



# Spatial distribution of mangrove forest species and biomass assessment using field inventory and earth observation hyperspectral data

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## Abstract

The objective of this research is to identify species, provide spatial distribution of the species and estimate the biomass in the mangrove Forest, Bhitarkanika India. Mangrove ecosystems play an important role in regulating carbon cycling, thus having a significant impact on global environmental change. Extensive studies have been conducted for the estimation of mangrove species identification and biomass estimation. However, estimation at a regional level with species-wise biomass distribution has been insufficiently investigated in the past because either research focuses on the species distribution or biomass assessment. Study shows that good relationship has been achieved between stem volume (field measured data) and Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) derived from satellite image and further these two indices are employed to estimate the biomass in the study site. Three models- linear, logarithmic and polynomial (second degree) are used to estimate biomass derived from EVI and NDVI. The hyperspectral data (spatial resolution ~ 30 m) is utilised to identify ten mangrove plant species. We have prepared the spatial distribution map of these species using spectral angle mapper. We have also generated mangrove species-wise biomass distribution map of the study site along with areal coverage of each species. The results indicate that the *Sonneratia apetala* Buch.-Ham. and *Cynometra iripa* Kostel has the highest biomass among all ten identified species, 643.12 Mg ha<sup>-1</sup> and 652.14 Mg ha<sup>-1</sup>. Our study provided a positive relationship between NDVI, EVI, and the estimated biomass of Bhitarkanika Forest Reserve Odisha India. The study finds a similar results for both NDVI and EVI derived biomass, while linear regression has more significant results than the polynomial (second degree) and logarithmic regression derived biomass. The polynomial is found slightly better than the logarithmic when using the EVI as compared to NDVI derived biomass. The spatial distribution of species-wise biomass map obtained in this study using both, EVI and NDVI could be used to provide useful information for biodiversity assessment along with the sustainable solutions to different problems associated with the mangrove forest biodiversity. Thus, biomass assessment of larger regions can be achieved by utilization of remote sensing based indices as concluded in the present study.

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**Keywords** Biodiversity · Species distribution · Mangrove · Biomass · Hyperspectral · Field inventory · NDVI · Regression model

## Introduction

Mangrove forest is an important part of wetland ecosystems and mangrove vegetation communities are formed by groups of salt tolerant species in the inter-tidal zones and estuary mouths (Kokaly et al. 2003; Lin and Liqun 2006; Pattanaik et al. 2008). Mangrove plant species plays an essential role in the ecological functioning of wetland environments (Adam et al. 2010; Kokaly et al. 2003) and mostly found tropical and subtropical coasts. Mangroves forests act as a protecting shield for the coastal region from sea disaster, frequent flood, flash floods protecting the landscape and surrounding environment (Srivastava et al., 2015). Mangroves acts like a shield for the coastal area because it protects the land surface from frequent flood and tsunamis. For example, in case of cyclone disaster (1999) in Odisha, the area covered with mangrove plants species were relatively less affected as compared to non-vegetated regions at Bhitarkanika Forest Reserve (Shanker 2005). There is a need to monitor the mangrove plant species to protect the wetland ecosystems in order to conserve forest as well as human life at surrounding places. At present, the scenario is presenting an alarming signal due to degradation and declining conditions of the mangrove forests area by almost 50%, and most Asian countries are worst affected, where degradation rate is as high as 61% and it is still continuing at faster rate (Macintosh and Ashton 2002).

Vegetation types in wetland ecosystems act as a key indicator of early signs of degradation and damage to the ecosystem either physical or chemical in nature (Dennison et al. 1993). Earlier, traditional species mapping requires rigorous field work that is costly, time consuming, labor intensive and mostly inapplicable due to poor accessibility to dense forest region or inaccessible regions and is thus confined to relatively smaller regions (Lyon and McCarthy 1995). Therefore, mangrove forest species identification and their spatial distribution mapping over a large scale are rigorous and complicated in nature using field-based inventory.

Remote sensing techniques on the other hand, offer an economical and practical means to assess biomass, and species distribution mapping. Thus, it overcomes the rigorous field problem by providing synoptic view over the large area covering inaccessible regions too, making sampling more focused and efficient using multispectral (Harvey and Hill 2001; Kumar et al. 2013, 2015; May et al. 1997) and Hyperspectral data (Belluco et al. 2006; Rosso et al. 2005; Schmidt and Skidmore 2003; Vaiphasa et al. 2007) to wetland vegetation at the species level. Therefore, the advantage of the integrating remote sensing techniques with field measurements would help to achieve the accurate results over a large coverage with reduced ambiguity.

There are several researches that address the wetland and mangrove vegetation mapping using multispectral data, using image analysis methods such as unsupervised and supervised classification (Harvey and Hill 2001; May et al. 1997; McCarthy et al. 2005; Singh et al. 2014) and vegetation index clustering (Nagler et al. 2001; Yang 2007). Yang (2007) revealed that major challenges with wetlands and mangrove plant species discrimination is affected by the low spectral resolution and coarse spatial resolution of the satellite datasets, thus limiting their applications in classification and mapping. Thus, the limitation with multispectral data is its low spectral resolution in separating shrubs from meadows (Adam et al. 2010). This limitation is overcome by the incorporation of Hyperspectral remote sensing techniques, due

to its greater spectral dimensionality which has ability to allow in-depth examination and discrimination of vegetation types that were impossible with multispectral images (Cochrane 2000; Govender et al. 2007; Mutanga et al. 2003; Pandey et al. 2014; Petropoulos et al. 2015; Schmidt and Skidmore 2003).

Due to its ability to measure reflectance precisely using narrow spectral bands, Hyperspectral data has a wide range of applications in species identification (Apan and Phinn 2006; Kuezner et al. 2011). Anderson (1970) was the first to discriminate the wetland species based on the spectral properties and evaluated ten marsh species to conclude the reason as spectral difference is more prominent in near-infrared as compared to the visible region.

Generally the pixel based classification approach is used to classify the tropical species which include Maximum Likelihood Classification (MLC), Spectral Unmixing (SU) and Spectral Angle Mapper (SAM) (Demuro and Chisholm 2003; Held et al. 2003; Yang et al. 2009). In present study supervised classification algorithm SAM is employed in the classification of mangrove species by developing a set of spectral signature. Todd et al. (2010) tried to estimate the above ground biomass using the hyperspectral data with a high spatial resolution of 30 m provided at a high precision.

Above ground biomass is an important variable for evaluating the ecological landscape and the variation ecological structure (Brovkina et al. 2015). According to Brown (1997), estimation of biomass can be broadly divided into two phases, estimation of biomass using field data collection and estimating biomass using remote sensing based approach. The conventional method for biomass estimation includes parameters like tree height, diameter at breast height and wood density to calculate the biomass of a tree which is used as a inputs in vegetation indices derived from satellite data to estimate the biomass for a given region. There are some article that reported the estimation of plant physical parameter incorporating vegetation indices using Hyperion earth observation data (Gong et al. 2003), whereas Buddenbaum et al. (2005) conclude with his study that Hyperspectral data are mostly used to analyze vegetation indices for species classification.

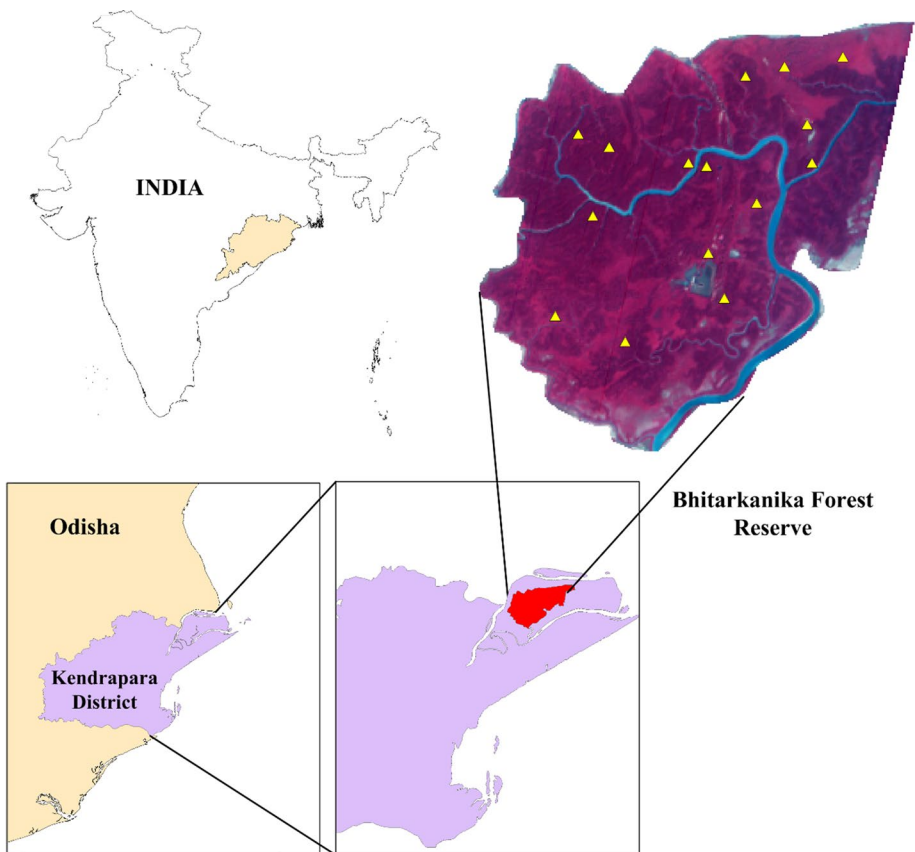
In a view of significance of biomass and species role in ecological functioning of mangrove forest for biosphere–atmosphere interaction (Roy and Ravan 1996), the present research focuses on the biomass assessment, species spatial distribution mapping and their biomass mapping along with NDVI, and EVI and their correlation using field based measurements in the Bhitarkanika Forest Reserve, India. This research involves different regression models (Linear, Logarithmic and Polynomial) and field inventory data for species distribution map and biomass assessment using spectral indices derived from Hyperion datasets. Therefore, in order to understand mangrove ecosystem functioning and any changes in Bhitarkanika forest, it's necessary to know the spatial distribution of plant species and biomass estimation of the landscape. It is imperative to assess NDVI and EVI for biomass estimation and correlation assessment among these two indices. This research aims to present how vegetation parameters derived from Hyperion data (NDVI and EVI) are related with the field measured values and how they affect the biomass particularly. This study also generate species spatial distribution map and their biomass derived from NDVI and EVI parameters. Therefore, an attempt has been made to estimate biomass of the Bhitarkanika forest region using Hyperion data and field inventory data.

## Materials and methods

This section deals with the study area, materials/datasets and methodology adopted in the study to generate spatial distribution map of mangrove species and estimate forest biomass in the Bhitarkanika Forest Reserve. This section also demonstrates spectral indices: vegetation indices estimation, biomass assessment using regression models and their relationships.

### Study area

The study is conducted along the protected forest, Bhitarkanika Forest Reserve, Odisha India, study site is located at  $20^{\circ}41'36.70''$  and  $24^{\circ}45'28''$ N latitudes and  $86^{\circ}54'17.29''$  and  $86^{\circ}92'8.96''$ E longitude covering an area of  $41.05 \text{ km}^2$  with elevation range of 10 m–25 m above Mean Sea Level (MSL) (Fig. 1). The study area is predominantly inter-tidal region i.e. 60% is surrounded on three sides by a Bay of Bengal sea. Bhitarkanika Wildlife Sanctuary is a unique habitat of mangrove forests that is located in the estuarial region



**Fig. 1** Location map of the study site with sample plot locations in Bhitarkanika Forest Reserve, Odisha India, the satellite data Hyperion RGB image is used to illustrate the study area

of Bramhani-Baitarani, in the north-eastern place of Kendrapara district of Odisha, India. There is tidal maze of muddy criss-cross creeks, muds and mangroves formed by the three rivers i.e. Brahmani, Baitarani, Dhamra and Mahanadi River meeting sea at estuary region. It is second largest mangrove ecosystem in India and habitat pace to diverse flora and fauna (Mohanty et al. 2008; Odisha 2017). Table 1 illustrates the major species with local name present in the Bhitarkanika forest.

This study area is chosen due to its peculiarity as mangrove forest. The climate of Bhitarkanika is characterized by humid sub-tropical climate with three distinct seasons such as summer, monsoon and winter. The summer months are hot and temperatures in summer are 43 °C and the winters are cold with 10 °C temperature. Bhitarkanika mangrove forest has a rich biodiversity with flora and fauna. A total of major ten plant species were dominant in the study site as described in Table 1. These are *Excoecaria agallocha*, *Cynometra iripa* Kostel, *Aegiceras corniculatum*, *Aegiceras corniculatum*, *Heritiera littoralis* Dryand ex Ait., *Heritiera fomes* Buch.-Ham., *Xylocarpus granatum* Koenig, *Xylocarpus mekongensis* Pierre, *Intsia bijuga* (Colebr.) Kuntze, *Cerbera odollam* Gaertn., and *Sonneratia apetala* Buch.-Ham.

### Satellite data used

The study has utilized Earth Observation-1 (EO) satellite Hyperion data has been utilized for species distribution and species wise biomass mapping. The EO-1 satellite Hyperion datasets (L1Gst data) of the study site is acquired from USGS (United States Geological Survey, available at <http://earthexplorer.usgs.gov/>). The Hyperion satellite data is acquired according to the field measurement date. The description of the satellite datasets utilized in the study has been provided in the Table 2. EO-1 Hyperion sensor has 242 spectral channels with spatial resolution of 30 m. Out of 242 spectral bands, only 196 bands contain useful information and rest are bad bands with noises. These bad bands were removed while processing the Hyperion data. Hyperion Tool kit was used in the ENVI to generate HDR file from MTL file, along with scale factors text file (40 for Vis–NIR and 80 for SWIR), interpolate data to common wavelength (as there are some overlap of the bands). The scaling factors, 40 for VNIR and 80 for SWIR bands has a detailed descriptions mentioned in EO–1 user Guide 2003. The data was processed to remove bad bands due to overlap, water absorption and not illuminated, as listed 1–7 (not illuminated), 58–78 (overlap

**Table 1** Descriptions of plant species present in Bhitarkanika forest reserve

	Scientific name	Family name	Local name
1	<i>Excoecaria agallocha</i>	Euphorbiaceae	Gaun
2	<i>Cynometra iripa</i> Kostel	Caesalpiniaceae	Singhada
3	<i>Aegiceras corniculatum</i>	Myrsinaceae	Kharsi
4	<i>Heritiera littoralis</i> Dryand ex Ait.	Sterculiaceae	Dhala Sundari
5	<i>Heritiera fomes</i> Buch.-Ham.	Sterculiaceae	Bada sundari
6	<i>Xylocarpus granatum</i> Koenig	Meliaceae	Sisumar
7	<i>Xylocarpus mekongensis</i> Pierre	Meliaceae	Patamari
8	<i>Intsia bijuga</i> (Colebr.) Kuntze	Caesalpiniaceae	Maasitha
9	<i>Cerbera odollam</i> Gaertn.	Apocynaceae	Paniamba
10	<i>Sonneratia apetala</i> Buch.-Ham.	Sonneratiaceae	Keruan

**Table 2** Description of satellite datasets used in the study

Satellite data	Hyperion Hyperspectral
Path	139
Row	45
Spatial Resolution	30
Date	31-Dec-2015
Time	03:02:07

regions), 120–132 (water absorption region), 165–182 (water absorption region), 185–187 (identified bad bands), 221–224 (water absorption region), and 225–242 (not illuminated). Thereafter, data was processed for cross track illumination and atmospheric correction is performed using ENVI 5.1 FLAASH (Fast Line-of-sight Atmospheric Analysis of hyper Spectral-cubes) module to remove the atmospheric effects to generate reflectance image. The different input parameters required for FLAASH module were determined from the metadata of the Hyperion image files. The altitude, pixel size, acquisition date, flight time in GMT, aerosol model, atmospheric model, water retrieval, visibility. This information is located from header file and parameters are provided according to acquired data date. Reflectance image is processed to extract endmembers with the help of GPS locations for the sampled plant species. These are used for classification and validation of the results.

### Field-inventory based biomass measurement

First of all, field sampling was carried out during the year 2015 for the study site. The foremost steps are the prior knowledge of the mangrove plant species, their location and its structure is essential to collect the sample data for geospatial analysis. Small part of Bhitarkanika forest was surveyed to select representative positions of vegetation cover and its parameters such as height, tree number, Diameter at Breast Height (DBH) to estimate the biomass. As the study site selected is 41.50 km<sup>2</sup> falling within the range of Hyperion data strip,

EO-1 Hyperion image has limited coverage over the Bhitarkanika forest range, so we have selected region which falls within the data. The samples were collected by making a 90×90 sq m. grid and it is further divided into 9 equal 30×30 sq m. sub-grids i.e., 90 sub-grids were examined, and the most homogenous grid is taken into consideration. This process is further repeated to identify ten most homogenous mangrove plant species within the study area and samples were collected using GPS and Clinometer. The field data records the vegetation parameters using GPS in multiple directions and number of tree species were counted within the plot in random sampling design in the Bhitarkanika Forest Reserve as illustrated in Fig. 2a (Pattanaik et al. 2008).

Rapid and repeated investigation are undertaken to develop an idea about the variety of communities present, the area they occupy, dominant and homogenous species, significant environmental variation and accessibility of different parts of the study area. In a stratified random design, the study area is first subdivided into homogeneous stands or units, and then place samples in each unit randomly. The number of transect sampling units was calculated by following equation (Chacko 1965).

$$N = \frac{t^2(CV)^2}{E^2} \quad (1)$$

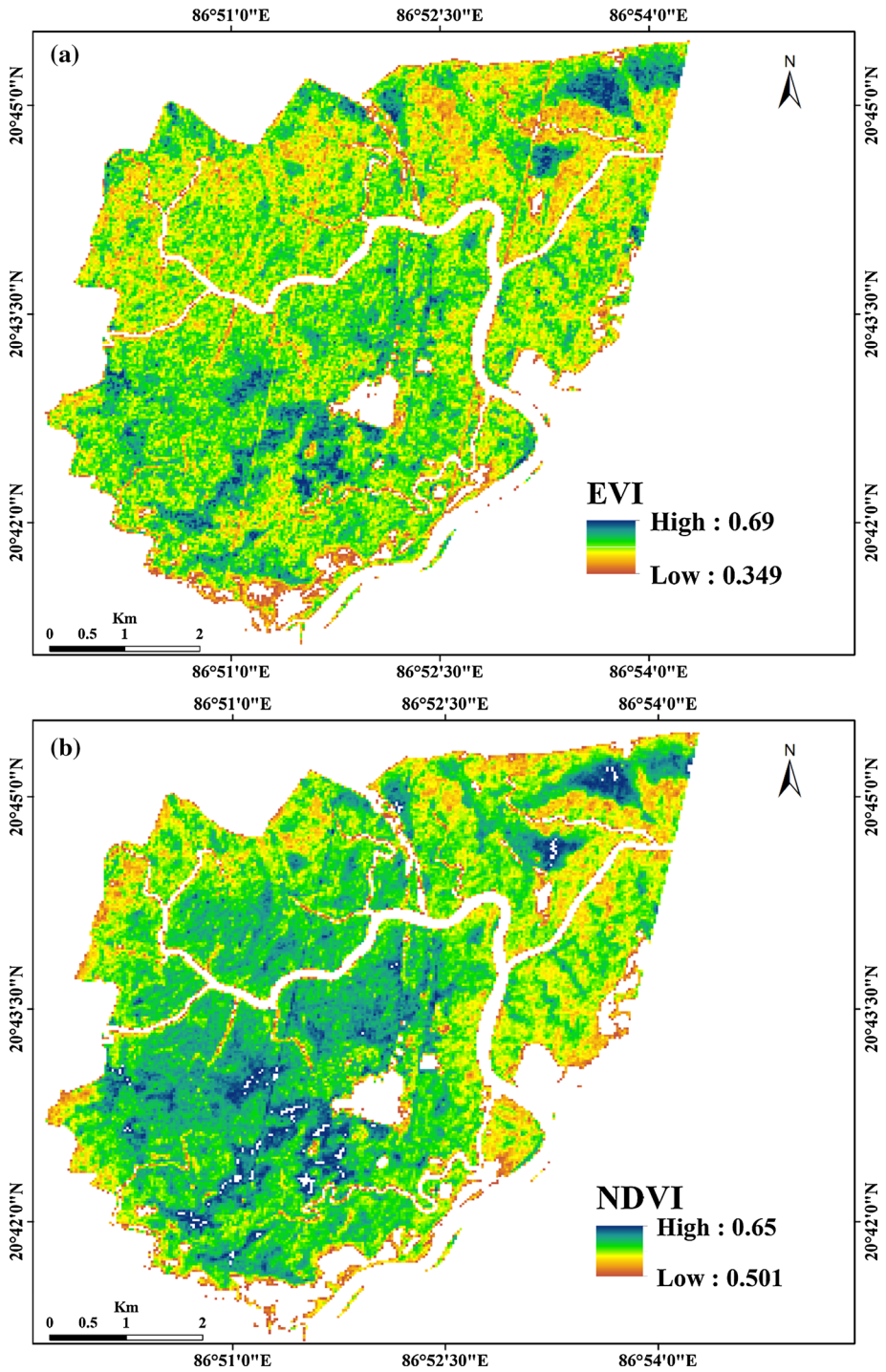


Fig. 2 a EVI map and b NDVI map of Bhitarkanika forest reserve

where N is the Number of sample required for allowable error, t is the value of Students' *t*-static's at given level of probability 95% level significance (1.96), CV is the co-efficient of variation (%) and E is the confidence interval expressed as % of mean.

During the field survey, ten sites with transects of 30×30 sq m. size were laid in a protected area of Bhitarkanika Forest Reserve, India for field sampling and further five sites were recorded for the validation of the present study, where latitude, longitude, number of trees, tree height (using clinometers), stem volume and DBH (Height at Breast Height) were recorded as illustrated in Table 3. Each mangrove species was recorded and girth measured at ≥ 10 cm diameter at breast height DBH at 1.32 m from the ground surface in the sample plot. Tree heights were recorded by clinometers and GPS is utilised to record parallels and meridians. Ten dominant and homogenous species were identified and recorded during field measurement as demonstrated in Table 3. The field measured biomass was calculated using following equation.

$$Y = e\{-2.4090 + 0.9522 \ln(D^2 \times H \times S)\} \quad (2)$$

where H is the height of the tree, D is the diameter of the tree at Breast Height (DBH), S is the wood density. The standard average value of wood density for each species is acquired from the database of International Council for Research in Agroforestry (ICRAF) in which *Excoecaria agallocha* has shown the lowest wood density of 0.49 g/cm<sup>3</sup> whereas *Heritiera littoralis* Dryand ex Ait. shown a wood density of 1.06 g/cm<sup>3</sup>.

## NDVI and EVI

This section deals with the NDVI, EVI and their estimation using the Hyperion datasets. NDVI is considered as one of the most preferred spectral indices to differentiate vegetated regions from non-vegetated regions. The NDVI is a term which indicates the photo synthetically active radiation for vegetation (Rani et al. 2018) that is strongly affected by climatic conditions, and surrounding factors such as soil, geomorphology as well as physio-chemical characteristics of plant and leaf texture. It transforms image of NIR and Red channels into a single band image with values ranging between− 1 and +1 (Tucker 1979). The values of NDVI indicate the amount of chlorophyll content present in vegetation, where higher NDVI value indicate dense and healthy vegetation and lower value indicate and sparse vegetation bare soil, negative value indicate waterbodies. Thus reasons assigned for high NDVI values for the dense forest are due to relatively higher reflectance value in NIR and lower in the red band (Tomar et al. 2013; Tucker 1979) to monitor vegetation health, changes, types, amount and condition.

$$NDVI = \frac{(R_{800} - R_{670})}{(R_{800} + R_{670})} \quad (3)$$

where  $R_{800}$  is the surface reflectance in Near-Infrared region, and  $R_{670}$  is the surface reflectance in red region. NDVI values range from − 1 to + 1.

EVI was originally developed as an improvement over NDVI by optimizing the vegetation signal in areas of high leaf area index where NDVI may saturate (Heute et al. 1997, 2002). EVI uses the blue region of spectrum to correct for soil background signals in order to reduce atmospheric influences such as aerosol scattering. Thus, EVI enhance vegetation signal with improved sensitivity to high biomass. EVI is calculated using the following equation:



**Table 3** Descriptions of field parameters measurement for Bhitarkamika forest reserve

	Scientific name	Tree height (m)	DBH (cm)	No. of trees	Wood density (g/cm <sup>3</sup> )	Stem volume (m <sup>3</sup> )	Biomass (Mg ha <sup>-1</sup> )
1	<i>Excoecaria agallocha</i>	18.453	20.14	11	0.49	6.46	222.74
2	<i>Cynometra iripa</i> Kostel	17.23	16.54	10	0.81	3.70	231.43
3	<i>Aegiceras corniculatum</i>	15.032	22.165	9	0.59	5.22	262.44
4	<i>Heritiera littoralis</i> Dryand ex Ait.	18.166	17.21	10	1.06	4.22	339.13
5	<i>Heritiera fomes</i> Buch.-Ham.	12.35	18.83	12	0.88	4.13	287.66
6	<i>Xylocarpus granatum</i> Koenig	14.13	27.52	5	0.67	4.20	379.64
7	<i>Xylocarpus mekongensis</i> Pierre	15.382	20.28	8	0.73	3.97	162.13
8	<i>Intsia bijuga</i> (Colebr.) Kuntze	12.294	26.69	9	0.84	6.18	196.92
9	<i>Cerbera odollam</i> Gaertn.	12.24	28.56	6	0.33	4.70	355.36
10	<i>Sonneratia apetala</i> Buch.-Ham.	11.25	21.85	10	0.53	4.22	351.14

$$EVI = 2.5 \times \frac{(NIR - Red)}{(NIR + 6 \times Red - 7.5 \times Blue + L)} \quad (4)$$

where NIR, Red and Blue are surface reflectance and  $L=1$ , value is the canopy background adjustment that addresses non-linear, differential NIR and Red radiant transfer through a canopy, 6 and 7.5 are coefficient of aerosol resistance term and 2.5 is gain factor.

NDVI is chlorophyll sensitive, while EVI is more responsive to canopy structural variations, including leaf area index (LAI), canopy type, plant physiognomy, and canopy architecture. The two vegetation indices complement each other in global vegetation studies and improve upon the detection of vegetation changes and extraction of canopy biophysical parameters. Further, the field sample points were used to extract the NDVI and EVI values to incorporate in the linear regression modeling for biomass estimation.

### Biomass estimation through Linear and Non-linear approaches

The aim of study is to provide accurate estimation of biomass distribution over the Bhitarkanika forest Reserve. This objective is achieved through the integrated use of EO-1 Hyperion sensor and field based inventory of training datasets to reduce discrepancy in the results, as this will be validated with the remaining 1/3rd field based measurements. This will preserve the merits of both the field inventory measurements and the spatial pattern of remotely sensed derived vegetation indices altogether. The field estimated biomass values were used with the NDVI and EVI vegetation indices using linear, logarithmic and polynomial (second degree) regression model to generate biomass maps for the study site.

## Results

The present study illustrates the biomass assessment and relationship between EVI and NDVI, relationship between measured biomass and estimated biomass using satellite datasets and field survey measurements at Bhitarkanika Forest Reserve. The Satellite derived NDVI, EVI and Biomass is provided along with the relationship between derived and estimated values. Moreover, the validation results were also demonstrated for the results to ensure accuracy of the study.

### NDVI and EVI indices

This section provides brief description of the NDVI and EVI products derived from space-borne data. Based on the prior knowledge, field surveys were conducted in the study sites for the training as well as validation purposes during the proposed research. To identify and assess the relationship between NDVI and EVI of the study sites, regression analysis is employed in the study. We generated NDVI product and EVI product from the satellite dataset using Eqs. (3) and (4) respectively as described earlier. NDVI and EVI values ranges from  $-0.21$  to  $0.65$  and  $0.0$  to  $0.69$  respectively in the study site, and thereafter only forest region were extracted, after masking the soil and water region. NDVI values derived from satellite data of forest region only ranges from  $0.5$  (low) to  $0.65$  (high), whereas EVI values ranges from  $0.35$  to  $0.69$  in the study area as shown in the Fig. 2a, b. The relationship between NDVI and stem volume are obtained as  $R^2=0.78$ , while with EVI it is found as  $R^2=0.66$ , this shows that NDVI has good correlation with stem volume of the study site.

## Spatial distribution of species

The mangrove plant species (such as *Excoecaria agallocha*, *Cynometra iripa* Kostel, *Aegiceras corniculatum*, *Aegiceras corniculatum*, *Heritiera littoralis* Dryand ex Ait., *Heritiera fomes* Buch.-Ham., *Xylocarpus granatum* Koenig, *Xylocarpus mekongensis* Pierre, *Intsia bijuga* (Colebr.) Kuntze, *Cerbera odollam* Gaertn., and *Sonneratia apetala* Buch.-Ham) were identified and their spectral profiles are derived from the Hyperion data. These species cover an area of 36.42 km<sup>2</sup> as shown in Table 3 as we have removed the water-bodies for area estimation. The supervised classification algorithm SAM is used to classify the study site for the above mentioned plant species. SAM is a procedure that determines the similarity between a pixel and each of the reference spectra based on the calculation of the “spectral angle” between each feature (Boardman 1993). It had been treating both the known and unknown spectra as vectors and calculated the spectral angle between them. A smaller angle differences between the two spectra and the pixels were identified as the fixed class else as a separate class. This classification carried following equation (Research Systems 2000) and easily achieved through the ENVI software. Figure 3 illustrates the species distribution map at the study site. The result of the SAM classification is illustrated in Fig. 3. The overall accuracy was found as 84% with  $\kappa$  (kappa coefficient) value of 0.81.

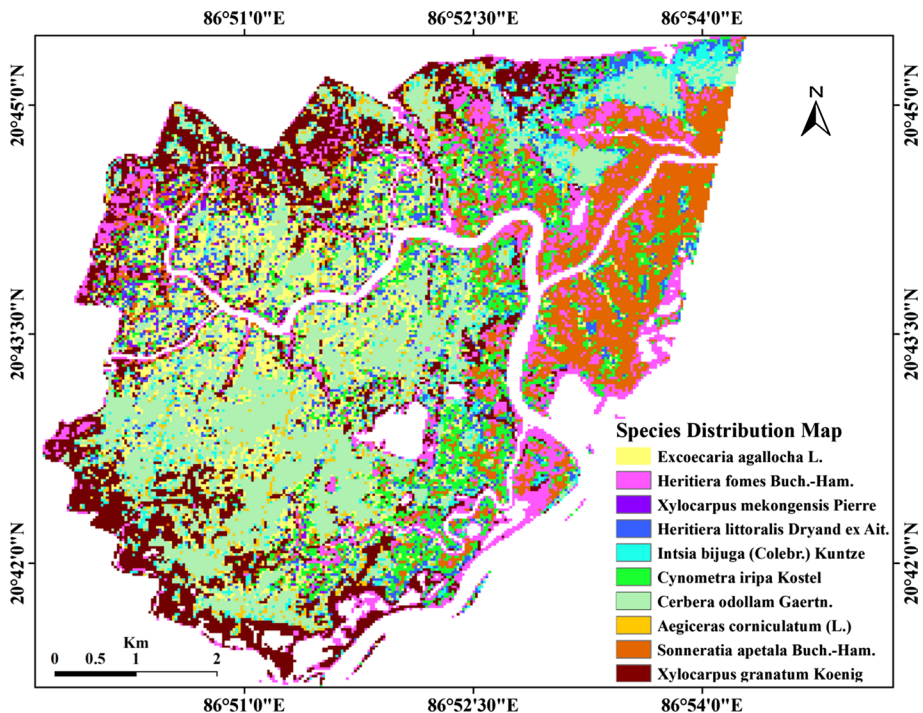


Fig. 3 Spatial distribution of species of Bhitarkanika Forest Reserve

## Biomass assessment and species-wise biomass estimation

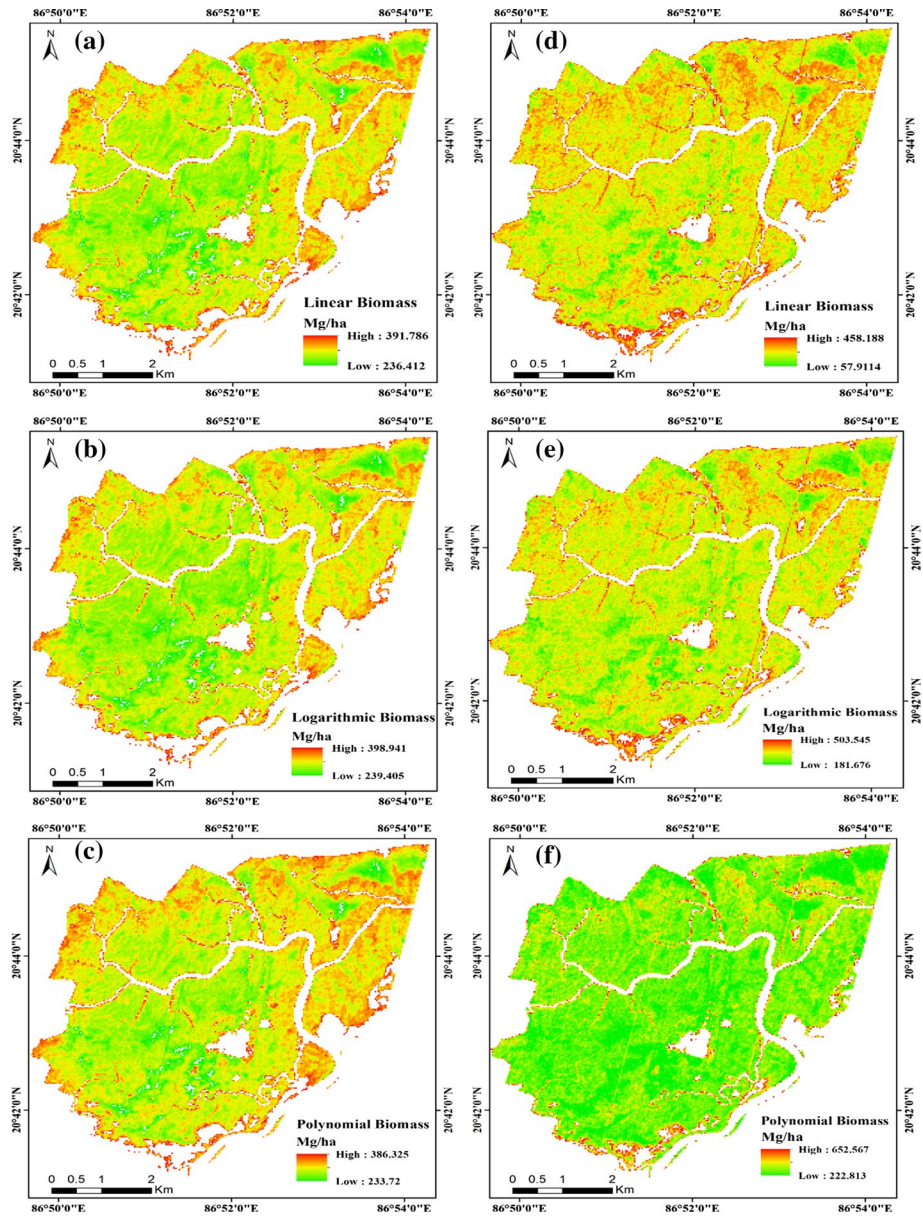
The average biomass of the plant species ranges from 247.64 to 395.80 Mg ha<sup>-1</sup> derived from EVI and 270.79 to 346.22 Mg ha<sup>-1</sup> derived from NDVI. Maximum EVI derived biomass calculated was 652.14 Mg ha<sup>-1</sup> for *Cynometra iripa* Kostel. species, which covers an area of 3.77 km<sup>2</sup>. Lowest EVI derived biomass was 222.81 Mg ha<sup>-1</sup> for plant species *Xylocarpus granatum* Koenig covering an area of 6.41 km<sup>2</sup>. In case of NDVI derived biomass, highest value was 386.32 Mg ha<sup>-1</sup> for *Cerbera odollam* Gaertn and lowest was 233.72 Mg ha<sup>-1</sup> for *Heritiera littoralis* Dryland ex Ait. with areal coverage of 8.34 km<sup>2</sup> and 2.07 km<sup>2</sup> respectively. Figure 4 illustrate the biomass derived from EVI and NDVI using linear regression, logarithmic and polynomial (second degree) model. The average biomass of each species derived from NDVI and EVI is shown in Table 3 along with area covered by them. Results generated from species classification were used to derive the species wise biomass map of the Bhitarkanika forest Reserve, and provide an estimate of area covered by each species in the study site. Figure 6 illustrates the NDVI and EVI derived biomass for each species demonstrating the species wise biomass distribution map. Thus, EVI has shown high amount of biomass variations and thus it is more sensitive to biomass calculation as compared to the NDVI as illustrated from the Fig. 5 and Table 3 while, NDVI has shown more consistent outputs. Species wise box-plot results has been shown in Fig. 6, where median, 25% and 75% quartile along with minima and maxima were provided (Table 4).

The average biomass measured during field survey is 278.85 Mg ha<sup>-1</sup>. The average EVI derived biomass ranges from 247.64 to 395.80 Mg ha<sup>-1</sup>, while for NDVI it ranges from 270.79 to 346.22 Mg ha<sup>-1</sup>. Thus, it is conferred that EVI is more sensitive to biomass estimation with variation with model used while NDVI has shown a consistent range for the biomass. This clearly illustrates an impression of the mangrove plant species, spatial distribution and their biomass distribution extent over the Bhitarkanika forest reserve, which is likely to be sparse or less dense according to the satellite derived spectral vegetation indices.

## Statistical analysis and regression models for estimated biomass

The field estimated biomass values were used with the NDVI and EVI vegetation indices using linear, logarithmic and polynomial (second degree) regression model as illustrated in Fig. 7. Vegetation indices such as NDVI and EVI were incorporated in order to find the relationship between fields measured biomass and estimated biomass from Hyperspectral data. Some of the very high values and negative values were removed from the results which were considered to be outliers in order to preserve the consistency in the results.

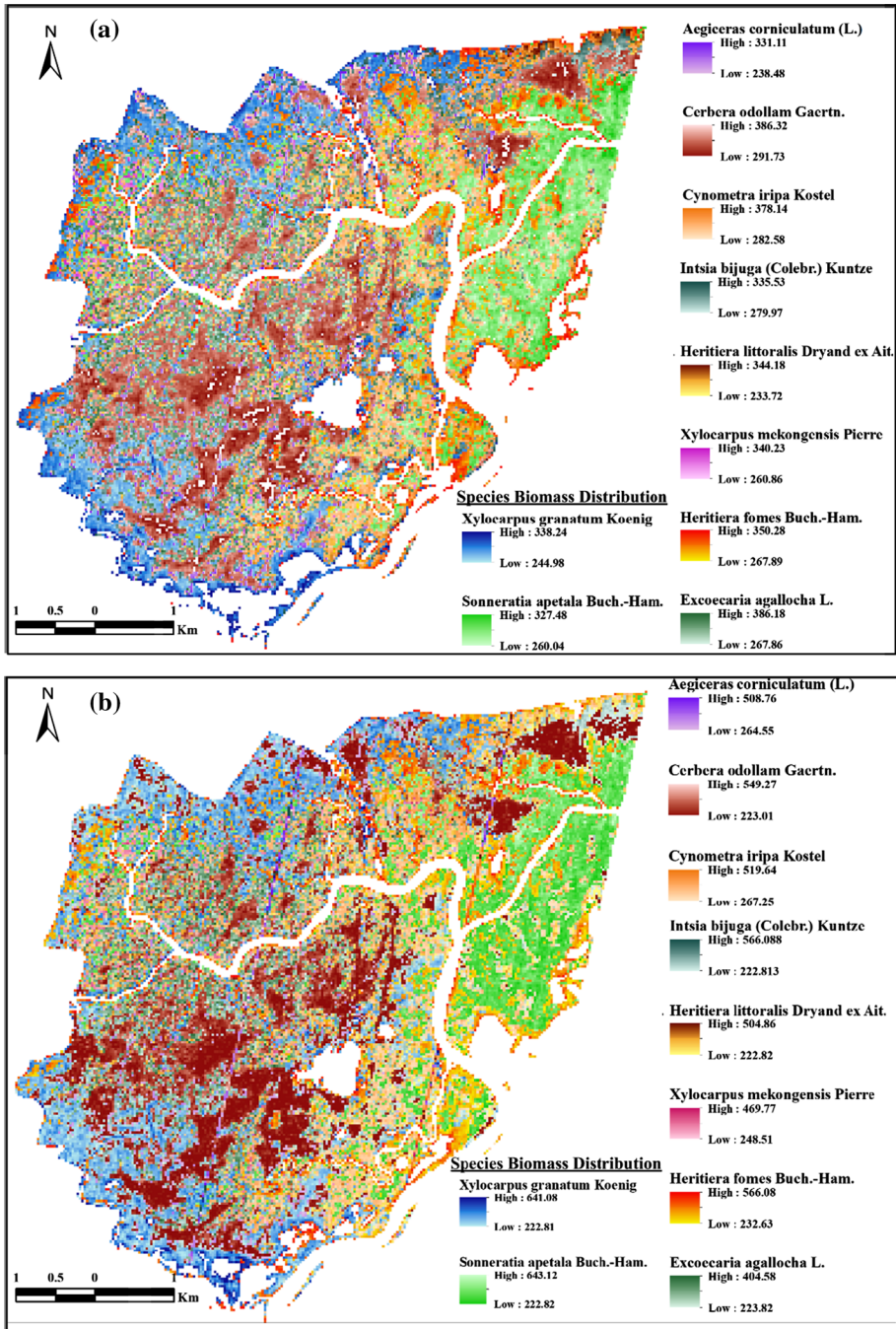
The linear regression model between observed biomass and EVI generated an equation  $y = 2801.9x - 1420.3$  with  $R^2$  of 0.823 at  $p < 0.05$ , where,  $y$  = observed biomass, and  $x$  is the EVI. Similarly, NDVI linear regression model with observed biomass provided an equation  $y = 1608.4x - 562.79$  with  $R^2$  of 0.839 at  $p < 0.05$ , where,  $x'$  is the NDVI value. The Logarithmic model between estimated biomass and EVI generated an equation  $y = 847.14 \ln(x) + 829.6$  with  $R^2$  of 0.846 at  $p < 0.05$ . While for NDVI, the equation obtained as  $y = 1688.9 \ln(x') + 1124.4$  with  $R^2 = 0.819$  at  $p < 0.05$ . The polynomial (second degree) regression model between observed biomass and EVI generated an equation



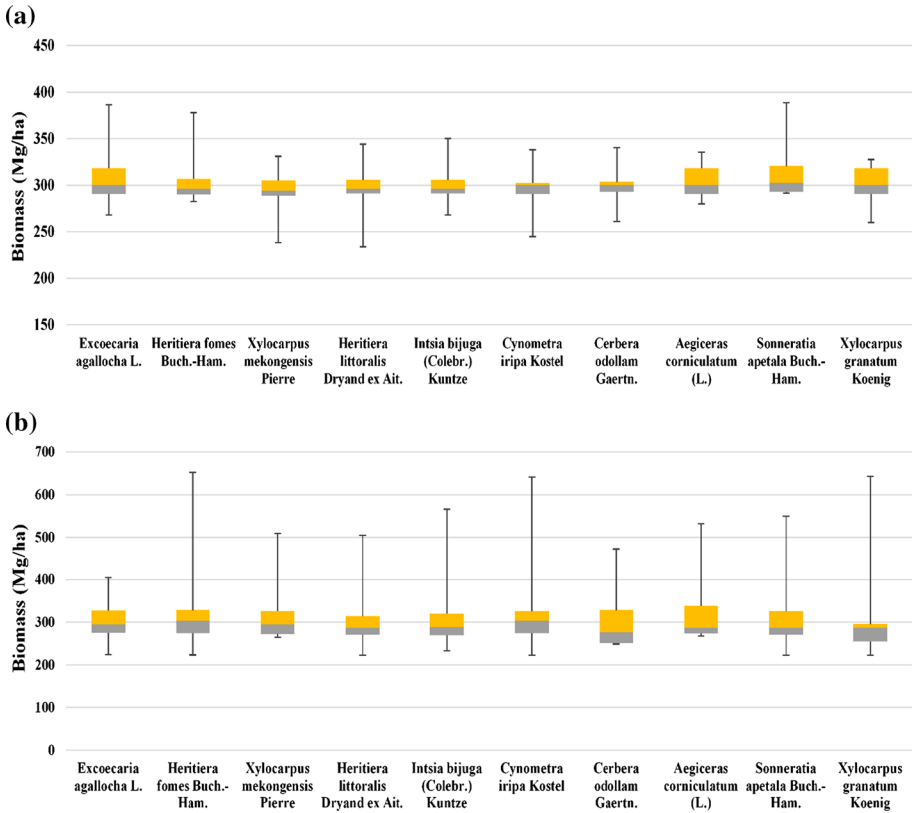
**Fig. 4** Estimated biomass spatial distribution of Bhitarkanika forest reserve for **a** linear biomass, **b** logarithmic, **c** polynomial (second degree) relationship derived from NDVI while **d** linear biomass, **e** logarithmic, **f** polynomial relationship derived from EVI vegetation indices respectively

$y = -8584.7x^2 + 10643x - 2928.5$  with  $R^2 = 0.861$  at  $p < 0.05$ , while for NDVI the equation obtained as  $y = 19163x^2 - 20376x + 5580.8$  with  $R^2 = 0.838$  at  $p < 0.05$ .

The estimated biomass and observed biomass is compared with each other and a scatter plot is generated. Approx. 2/3rd of the field values is utilized during biomass assessment.



**Fig. 5** Species wise estimated biomass distribution ( $Mg\ ha^{-1}$ ) of Bhitarkanika forest reserve **a** biomass derived from NDVI and **b** biomass derived from EVI



**Fig. 6** Box Plot of Species wise biomass distribution derived from **a** NDVI and **b** EVI vegetation indices. Middle line represent median of the data, the interquartile range box represents the middle 50% of the data. The whiskers represent the ranges for the bottom 25% (lower whiskers) and the top 25% (upper whiskers) of the data values, excluding outliers

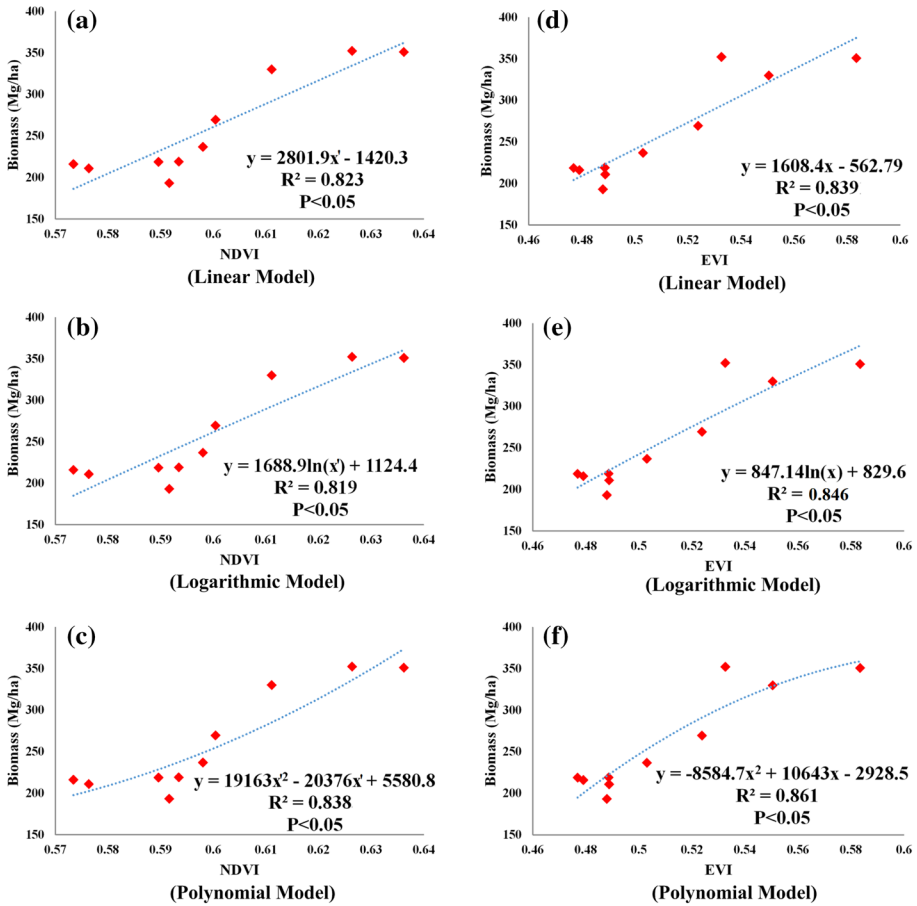
The validation of the biomass assessment using vegetation indices derived results was performed in order to check the results accuracy. The validation results showed a good  $R^2$  of 0.84 with EVI and 0.81 with NDVI derived biomass at significance level of  $p < 0.05$ . The results also illustrate a good correlation between estimated and measured biomass over a time period. EVI provided a consistent values while NDVI has varying values, thus EVI is more sensitive to the biomass estimation and more dependent vegetation indices as compared to NDVI, whose value varies with the regression models.

The spatial distribution of NDVI shows a good proportion of area is under dense coverage of the plant species, NDVI values ranging from 0.50 to 0.65 is also noticed, which reflects the distribution of dense, healthy mangrove forest in homogenous condition. Similarly using the other vegetation parameter i.e. EVI we have noticed values ranges from 0.35 to 6.9 illustrating the even nature of the vegetation and more sensitive to plant parameters, avoiding the soil background and atmospheric effects. Middle parts of the study site are having higher EVI and NDVI values, which indicates that EVI and NDVI are correlated with  $R^2 = 0.73$ . The highest values were confined to the middle part, upper part northern part and above southern part of the study site. These high value EVI and NDVI sites also

**Table 4** Descriptions of biomass species-wise biomass derived from EVI and NDVI in Bhitarkamika forest reserve

Species name	Area (km <sup>2</sup> )	EVI derived biomass				NDVI derived biomass			
		Min biomass (species wise) (Mg ha <sup>-1</sup> )	Maximum biomass (Mg ha <sup>-1</sup> )	Average biomass (Mg ha <sup>-1</sup> )	SD	Min biomass (Species wise) (Mg ha <sup>-1</sup> )	Maximum biomass (Mg ha <sup>-1</sup> )	Average biomass (Mg ha <sup>-1</sup> )	SD
1 <i>Excoecaria agallocha</i>	3.80	223.82	404.58	279.01	29.13	267.86	386.18	323.79	19.67
2 <i>Cynometra iripa</i> Kostel	3.77	223.10	652.14	395.80	87.24	282.58	378.14	322.21	12.52
3 <i>Aegiceras corniculatum</i>	0.96	264.55	508.76	351.60	40.13	238.48	331.11	283.28	15.015
4 <i>Heritiera littoralis</i> Dryand ex Ait.	2.07	222.82	504.86	286.14	36.84	233.72	344.18	270.79	15.731
5 <i>Heritiera fomes</i> Buch.-Ham.	4.21	232.63	566.08	267.35	37.44	267.89	350.28	306.96	10.58
6 <i>Xylocarpus granatum</i> Koenig	6.41	222.81	641.08	303.63	44.25	244.98	338.24	290.19	13.746
7 <i>Xylocarpus mekongensis</i> Pierre	0.48	248.51	469.77	247.64	25.08	260.86	340.23	296.34	11.73
8 <i>Intsia bijuga</i> (Colebr.) Kuntze	1.66	267.25	519.64	273.65	49.23	279.97	335.53	304.63	9.89
9 <i>Cerbera odollam</i> Gaertn.	8.34	223.01	549.27	328.12	51.84	291.73	386.32	346.22	19.103
10 <i>Sonneratia apetala</i> Buch.-Ham.	4.72	222.82	643.12	325.71	60.74	260.04	327.48	291.79	8.826
Total area	36.42								





**Fig. 7** Relationship between vegetation indices and estimated biomass (Mg ha<sup>-1</sup>) **a–c** for linear, logarithmic and polynomial (second degree) based models derived from EVI and **d–f** for linear, logarithmic and polynomial (second degree) based models derived from NDVI

have high biomass ranging from 327.48 to 652.14 Mg ha<sup>-1</sup>. Middle part of the study site has coverage of high value biomass (> than 450 Mg ha<sup>-1</sup>) is assigned to the fact that this regions are dense with closed canopy vegetation and strongly correlated with forest age pertaining to mature trees.

### Conclusion

Our analysis results demonstrate that the geospatial analysis along with field inventory approach is effective for the biomass estimation of tropical mangrove forest based on vegetation indices derived from high spectral resolution data. The study concluded that the NDVI and EVI vegetation indices are useful for estimating biomass with field measured data and thus can be useful for forest monitoring and management. In this study, accurate estimation of forest biomass has been attempted and validated against the actual

measured forest biomass. This study also proposed different allometric models to estimate forest biomass of the Bhitarkanika Forest, which indicates strong and positive correlations between the estimated and observed biomass, along with the species spatial distribution mapping and their biomass assessment.

Future work at this site may include carbon stock estimation; monitoring, habitat characterization, and water quality monitoring at a given time or over a continuous period and mangrove forest degradation assessment, as the theme revolve around the plant species. The results obtained can be utilized by the forest department for wide range of functions in sustainable management of the wetlands vegetation. Therefore, species spatial distribution and biomass estimation results are of great assistance for improving our knowledge and understanding the complex dynamics of mangrove forests. Moreover, it is essential for forest management to have updated information of the plant species present in the mangrove forest in order to protect plant species and provide restoration facilities.

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## Compliance with ethical standards

**Conflicts of interest** No potential conflict of interest was reported by the authors.

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