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Elucidating the phenology of the Sundarbans mangrove forest using 18-year time series of MODIS vegetation indices

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ABSTRACT Mangrove forests are the most carbon-rich ecosystems in the world however, baseline information on its phenology is poor. Information on seasonal changes in canopy greenness, which reflects the level of photosynthetic activity, is helpful for understanding seasonal patterns of carbon uptake by mangrove forests. To elucidate the periodicity, timing, and length of the active photosynthetic season, we examined temporal patterns in enhanced vegetation index (EVI) and normalized difference vegetation index (NDVI) derived from 18-year (2001–2018) Moderate Resolution Imaging Spectroradiometer images for four major forest types in the Sundarbans, Bangladesh. We identified a dominant cycle for the time-series of EVI and NDVI after Fourier transformation. We also estimated four phenological dates among the forest types: the start of the season (SOS), time of maximum greenness (MaxGreen), end of the season (EOS), and length of the season (LOS). Fourier analysis revealed that both the NDVI and EVI exhibited distinct cycles per year for all forest types, suggesting that there are annual cycles of canopy greenness. The SOS as estimated using the EVI and NDVI was consistently from late May to mid-June across forest types. However, the MaxGreen, EOS and LOS estimated varied between the two indices. Because EVI-based phenological dates match better with phenological information at the ground level than do NDVI-based dates, the EVI would be better than the NDVI for depicting changes in canopy greenness. The results of this study provide baseline information for future phenological changes in the Sundarbans.

Key words: Fourier, NDVI, EVI, seasonality, Google Earth Engine

INTRODUCTION

Mangroves are discrete collections of woody plants found at the juncture between land and sea in tropical and subtropical latitudes where high salinity, extreme tides, strong winds, high temperatures, and muddy anaerobic soils are common (Kathiresan and Bingham 2001; Tomlinson 2016). Mangrove ecosystems are very important, as they not only provide habitat for both aquatic and terrestrial flora and fauna but also protect coastal areas by attenuating storm impacts (Zhang et al. 2012; Das and Crepin 2013; Friess 2016). Despite occupying 0.1% of the Earth’s land surface area, mangrove forests contain on average 1,023 Mg of carbon per hectare, thus storing three to four times more carbon than any other forest type (Donato et al. 2011; Giri et al. 2011; Alongi 2012; Siikamäki et al. 2013; Castañeda-Moya et al. 2013). However, mangroves have undergone deforestation over the last few decades (Duke et al. 2007; Giri et al. 2008; Richards and Friess 2016). Recently many conservation initiatives and efforts reduced deforestation rates of mangrove forests compared to the past decades, yet the future of mangrove ecosystem is uncertain (Friess et al. 2020).

Phenology is the study of recurring biological events in plant and animal life cycles, and phenological data allow links between biological events and climate change to be measured (Cleland et al. 2007; Tang et al. 2016). Specifically, because the phenology of leaves at the landscape level directly influences ecosystem productivity, it is of great importance for ecosystem carbon cycling, terrestrial carbon sequestration, and mitigation of anthropogenic CO2 emissions. Shifts in phenological events, such as the start, senescence, and length of the growing season in plants, significantly impacts photosynthesis and carbon recycling (Richardson et al. 2012; Tang et al. 2016). Information on phenology at the landscape level, such as the seasonality of canopy greenness (as an indicator of photosynthetic activity), is important for understanding the dynamic relationships between mangrove forests and environmental
drivers. Mangrove forest phenology has often been studied using field measurements (Gill and Tomlinson 1971; Saenger and Moverley 1985; Duke 1990; Kamruzzaman et al. 2019a) (Table 1); however, such *in situ* studies often have spatial and temporal (1–4 years) limitations due to difficulties in accessing the habitat and maintaining facilities, which inhibit our understanding of the long-term and large-scale patterns of forest phenology and phenological responses to climate change (Hanes et al. 2014; Pastor-Guzman et al. 2018).

Remote sensing is well-suited for such large spatio-temporal assessments and is being increasingly used (Wardlow and Egbert 2010; Son et al. 2014). For the past six decades, remote sensing has been used for mapping mangrove species distribution and measuring the height and biomass, photosynthetic activity, and characterizing ecosystem processes (e.g. carbon cycling) from regional to global scale (Heumann 2011; Giri et al. 2015; Wang et al. 2019). Satellite-sensor-derived measurements of the land surface, known as land surface phenology, provide valuable information about vegetation at large spatial scales (e.g., continental and regional scales) (Hanes et al. 2014; Zeng et al. 2020). Among satellite images, the Moderate Resolution Imaging Spectroradiometer (MODIS) has provided multi-temporal images of earth freely since 2001. Also, with recent developments in cloud computing, such as the Google Earth Engine (GEE), image processing and analysis are becoming much easier and faster (Gorelick et al. 2017) and has been successfully used for mangrove mapping (Giri et al. 2015; Chen et al. 2017; Tieng et al. 2019). Therefore, studies using satellite images enable us to study mangrove forest phenology at greater spatiotemporal scales as well as the relationship between phenology and various climatic drivers. For the first time, Pastor-Guzman et al. (2018) used MODIS data to characterize mangroves on the Yucatan Peninsula at the landscape scale; however, such studies have yet to be conducted in other mangrove forests.

The Sundarbans is the largest single tract of mangrove forest situated across Bangladesh and India. Although the major mangrove species in this forest is evergreen, some species are reported to exhibit seasonality in leafing and leaf shedding, flowering, and fruiting (Table 2). However, phenological data are still lacking for most species and limited in spatiotemporal scale. Thus, phenological information derived from satellite images over longer time periods (>10 years) and larger spatial scales (>1,000 km²) will be helpful for understanding the forest phenology of the Sundarbans as a whole. We hypothesized that, at the landscape scale, the

| No | Place                | Mode      | Parameters       | Observed peak | Species                                      | References                      |
|----|----------------------|-----------|------------------|---------------|----------------------------------------------|---------------------------------|
| 1  | Queensland, Australia | Unimodal-Bimodal | Leafing, shedding | Summer        | *Excoecaria agallocha, Heritiera littoralis, Avicennia marina* | Saenger and Moverley 1985       |
| 2  | Sundarbans, Bangladesh | Bimodal | Leaf litterfall | Winter, Summer | Mixed mangrove | Kamruzzaman et al. 2019a                     |
| 3  | Pará, Brazil         | Unimodal | Litterfall       | Summer        | *Rhizophora mangle* | Mehlig 2006                                 |
| 4  | Kerala and Orissa, India | Unimodal | Litterfall, flowering | Summer, Rainy | Mixed mangrove | Upadhyay and Mishra. 2010; Rani et al. 2016 |
| 5  | Okinawa, Japan       | Unimodal | Litterfall       | Summer, Winter | *Bruguiera gymnorrhiza* | Kamruzzaman et al. 2016               |
|    |                      | Unimodal | Leaf flushing    | Summer, Winter | *Rhizophora stylosa, Bruguiera gymnorrhiza, Kandelia obovate* | Sharma et al. 2012              |
| 6  | Gazi, Kenya          | Unimodal | Litterfall       | Summer, Post-dry | *Avicennia marina* | Ochieng and Erflemeijer 2002              |
| 7  | Yucatán, Mexico      | Unimodal | Leaf litterfall  | Rainy, Winter | Mixed mangrove | Pastor-Guzman et al. 2018                  |
| 8  | Florida, USA         | Unimodal | Litterfall       | Rainy, Dry    | *Rhizophora mangle* | Castañeda-Moya et al. 2013               |
Phenology of the Sundarbans mangrove forest

Canopy greenness of the Sundarbans has an annual (unimodal) cycle in response to a clear unimodal pattern in annual rainfall and temperature there (Fig. 1). Thus, trees would have more leaves and/or higher chlorophyll concentration in leaves to promote photosynthetic activity in the wet period and become less green in the dry winter period due to limited water availability and higher salinity levels. To elucidate the temporal pattern in canopy greenness in the Sundarbans mangrove forests, we asked the following three questions: (i) Do the mangrove forests in the Sundarbans exhibit annual periodicity in canopy greenness? (ii) When are the peak periods and off-peak periods of canopy greenness? (iii) Are there differences in patterns of canopy greenness among forest types? Therefore, we examined periodicity in canopy greenness and estimated phenological parameters for each forest type using time-series vegetation indices derived from MODIS data.

MATERIALS AND METHODS

Study area

The study site was in the Bangladeshi part of the Sundarbans, which occupies about 60% of the total Sundarbans (Fig. 2). The forest is rich in biodiversity and was declared a world heritage site by UNESCO in 1987. The elevation of the forest is 0.9–2.1 m above mean sea level (Laskar 2000). The monsoon rainfall is prevalent in June–September when about 71% of total rainfall is observed between 2001–2014 (Fig. 1). The mean monthly temperature is approximately 23–35 °C. The months following the monsoon until the next pre-monsoon period (March–May) are particularly dry (Islam and Uyeda 2007; Rahman and Asaduzzaman 2013).

Mangrove plants in the Sundarbans occur from mono-dominant patches to a mix of different species in various proportions. Three ecological zonation were made based on salinity viz freshwater (Oligohaline), moderately saline water (Mesohaline) and saltwater (Polyhaline) zones. Northern and eastern parts (Oligohaline zone) of the Bangladesh Sundarbans are rich in species diversity than the rest due to continuous freshwater supply, which lowers salinity level there. A total of 115 plant species, of which 17 are true mangrove species, are reported; however, the forest is mainly dominated by three mangrove species Heritiera fomes Buch.-Ham. (Malvaceae), Excoecaria agallocha L. (Euphorbiaceae) and Ceriops decandra (Griff.) Ding Hou (Rhizophoraceae) (FD 2010; Aziz 2015). H. fomes is particularly sensitive to salinity, E. agallocha is moderately tolerant and C. decandra is most salt loving. The other major mangrove tree species, though their occurrences are less proportions, are Avicennia officinalis L. (Acanthaceae), Bruguiera gymnorrhiza (L.) Lamk. (Rhizophoraceae) and Sonneratia apetala Buch.-Ham. (Lytaceae), and Xylocarpus mekongensis Pierre (Meliaceae) and Xylocarpus granatum Koenig (Meliaceae).

The past forest inventories designated the forest into nine blocks and a total of 55 compartments (Chaffey et al. 1987; Revilla et al. 1998). Revilla et al. (1998), during the forest inventory 1998, classified Bangladesh Sundarbans into eight forest types of mainly H. fomes, E. agallocha, C. decandra and their intra mixture with other less abundant species. As MODIS resolution was not suitable for finer scale, we reclassified the Bangladesh Sundarbans into larger scale. Based on the mangrove species composition data for the nine blocks collected by Forestry Department, we combined blocks with similar species composition and reclassified them into four major forest types: (F1) forests dominated by H. fomes; (F2) forests dominated by E. agallocha; (F3) forests dominated by C. decandra; and (F4) mixed forests of H. fomes, E. agallocha, and C. decandra.

Table 2. Literature on mangrove phenology in Sundarbans

| No | Species | SBN | Parameters | References |
|----|---------|-----|------------|------------|
| 1  | Heritiera fomes | BD  | Leaf flush: March–June; Leaf shedding: May–Sep | Rahman and Islam 2015 |
|    |         | -   |            |            |
| 2  | Excoecaria agallocha | BD  | Leaf flush: March–May; Leaf shedding: April–Jun | Chowdhury et al. 2016 |
|    |         | -   |            |            |
| 3  | Ceriops decandra | BD  | Leaf flush: March–May; Leaf shedding: April–Jun | Chowdhury et al. 2016 |
|    |         | -   |            |            |
| 4  | Xylocarpus mekongensis | BD  | Leaf flush: March–May; Leaf shedding: April–Jun | Chowdhury et al. 2016 |
|    |         | -   |            |            |
| 5  | Bruguiera sexangula | BD  | Leaf flush: March–May; Leaf shedding: April–Jun | Kamruzzaman et al. 2017 |
|    |         | -   |            |            |

* Vary with salinity level. BD- Bangladesh part of the Sundarbans, India- Indian part of the Sundarbans
The MODIS-Terra MOD13Q1 product provides 16-day composite images of vegetation indices (Didan 2015). The spatial resolution of the product was 250-m with a temporal resolution of 16-days slot. The product was developed by selecting best available pixel values from all acquisition from 16-day period. We used two indices, the normalized difference vegetation index (NDVI) and enhanced vegetation index (EVI). Images were accessed using GEE (Gorelick et al. 2017), followed by filtering, cloud-masking and computing the time series between January 2001 and December 2018.

\[
\text{NDVI} = \frac{\rho_{\text{red}} - \rho_{\text{NIR}}}{\rho_{\text{red}} + \rho_{\text{NIR}}}
\]

\[
\text{EVI} = G \left\{ \frac{\rho_{\text{NIR}} - \rho_{\text{red}}}{\rho_{\text{NIR}} + C_1 \times \rho_{\text{red}} + C_2 \times \rho_{\text{blue}} + L} \right\}
\]

Where \( \rho \) are atmospherically corrected surface reflectances, \( L \) is canopy background adjustment, \( C_1 \) and \( C_2 \) are coefficients of the aerosol resistance term. \( G \) is gain factor (Huete et al. 2002). The NDVI uses the proportions of near-infrared and red bands to quantify vegetation cover. Although it is widely used, the NDVI saturates at high biomass concentrations and is affected by soil background and atmospheric conditions. On the other hand, the EVI offers improved sensitivity at a high biomass by adding the blue band to the red and infrared bands to ameliorate the issues of the NDVI (Huete et al. 2002; Qiu et al. 2018). We chose the highest quality pixels using the MODIS QA band provided with the MOD13Q1 product and non-mangroves were masked out. We computed the mean NDVI and EVI values for each 16-day composite image for each forest type. We set a threshold of 0 for NDVI and EVI values as vegetation should produce higher values. A detailed

Fig. 1. Monthly total rainfall and maximum and minimum temperature in the Sundarbans, Bangladesh. Data were collected from Bangladesh Meteorological Department for the year 2001–2014 at Satkhira station.
The raw time-series data contain noise, reflection error, and missing values, which are beneficial to remove. For our study, we eliminated NDVI and EVI values less than 0 and used the Savitzky–Golay filter to filter and smooth the raw time series. We paid close attention to preserving the shape and information of the original time series, while still removing obvious errors. Therefore, we experimented with various combinations of filter order and filter length before settling on values that provided satisfactory results (filter order = 5, filter length = 5). Hereafter, we refer to such time series as "SG-filtered time series."

To determine the periodicity of NDVI and EVI time-series data, we used the discrete Fourier transform (DFT), which decomposes time-series data into sine and cosine waves of underlying frequencies, following Bush et al. (2016) and Nakagawa et al. (2019).

We used the Daniell kernel moving average smoother with the Spectrum function in R software (R Core Team 2019) to smooth all spectral estimates. The width of the spans, a user-specified value, was set to (3,3), which gave a smoothed spectral estimate with a bandwidth close to 0.005. This combination was selected because it provided a satisfactory resolution for identifying dominant peaks in the periodogram (Bush et al. 2016). The shortest possible length of the cycle was about 1 month, which was twice the observation interval and longest possible length was about the entire length of the 18-year series. We identified the periodicity by assessing whether the power of a dominant cycle was above the 95% confidence interval. Only the
dominant cycle was tested for statistical significance.

Following the DFT, each time series was reconstructed by summing the extracted sinusoids with their frequencies (harmonics), a process called inverse Fourier transformation, to form a smooth wave that resembled the original time-series profile.

**Phenological date parameters**

The 18-year SG-filtered and reconstructed NDVI and EVI time-series were divided into 17 annual seasons based on the annual cycle predicted from Fourier analysis. After investigating peaks and troughs of the vegetation indices, 23 data points for each year (16-day interval, Appendix A1) were extracted starting from day of the year (DOY) 97 to the next year’s DOY 81 (Fig. 4a, d). The following phenological date parameters were estimated: the start of the season (SOS), the time of maximum greenness (MaxGreen), the end of the season (EOS), and the length of the season (LOS).

**Statistical analysis**

In order to test whether the value of vegetation indices was significantly different among forest types, we compared the mean NDVI and EVI values of each forest type at SOS, MaxGreen and EOS for 17 years with one-way analysis of variance (ANOVA). Where means were significant (p < 0.05) Tukey pairwise comparison test for mean separation. All statistical analyses were conducted in the R environment (R Core Team 2019).

**RESULTS**

**Periodicity of the VIs**

The SG-filtered time-series data (Fig. 5) revealed that the NDVI and EVI fluctuated on an annual basis for all four forest types. The annual cycle was also observed in the smoothed periodogram, which showed that there was a significant dominant cycle of 22.73 observations (each year had 23 observations) for all forest types (Fig. 6). Both VIs exhibited the same significant peak within one cycle per year.

**Differences in VIs among forest types**

The mean NDVI values at the SOS (ANOVA; F-value \(= 26.7, df=3, p<0.001\)), MaxGreen \(= 50.2, df=3, p<0.001\), and EOS \(= 25.58, df=3, p<0.001\) were significantly different among forest types (Fig. 7, Appendix A2). The mean EVI values were significantly different at the SOS \(= 9.166, df=3, p<0.001\), MaxGreen \(= 9.925, df=3, p<0.001\) and the EOS \(= 2.714, df=3, p<0.05\). The mean NDVI values at the SOS, MaxGreen and EOS were higher in F1 and F2 than in F3 and F4. Similarly, the mean EVI values at the
SOS and MaxGreen were higher in F1 and F2 than F3 and F4, and those at the EOS were higher in F1, F2 and F3 than F4. Overall, F1 and F2 produced higher NDVI and EVI values than did F3 and F4, although the difference was smaller for EVI than for NDVI.

Differences in seasons among forest types and VIs

Based on the NDVI, the median date of the SOS was DOY 161 (June 10) for all forest types (Fig. 8, Appendix A3). For MaxGreen date was slightly earlier for F1 and F4 (DOY 289; October 16) than for F2 and F3 (DOY 305; November 01). That of the EOS was DOY 49 (February 18) for F1. (d–f) Estimation of phenological metrics from enhanced vegetation indices (EVI) for forests dominated by H. fomes, E. agallocha and C. decandra (F4). DOY stands for day of the year (DOY 1 = 1st January).
DOY 225 (August 13) for F1, F2, and F3 and DOY 257 (September 14) for F4. The EOS based on EVI data was also earlier than that based on NDVI data by 61 (F3 and F4) to 77 (F1 and F2) days; the median dates were DOY 337 (December 03) for F1 and DOY 353 (December 19) for F2, F3, and F4. Consequently, the EVI-based LOS was 176 (F1) to 208 days (F3) shorter than the NDVI-based LOS.

**DISCUSSION**

In this study, using NDVI and EVI values derived from an 18-year time series of MODIS data, we detected an annual cycle of canopy greenness for all four mangrove forest types in the Sundarbans. Studies on leaf phenology in mangroves are few compared to the large body of literature focused on their productivity and decomposition (Sharma et al. 2012); however, some *in situ* studies have used litter-trap data to assess the seasonality of leaf shedding, flowering, and fruiting for some mangrove species in the Sundarbans (Table 2). It has been reported that mangroves generally have a unimodal, or in some cases bimodal, leafing pattern (Saenger and Moverley 1985; Upadhyay and Mishra 2010). Mangrove phenology is closely related to rainfall, temperature, radiation, and windspeed (Sharma et al. 2012; Kamruzzaman et al. 2016; Rani et al. 2016). Past studies based on ground-level monitoring have also revealed that the Sundarbans mangrove trees exhibit unimodal characteristics (Rahman and Islam 2015). Our study at the landscape scale confirmed this pattern across all four forest types in the Sundarbans in Bangladesh.

The phenology of forest trees, particularly the flushing and shedding of leaves, is often related to their corresponding reproductive phenology (Rahman and Islam 2015) and to climatic variables such as temperature, radiance, day-length, rainfall, and water availability. Rainfall in the
Sundarbans is highly seasonal due to its monsoonal climate (Fig. 1). The Sundarbans receive heavy rainfall during the monsoon months, which provides an enormous supply of freshwater for the major rivers, canals, and creeks dissecting the Sundarbans. The freshwater supply leads to vegetative growth and leaf flushing (Chowdhury et al. 2016).
The phenology of the Sundarbans mangrove forest exhibits a clear seasonality, probably in response to the seasonality of environmental conditions (Ghosh and Banerjee 2013; Rahman and Islam 2015; Rani et al. 2016). The seasonality of litterfall in relation to differences in rainfall, temperature, freshwater availability, level of salinity, and low tides between pre- and post-monsoon months has been documented in the Sundarbans (Chowdhury et al. 2016; Kamruzzaman et al. 2019a). *H. fomes*, *E. agallocha*, and *C. decandra* start flowering and reproducing at the onset of the rainy season, which is accompanied by relatively high temperatures, after the cold, dry winter. Mangrove species in general produce more litter, which includes mature leaves, branches, and reproductive parts, during a dry winter period (Tomlinson 2016; Kathiresan and Bingham 2001), thus supporting our findings.

The SOS estimated using NDVI and EVI data was almost consistent among forest types, suggesting that the timing when ratio of VIs exceeded 0.2 first time in a year was similar across all forest types, irrespective of type of VIs. On the other hand, EVI-based dates for the MaxGreen and EOS were earlier, and the EVI-based LOS was shorter, than those based on NDVI data. Inconsistency among different phenological indices is reportedly due to the sensitivity of these indices (Pastor-Guzman et al. 2018). The differences between the two phenological indices may be primarily due to the characteristics of the vegetation index. Because the NDVI is known to saturate at higher greenness levels, whereas the EVI correlates more accurately with canopy cover, leaf area index, and leaf structure (Gao et al. 2000), EVI-based estimations of phenological dates may be more accurate.

Field data and observations also provide some support for the EVI over the NDVI. A forest dominated by *E. agallocha* (F2) achieved maximum leafing between March and May (Table 2) (Rahman and Islam 2015), which is consistent with the period between the SOS and MaxGreen estimated using EVI data. We have also observed that some major species in the Sundarbans, such as *H. fomes*, *E. agallocha*, *C. decandra*, and *X. mekongensis*, tend to have yellowish or pale leaves and shed their leaves more actively in winter (November–January), open new leaves in spring (March–May), and have green and abundant leaves in summer (July–September) (M. Kamruzzaman, pers. obs.).
Although this leaf phenology is not distinct from that based on litterfall (e.g., Kamruzzaman et al. 2019a), it is consistent with the seasonal pattern in the EVI. Therefore, EVI-based estimations are likely more accurate than NDVI-based ones.

Tropical cyclones, which frequently hit the Sundarbans mangrove forests, may also have effects on canopy greenness level by severely damaging the canopy. Studies reported that several strong cyclones affected about 19–31% of Sundarbans area in 2001–2018 though forests recovered quickly (GOB 2008; Dutta et al. 2015). We also observed a decline of NDVI values after some cyclones, particularly strong ones in 2007 (category 5: Cyclone Sidr) and 1988 (category 3) (Mandal and Hosaka 2020). The cyclones, however, had little impacts on the seasonal pattern of VIs because it shows a constant annual cycle throughout the study period (Fig. 5). Therefore, it would be important to consider such seasonal changes of VIs when we assess the cyclone impacts using VIs.

This study used MODIS data with 250-m pixel size to depict canopy greenness pattern of each forest type. Since there were some mangrove species co-occurring with the dominant one within each forest type, multiple species were probably mixed in the pixel. If this is the case, the temporal pattern of canopy greenness in the pixel becomes unclear when different species have different patterns. Therefore, it should be noted that the pattern of canopy greenness clarified in this study can’t be ascribed to a phenological
behavior of a particular species, but that of whole mangrove forest involving multiple species. Future studies using satellite images with higher spatial resolution (e.g. Landsat, Sentinel, Radar) will be helpful for detecting differences in phenological pattern among co-occurring mangrove species (Chen et al. 2018). Further, future studies should include more detailed validation on the relationship between leafing phenology of mangrove trees and changes in remote sensing parameters such as NDVI, EVI and leaf area index (LAI). For this purpose, long-term ground-level information on the seasonality of leaf flushing, shedding, coloration, and biomass in the canopy is critical, although such dataset is currently not available for the Sundarbans. Besides the ground survey, multi-spectral and high-resolution images taken by unmanned aerial vehicles will be useful for quick assessment of leaf biomass, color, and photosynthetic activity in the mangrove forest canopy.

CONCLUSION

Using NDVI and EVI time-series data derived from 18 years of 16-day MODIS composite images and GEE, we showed that there was a clear annual seasonality in canopy greenness in the Sundarbans mangrove forests at the landscape scale. Based on the EVI, canopy greenness increased from late May to mid-June, peaked from mid-August to mid-September, and decreased from mid-October to early November. Estimates of seasonal changes derived from EVI and NDVI data differed somewhat; EVI-based estimation is probably more accurate because estimates are more consistent with ground-level information. As canopy greenness is directly related to the level of photosynthetic activity in forests, changes in climatic conditions (e.g., temperature and solar radiation) around the peak period (July–October) will strongly affect carbon uptake by the forest ecosystem. The phenological calendar maps estimated here are the first to be developed for the Sundarbans mangrove forest at the landscape level and thus, can serve as base maps for future studies. When these data are coupled with biophysical parameters such as temperature, rainfall, salinity, storm surge, and wind, it is possible to predict phenological changes in the forest in response to future climate change.

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APPENDICES

A1. Days of the year (DOY) with corresponding calendar dates

| No | DOY | Date     | No | DOY | Date     |
|----|-----|----------|----|-----|----------|
| 1  | 1   | January 01 | 13 | 193 | July 12  |
| 2  | 17  | January 17 | 14 | 209 | July 28  |
| 3  | 33  | February 02 | 15 | 225 | August 13 |
| 4  | 49  | February 18 | 16 | 241 | August 29 |
| 5  | 65  | March 06   | 17 | 257 | September 14 |
| 6  | 81  | March 22   | 18 | 273 | September 30 |
| 7  | 97  | April 07   | 19 | 289 | October 16 |
| 8  | 113 | April 23   | 20 | 305 | November 01 |
| 9  | 129 | May 09     | 21 | 321 | November 17 |
| 10 | 145 | May 25     | 22 | 337 | December 03 |
| 11 | 161 | June 10    | 23 | 353 | December 19 |
| 12 | 177 | June 26    |    |     |          |

A2. NDVI and EVI mean values for 17 seasons of four forest types at SOS, Max Green, EOS

| VIs  | Phenological profile | DOY | Date     | DOY | Date     | DOY | Date     | DOY | Date     |
|------|----------------------|-----|----------|-----|----------|-----|----------|-----|----------|
| NDVI | SOS*                 | 0.61 ± 0.01^a | 0.60 ± 0.01^b | 0.54 ± 0.01^a | 0.54 ± 0.01^a |
|      | Max Green*           | 0.73 ± 0.01^a | 0.74 ± 0.01^b | 0.69 ± 0.01^a | 0.69 ± 0.01^b |
|      | EOS*                 | 0.65 ± 0.01^a | 0.64 ± 0.01^b | 0.58 ± 0.01^b | 0.59 ± 0.01^b |
| EVI  | SOS*                 | 0.35 ± 0.01^a | 0.34 ± 0.01^b | 0.30 ± 0.01^a | 0.30 ± 0.01^b |
|      | Max Green*           | 0.47 ± 0.01^a | 0.47 ± 0.01^b | 0.44 ± 0.005^b | 0.43 ± 0.01^b |
|      | EOS*                 | 0.35 ± 0.01^a | 0.35 ± 0.003^b | 0.34 ± 0.004^b | 0.33 ± 0.003^b |

(Values represent mean ± SE, * significant at 0.05, means with same letter are not significantly different)

A3. Table showing different day of the year (DOY) for four forest types at SOS, Max Green, EOS and LOS in days

| Phenological profile | F1            | F2            | F3            | F4            |
|---------------------|---------------|---------------|---------------|---------------|
| NDVI SOS            | DOY 161 (June 10) | DOY 161 (June 10) | DOY 161 (June 10) | DOY 161 (June 10) |
|                     | DOY 289 (October 16) | DOY 305 (November 01) | DOY 305 (November 01) | DOY 289 (October 16) |
|                     | DOY 49 (February 18) | DOY 65 (March 06) | DOY 49 (February 18) | DOY 49 (February 18) |
|                     | 253 days | 269 days | 253 days | 253 days |
| Max Green EOS       | DOY 161 (June 10) | DOY 145 (May 25) | DOY 161 (June 10) | DOY 161 (June 10) |
|                     | DOY 225 (August 13) | DOY 225 (August 13) | DOY 225 (August 13) | DOY 257 (September 14) |
|                     | DOY 337 (December 03) | DOY 353 (December 19) | DOY 353 (December 19) | DOY 353 (December 19) |
|                     | 176 days | 208 days | 192 days | 192 days |
| LOS                 | 253 days | 253 days | 253 days | 253 days |