A., 2017b. Forest protected area systems and biodiversity conservation in Bangladesh. In: Mukul, S.A., Rashid, A.Z.M.M. (Eds.), Protected Areas: Policies, Management and Future Directions. Nova Science Publishers, USA, pp. 157–177.

Mukul, S.A., Rashid, A.Z.M.M., Quazi, S.A., Uddin, M.B., Fox, J., 2012. Local peoples' response to co-management in protected areas: a case study from Satchari National Park, Bangladesh. For. Trees Livelihoods 21, 16–29. https://doi.org/10.1080/14728028.2012.669132.

Mukul, S.A., Quazi, S.A., 2009. Communities in conservation: protected area management and enhanced conservation in Bangladesh. In: Robin, N.L. (Ed.), The Future of Forests in Asia and the Pacific: Outlook for 2020. FAO, Bangkok.

Muradyan, V., Tepanosyan, G., Asmaryan, S., Saghatelyan, A., Dell'Acqua, F., 2019. Relationships between NDVI and climatic factors in mountain ecosystems: a case study of Armenia. Remote Sens. Appl.: Soc. Environ. 14, 158–169. https://doi.org/10.1016/j.rsase.2019.03.004.

Nagendra, H., Tucker, C., Carlson, L., Southworth, J., Karmacharya, M., Karna, B., 2004. Monitoring parks through remote sensing: studies in Nepal and Honduras. Environ. Manag. 34, 748–760. https://doi.org/10.1007/s00267-004-0028-7.

Niraula, R.R., Gilani, H., Pokharel, B.K., Qamer, F.M., 2013. Measuring impacts of community forestry program through repeat photography and satellite remote sensing in the Dolakha district of Nepal. J. Environ. Manag. 126, 20–29. https://doi.org/10.1016/j.jenvman.2013.04.006.

Pérez-Vega, A., Mas, J., Ligmann-Zielinska, A., 2012. Comparing two approaches to land use/cover change modeling and their implications for the assessment of biodiversity loss in a deciduous tropical forest. Environ. Model. Software 29, 11–23. https://doi.org/10.1016/j.envsoft.2011.09.011.

Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D., 2020. R Core Team. 2019. Nlme: Linear and Nonlinear Mixed Effects Models. R Package Version 3.1-149 [Online]. Available online at: https://cran.r-project.org/web/packages/nlme/. (Accessed 20 September 2020).

Pirnat, J., Hladnik, D., 2018. The concept of landscape structure, forest continuum and connectivity as a support in urban forest management and landscape planning. Forests 9, 584. https://doi.org/10.3390/f9100584.

Rahman, H.M.T., Deb, J.C., Hickey, G.M., Kayes, I., 2014. Contrasting the financial efficiency of agroforestry practices in buffer zone management of Madhupur National Park, Bangladesh. J. For. Res. 19, 12–21. https://doi.org/10.1007/s10310-013-0392-3.

Rahman, M., Islam, M., Bräuning, A., 2019a. Species-specific growth resilience to drought in a mixed semi-deciduous tropical moist forest in South Asia. For. Ecol. Manag. 433, 487–496. https://doi.org/10.1016/j.foreco.2018.11.034.

Rahman, M.M., Rahman, M.M., Guogang, Z., Islam, K.S., 2010. A review of the present threats to tropical moist deciduous sal (Shorea robusta) forest ecosystem of central Bangladesh. Tropical Conserv. Sci. 3, 90–102. https://doi.org/10.1177/194008291000300108.

Rahman, M.R., Hossain, M.K., Hossain, M.A., 2019b. Diversity and composition of tree species in Madhupur national park, Tangail, Bangladesh. J. Forest Environ. Sci. 35, 159–172. https://doi.org/10.7747/JFES.2019.35.3.159.

Rahman, M.S., Akter, S., Al-Amin, M., 2015. Forest and agro-ecosystem productivity in Bangladesh: a climate vegetation productivity approach. For. Sci. Technol. 11, 126–132. https://doi.org/10.1080/21580103.2014.957358.

Rashid, A.Z.M.M., Craig, D., Mukul, S.A., 2017. Shifting paradigm of governance in the natural resources management of Bangladesh: a centralist to pluralistic approach in the forest protected areas management. In: Mukul, S.A., Rashid, A.Z.M.M. (Eds.), Protected Areas: Policies, Management and Future Directions. Nova Science Publishers, USA, pp. 53–81, 2017.

Rashid, A.Z.M.M., Craig, D., Mukul, S.A., Khan, N.A., 2013. A journey towards shared governance: status and prospects for collaborative management in the protected areas of Bangladesh. J. For. Res. 24, 599–605. https://doi.org/10.1007/s11676-013-0391-4.

Revadekar, J.V., Tiwari, Y.K., Kumar, K.R., 2012. Impact of climate variability on NDVI over the Indian region during 1981–2010. Int. J. Rem. Sens. 33, 7132–7150. https://doi.org/10.1080/01431161.2012.697642.

Romero-Sanchez, M.E., Ponce-Hernandez, R., 2017. Assessing and monitoring forest degradation in a deciduous tropical forest in Mexico via remote sensing indicators. Forests 8, 302. https://doi.org/10.3390/f8090302.

Roy, D.P., Kovalskyy, V., Zhang, H.K., Vermote, E.F., Yan, L., Kumar, S.S., et al., 2016. Characterization of Landsat-7 to Landsat-8 reflective wavelength and normalized difference vegetation index continuity. Rem. Sens. Environ. 185, 57–70. https://doi.org/10.1016/j.rse.2015.12.024.

Salam, M.A., Pramanik, M.A.T., 2018. Forest cover change analysis using remote sensing techniques in Madhupur sal forest of Bangladesh. J. Environ. Sci. Nat. Resour. 10, 73–78. https://doi.org/10.3329/jesnr.v10i2.39015.

Soliku, O., Schraml, U., 2020. Protected areas management: a comparison of perceived outcomes associated with different co-management types. For. Pol. Econ. 118, 102258 https://doi.org/10.1016/j.forpol.2020.102258.

Song, C., Woodcock, C.E., Seto, K.C., Lenney, M.P., Macomber, S.A., 2001. Classification and change detection using landsat TM data: when and how to correct atmospheric effects? Rem. Sens. Environ. 75, 230–244. https://doi.org/10.1016/S0034-4257(00)00169-3.

Takahashi, R., Todo, Y., 2012. Impact of community-based forest management on forest protection: evidence from an aid-funded project in Ethiopia. Environ. Manag. 50, 396–404. https://doi.org/10.1007/s00267-012-9887-5.

Tarakeswara, N.M., Premavani, D., Suthari, S., Venkaiah, M., 2018. Assessment of tree diversity in tropical deciduous forests of Northcentral Eastern Ghats, India. Geol., Ecol., Landscapes 2, 216–227. https://doi.org/10.1080/24749508.2018.1452479.

Tuihedur, H.M.R., Deb, J.C., Hickey, G.M., Kayes, I., 2014. Contrasting the financial efficiency of agroforestry practices in buffer zone management of Madhupur National Park, Bangladesh. J. For. Res. 19, 12–21. https://doi.org/10.1007/s10310-013-0392-3.

Ullah, S.M.A., Tani, M., Tsuchiya, J., Rahman, M., Moriyama, M., 2022. Impact of protected areas and co-management on forest cover: a case study from Teknaf Wildlife Sanctuary, Bangladesh. Land Use Pol. 113, 105932 https://doi.org/10.1016/j.landusepol.2021.105932.

Vermote, E., Justice, C., Claverie, M., Franch, B., 2016. Preliminary analysis of the performance of the Landsat 8/OLI land surface reflectance product. Rem. Sens. Environ. 185, 46–56. https://doi.org/10.1016/j.rse.2016.04.008.

Woodcock, C.E., Loveland, T.R., Herold, M., Bauer, M.E., 2020. Transitioning from change detection to monitoring with remote sensing: a paradigm shift. Rem. Sens. Environ. 238, 111558 https://doi.org/10.1016/j.rse.2019.111558.

Zaman, S., Katoh, M., 2011. Assessment of forest covers change in tropical moist deciduous forest in thakurgaon, Bangladesh using ALOS data. J. Forest Plann. 16, 285–292. https://doi.org/10.20659/jfp.16.Special_Issue_285.

Zepner, L., Karrasch, P., Wiemann, F., Bernard, L., 2021. ClimateCharts.net – an interactive climate analysis web platform. Int. J. Digit. Earth 14, 338–356. https://doi.org/10.1080/17538947.2020.1829112.