Coastal Ecosystem Monitoring Using Long-Term Satellite Data Records: A case study of Chilika Lake, Odisha

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Abstract

Changing trend in coastal ecosystem can be quantified by performing time series analysis. Time series analysis performed using long term remote sensing data will help us to identify the dynamic changes happening in the coastal ecosystem and its surrounding regions. In the present study we performed time series analysis on northern sector of Chilika Lake and its nearby regions of Odisha, which is situated in the east coast of India using three decades of freely available Landsat archive data. In order to detect dynamic changes trend parameters were calculated by using available data sets from Landsat Thematic Mapper (TM) and Operational Land Imager and Thermal Infrared Sensor (OLI/TIRS) for the observation period from 1988 to 2017. Two multi-spectral indices i.e. NDVI and EVI were generated from the available data sets and the trend analyses were performed using Theil-Sen (T-S) regression method by identifying robust trend parameters (slope and pvalue). The average mean values for NDVI and EVI were recorded at 0.4 and 0.2. Significant positive trend was observed in both vegetation indices (NDVI and EVI) with a mean slope value of 0.004 and 0.003 and pvalue of 0.03 and 0.02 respectively.

Introduction

Coasts are dynamic in nature and contain various geomorphic features which keep changing over seasonal, annual and multi-decadal timescales (Cowell and Thom, 1994; Splinter *et al.*, 2013).

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Coastal ecosystems are undergoing rapid changes due to development activities and increasing population (Halpern, B. S. *et al*., 2008; He, Q. *et al*., 2014). Natural disturbance such as climate warming poses a major threat to these ecosystems by causing erosion, loss of biodiversity and overall sustainability of these ecosystems (Harley, C. D. *et al.*, 2006; Sara, G. *et al.*, 2014). Increasing population and technology advancement leads to disturbance of the coastal ecosystems and exploitation of coastal resources. Remote sensing provides a comprehensive way to monitor these coastal ecosystems and natural processes by providing large scale data on surface conditions that reveal the dynamic variation and allow detection and forecasting of trends (Ozesmi, S. L. *et al*., 2002; Lin, Q., 2012).

For better understandings the fate of these ecosystems over the last several decades, satellite program such as Landsat provides a long-term data archive (Cohen *et al.*, 2004; Wulder, M.A *et al.*, 2012). Landsat program was launched in 1972 with Multi Spectral Scanner (MSS) followed by Landsat Thematic Mapper (TM) in 1982, Landsat Enhanced Thematic Mapper Plus (ETM+) in 1999 and Landsat Operational Land Imager and Thermal Infrared Sensor (OLI/TIRS) in 2013. The spatial resolution available for TM, ETM+ and OLI are at 30m and for MSS at 60m. The Landsat sensor has a temporal coverage of every 16 days. The Landsat (MSS) has four spectral bands, Landsat (TM) with seven spectral bands, Landsat (ETM+) having six spectral bands, one thermal band and one panchromatic, while the Landsat 8 (OLI/TIRS) consist of eight spectral bands, one panchromatic and two thermal infrared bands.

Vegetation indices (NDVI and EVI) represent the Greenness activity of plant. These indices are widely used to monitor the surface vegetation for entire earth (http://profhorn.meteor.wisc.edu). NDVI is often used due to its 'ratio' properties which enable to eliminate the noise such as (topography, sun angle and clouds) present in the data (Matsushita B. *et al.*, 2007). EVI is considered as a modified NDVI due to its improved sensitivity towards higher biomass region and reduction in atmosphere influences (Huete A.R. and Justice C., 1999). Typical NDVI and EVI values ranges between -1 to +1, negative values represents snow and water while the positive values for NDVI represents vegetated areas and soil, with classified ranges for; sparse vegetation from 0.2 to 0.5 which is considered as moderate vegetation, from 0.6 and above are considered as dense vegetation while in EVI healthy vegetation falls between 0.2 to 0.8.

The time series analysis technique with temporal data can be used to perform seasonal and annual variations. This type of analysis provides a benefit in various fields such as land use/land cover change, agriculture, forest management, ecosystem changes and water management (Muttitanon W., 2004). To perform such analysis in remote sensing based studies, we require high spatial and temporal resolution satellite data such as Landsat (TM, ETM+ and OLI) at 30m spatial resolution and provides 16 days temporal resolution, which is provided by USGS at free of cost and it can be quite useful in performing time series analysis to identify seasonal and annual trends over decades. However Landsat is as an optical sensor and presence of cloud can profoundly affect the quality of data and time series analysis performed using this data. For detecting the seasonal response of vegetation, both NDVI and EVI time series are considered as efficient data products (Wardlow *et al.*, 2007), while for the short term interannual variability; Seasonal Trend Analysis (STA) proved to be robust technique and it is also very effective for long-term trends to identifying the gradual and abrupt changes (S. Eckert *et al.*, 2015). Lin, Q. (2012) performed times series analysis using MODIS derived product enhanced vegetation index (EVI) by using linear regression trend analysis method and maximum value method. Leon *et al.* (2012) examined the post-fire vegetation response by using the interannual trends in the NDVI time series data which is derived from the MODIS.

This study aims to monitor and understand the coastal ecosystem dynamics by performing trend analysis on 30m Landsat derived vegetation indices (NDVI and EVI). Here we presented multi-temporal analysis of Landsat based ecosystem monitoring for the northern sector of Chilika Lake and its nearby region, for the 1988 to 2017 period. We calculated the robust linear trend on vegetation indices [NDVI and EVI] to understand the dynamics of vegetation in Chilika Lake and its surrounding regions.

Study Area

Study Area

Chilika lagoon is the Asia largest brackish water lagoon. Our study area focuses on northern sector of Chilika Lake situated on east coast of India in the state of Odisha (Fig. 1). The study area experiences the southwest and northeast monsoon in May to August and November to December respectively. Chilika Lake is divided into four zones which are southern zone, northern zone, central zone and outer channel (Mohanty S. *et al.*, 2015). The lagoon is under constant pressure from both the natural and anthropogenic activities such as siltation, infestation and degradation in salinity which results in loss of productivity and biodiversity.

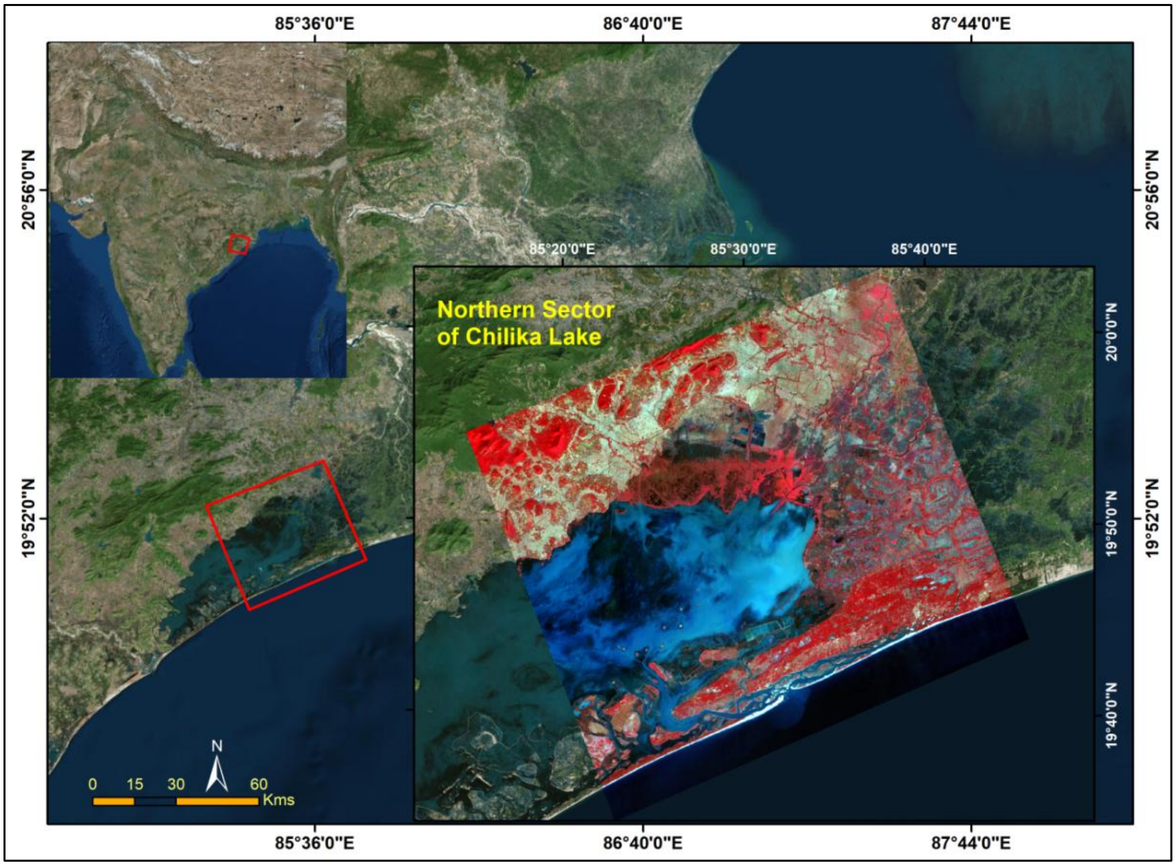

Figure 1 Location map of study area

Materials & Methods

Data

The 30 m spatial resolution Landsat Thematic Mapper (TM) and Operational Land Imager and Thermal Infrared Sensor (OLI/TIRS) data were downloaded from the USGS via Earth Explorer (https://earthexplorer.usgs.gov) for the period of 1988 – 2017. The acquired data are radio-metrically and geometrically terrain-corrected (Processing Level L1TP). The common spectral bands such as (blue, green, red, near-infrared/NIR, shortwave infrared 1 and 2 /SWIR1 and SWIR 2) were used for analysis while the remaining bands were excluded from processing. Total Landsat scenes observed for the study region is 240. All the available scenes were downloaded from 1988 to 2017. The time span taken for the study region is 29 years. List of data and bands used in this study are listed in *Table 1*.

Table 1 Details of bands used for the study

Landsat 4-5 (TM)			Landsat 8 (OLI/TIRS)		
Bands	**Wavelength (µm)**	**Res. (m)**	**Bands**	**Wavelength (µm)**	**Res. (m)**
1-Blue	0.45-0.52	30	1- Ultra blue	0.435-0.451	30
2-Green	0.52-0.60	30	2-Blue	0.452-0.512	30
3-Red	0.63-0.69	30	3- Green	0.533-0.590	30
4-NIR	0.76-0.90	30	4-Red	0.636-0.673	30
5-SWIR1	1.55-1.75	30	5-NIR	0.851-0.879	30
6-Thermal	10.40-12.50	120*(30)	6-SWIR1	1.566-1.651	30
7-SWIR2	2.08-2.35	30	7-SWIR2	2.107-2.294	30

(NIR = Near Infrared; SWIR = Short-wave Infrared).

Methods

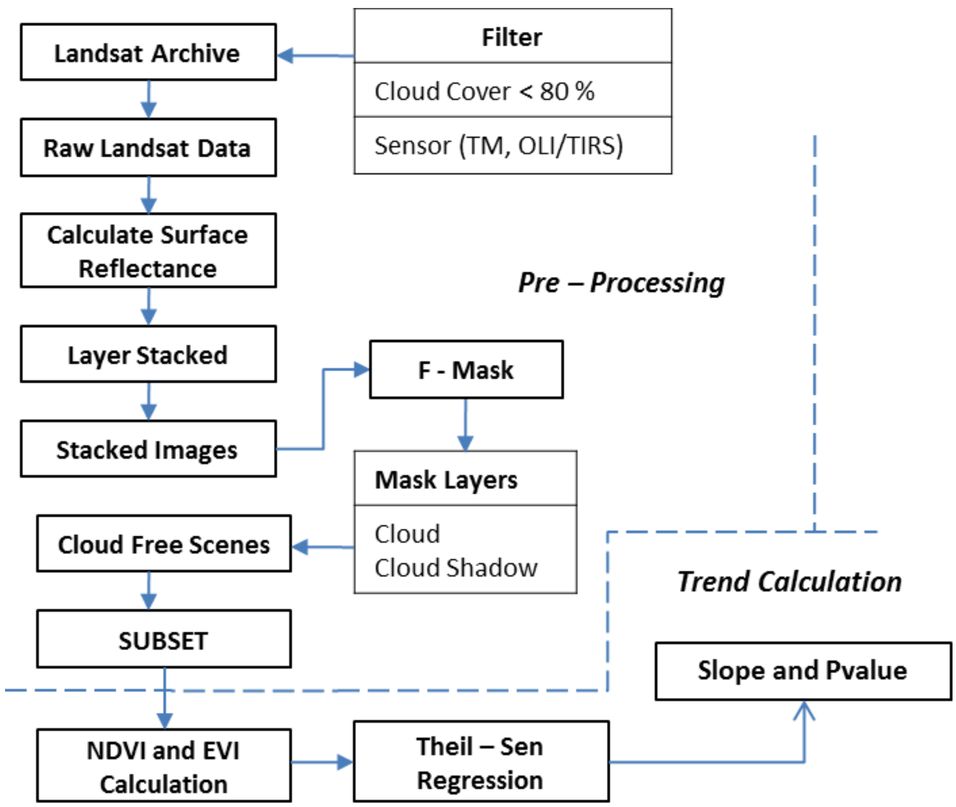

Figure 2 Landsat data processing workflow

The data processing workflow shown in (Fig. 2) depicting the process starting from data download to the final product generation. The flow chart is divided into two parts; first part consists of all the pre-processing activities such as conversion of raw DN values to surface reflectance, layer stacking, cloud masking and subset, while in second part we calculate vegetation indices and performed trend analysis on them using Theil – Sen (T-S) slope regression method.

Pre-Processing

Landsat archive data downloaded from the USGS Earth explorer and pre-processed it by using Semi-Automatic Classification plug-in (SCP) in QGIS software. SCP is a free opens source plugin developed by (Congedo Luca, 2016), which allows the user to perform pre-processing, post processing, raster calculations, supervised and unsupervised classifications of remote sensing images. It also facilitate to download remote sensing data at free of cost such as (Landsat, MODIS, Sentinel-2, Sentinel-3, ASTER). The SCP plug-in takes Metadata file of Landsat as input which contains required information for the conversion of raw DN values to surface reflectance values. The first process performed by SCP is conversion of raw DN values of individual bands to radiance values by using 'Equation (1)'.

$$L_{\lambda} = M_L * Q_{cal} + A_L \quad (1)$$

Where M_L and A_L are the multiplicative rescaling and additive rescaling factor from the Landsat metadata, Q_{cal} is the quantised and calibrated pixel values (DN). The next process performed by SCP Plugin is conversion of radiance value to Top of Atmosphere (TOA) reflectance which is calculated by 'Equation (2)'.

$$\rho_p = (\pi * L_{\lambda} * d^2) / (ESUN_{\lambda} * \cos\theta_s) \quad (2)$$

Where L_{λ} is the spectral radiance at the sensors aperture, d is the Earth-Sun distance, $ESUN_{\lambda}$ is the mean solar exo-atmospheric irradiances, and θ_s is the solar zenith angle in degrees.

The TOA reflectance was converted to surface reflectance with Dark Object Subtraction (DOS1) correction technique. DOS is an image based atmospheric correction method which rectifies the image containing pixels which are completely covered by the shadow and radiance received by the satellite due to atmospheric scattering. The path radiance was calculated by the 'Equation (3)'.

$$L_p = L_{min} - L_{DO1\%} \quad (3)$$

Where L_{min} is the radiance that corresponds to a digital count value, $L_{DO1\%}$ is the radiance of dark object. Finally the surface reflectance was calculated by using the ‘Equation (4)’.

$$\rho = [\pi * (L_\lambda - L_P) * d^2] / [T_v * ((ESUN_\lambda * \cos\theta_s * T_z) + E_{down})] \quad (4)$$

Where L_p is the path radiance, T_v is the atmospheric transmittance in the viewing direction, T_z is the atmospheric transmittance in the illumination direction and E_{down} is the down welling diffuse irradiance. Processed individual bands were layer stacked and cloud masking technique was performed on these images.

Cloud Removal

The open source cloud masking (Fmask) plugin tool developed by (Zhu & Woodcock, 2012) was successfully applied on each stacked image with its standard settings. This algorithm detects cloud, cloud shadow and snow/ice in Landsat scenes. Fmask separates Potential Cloud Pixel (PCPs) and Clear Sky Pixels based on the cloud physical properties and removes all non-valid data from the scenes i.e. Cloud, Shadow, and No Data (Fig. 3).

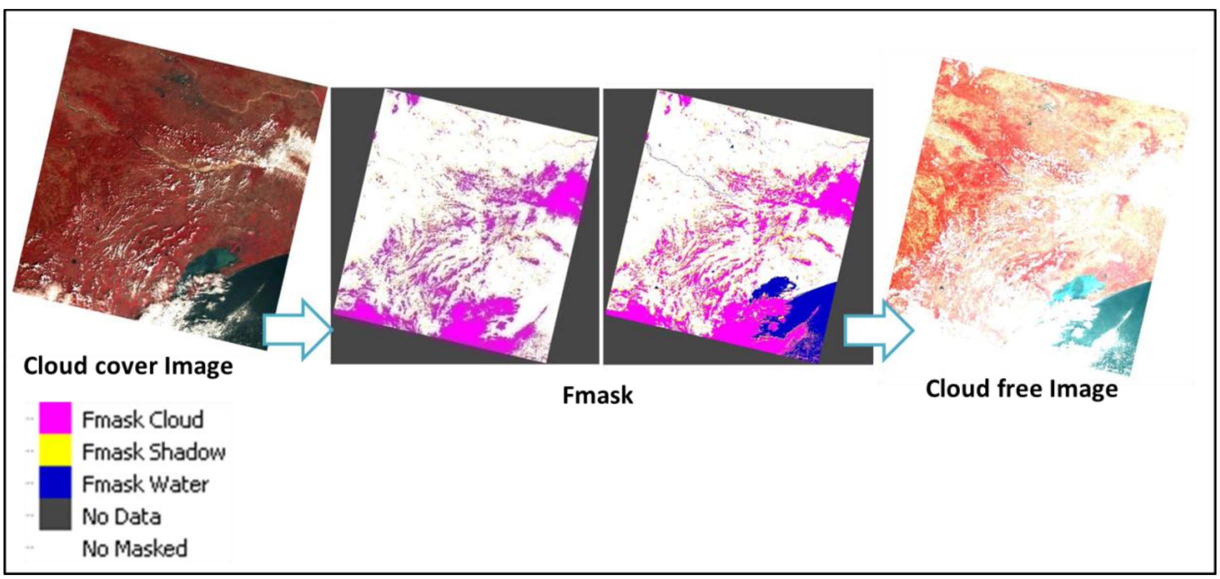

Figure 3 Overview of Fmask process

Index Calculation

Landsat TM and OLI/TIRS data are having different spatial extent, to achieve common spatial extent we created an area of interest (AOI) boundary for study region and all the data sets were subset to that boundary. Using the subset data we calculated vegetation indices NDVI and EVI. NDVI was calculated from Landsat surface reflectance band: near infrared band and red band and it is defined by 'Equation (5)'. EVI was calculated from Landsat surface reflectance of red, near infrared and blue band and it is defined by 'Equation (6)'.

$$\mathrm{NDVI} = \frac{\mathrm{NIR}-\mathrm{RED}}{\mathrm{NIR}+\mathrm{RED}} \tag{5}$$

Where NIR and RED is the spectral reflectance measurements acquired on the red and near infrared regions.

$$\mathrm{EVI} = \mathrm{G} * \frac{\mathrm{NIR}-\mathrm{RED}}{\mathrm{NIR}+(\mathrm{C1}*\mathrm{RED})-(\mathrm{C2}*\mathrm{BLUE})+\mathrm{L}} \tag{6}$$

Where *NIR, RED* and *BLUE* are reflectance in the near infrared, red and blue band respectively, *L* is the canopy background, *C1 & C2* are the coefficient of the aerosol resistance, and *G* is the gain factor.

Theil – Sen Regression Method

Theil-Sen method is a robust non-parametric statistical operator which is used to analyse trends (Osunmadewa B.A., 2014) and it is determined by calculating paired slopes, from every point in time to each other (Nitze, I., & Grosse, G., 2016). Remote sensing application such as estimation of leaf area, water quality and long term wind trend of wind speed and occurrence can be identified by using T-S regression method. O. Dubovyk *et al.* (2015) calculated the trends on EVI time series data using T-S estimator and the Mann-Kendall (MK) test.

In final process all datasets were stacked to make a one temporal image and trend were calculated for each multi-spectral index in the temporal domain by using robust Theil-Sen (T-S) regression method (Sen, 1968; Theil, 1992). The T-S regression method was applied on these spectral indices to calculate trend parameters such as *slope* and *pvalue*. T-S calculation was carried out in R Studio v 1.0.153 software followed by using *'trend'* package to get the trend statistics.

Results

Vegetation/greening

The Chilika region exhibits a moderate vegetation trend which can be seen in both the vegetation indices NDVI and EVI (Fig. 4). Annual mean NDVI and EVI value ranged between 0.2 and 0.87 with an average mean value of 0.4 and 0.2. Greening hotspot changes was observed in the northern sector of Chilika Lake which is the most active region and strongly influenced by infestation such as *Fragmites Karka* and water hyacinth.

J.Y. Kim *et al.* (2015) identified that the centre of lagoon consist of minimum NDVI values which can be due to siltation, while the maximum NDVI values was observed in the northern part of lagoon which may be due to presence of weeds. The satellite derived products will help us in quantifying the ecosystem changes which are happening due to the natural disturbances and artificial alterations (Goetz *et al.*, 2006; Goodin and Henebry, 1997).

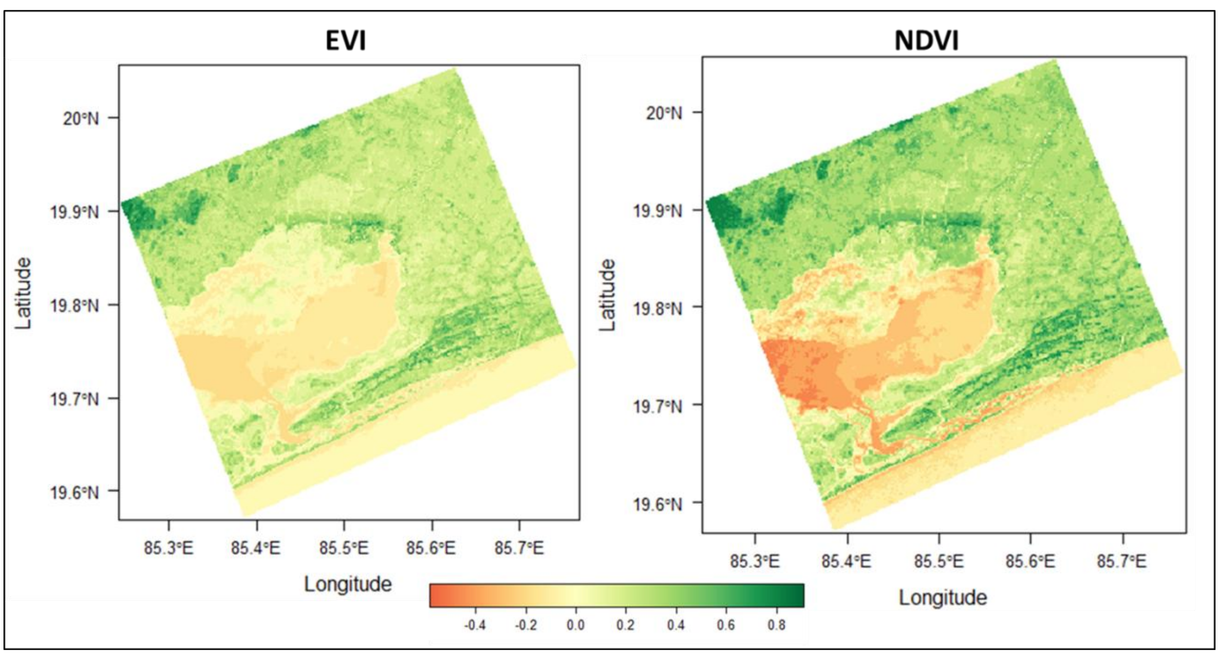

Figure 4 Annual composite of vegetation indices from 1988-2017.

Trend Analysis

Trend analysis refers to rate of change in times series analysis and results are often similar to ordinary linear regression which was used for long term series analysis (Osunmadewa B.A. *et. al.*, 2014). We calculated vegetation indices (NDVI and EVI) for the each temporal image and T-S regression method was applied on these indices and statistics were calculated to identify trend parameters (*slope* and *pvalue*) which are shown in *Table 2*. The mean slope values were estimated by performing T-S regression method and the final output was written in raster format. Trend slope maps were generated for both multi-spectral indices which are shown in (Fig. 5). Graph show in (Fig. 6) depicts temporal trend of annual mean NDVI and EVI composites and we observed a gradual increase in vegetation trend from 1988 to 2017.

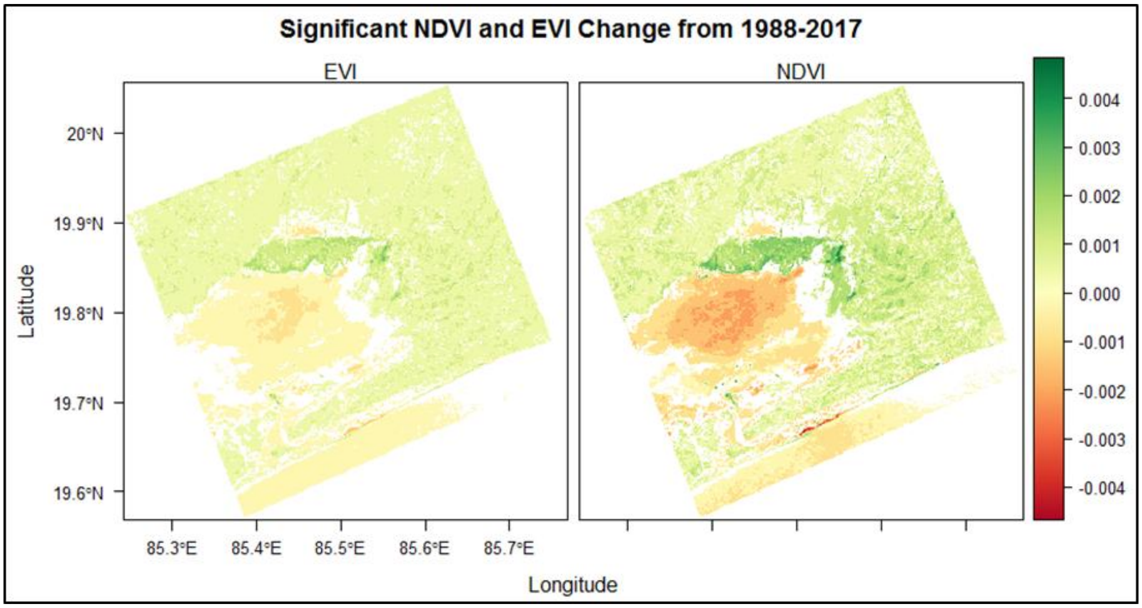

Figure 5 Significant NDVI and EVI change from 1988-2017

Table 2 Statistics of trend (slope and pvalue)

Index	Slope mean	P Value
NDVI	0.004	0.03
EVI	0.003	0.02

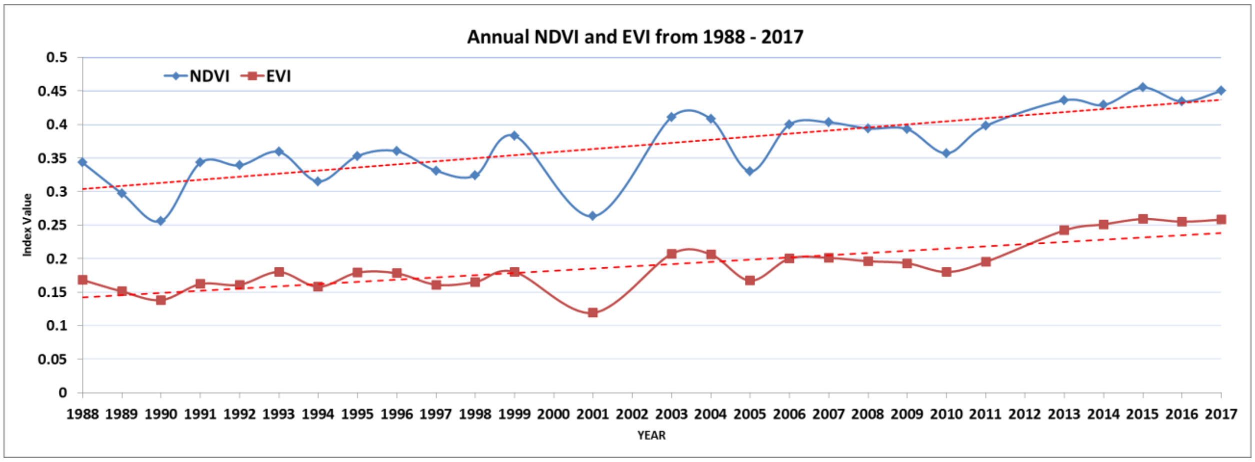

Figure 6 Graph depicting the temporal profile of multispectral indices with trend line

Local Changes

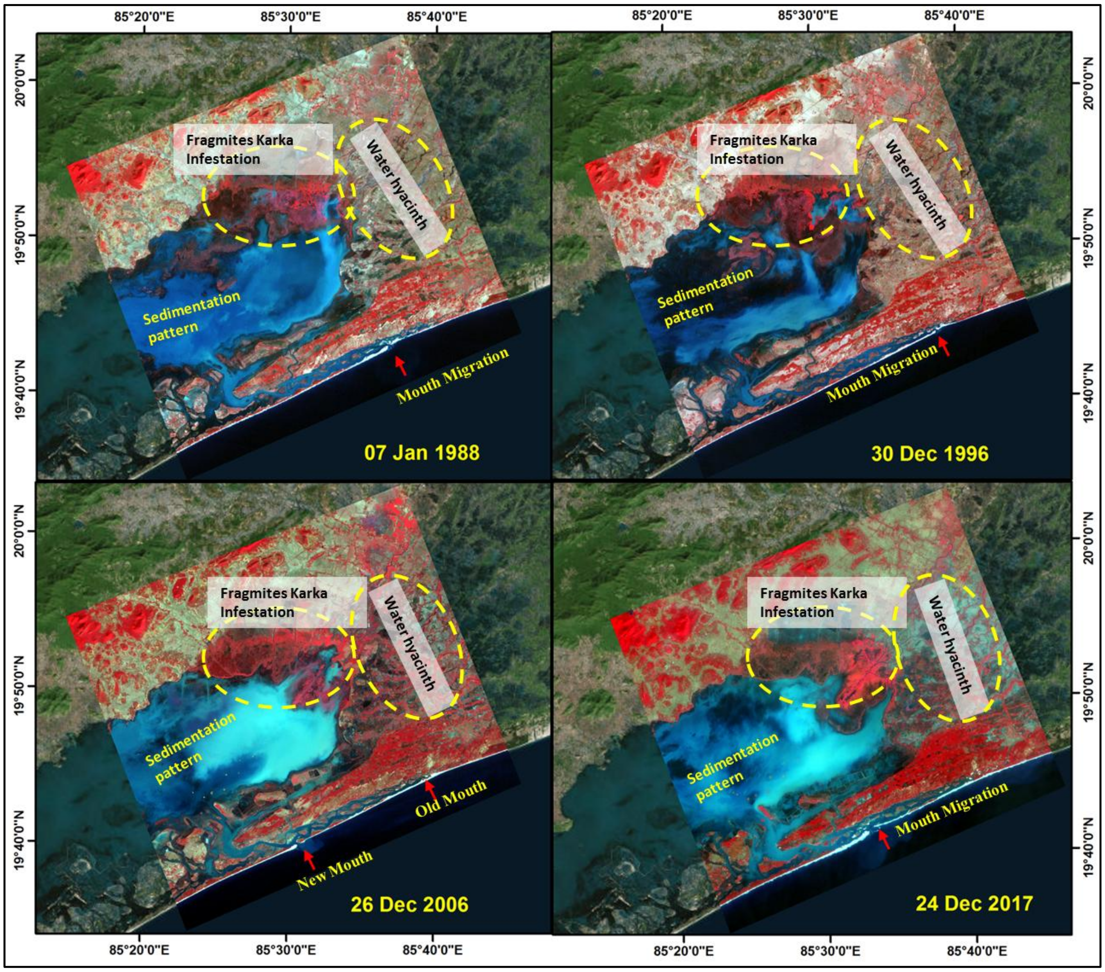

Figure 7 False colour RGB composite of Landsat image overlaid on base map depicts changes over the northern part of Chilika Lake

Chilika lagoon has change significantly in the past four and half decades due to constant pressure of natural and anthropogenic activities. These changes can be seen visually on the images shown in (Fig. 7). The lagoon is highly infected with *Fragmites Karka* which is deposited on northern part of lagoon and water hyacinth, marked with dotted circle in the images. The old mouth of Chilika Lake became inactive due to natural siltation, which can affect sea water exchange, so in year 2000 Chilika development Authority (CDA) created a new mouth in the outer channel by dredging the sand bar. The restoration of new mouth leads to increase of Lake Fish and a reduction of freshwater weeds, but after restoration of mouth in year 2000 the salinity level was increased in Chilika lagoon (J.Y. Kim *et al.*, 2015).

Discussion

Time series analysis performed using Landsat archive data can reveal an abrupt and gradual changes happening in the coastal ecosystem by performing a multi-temporal trend analysis. From satellite observations we can identify the changing trend in ecosystem productivity (Forkel, Matthias, *et al.*, 2013) by generating the Normalised Difference Vegetation Index (NDVI). The transformation of vegetation or crop land into dry land can be considered as gradual changes and during this period we can observe a slight decline in trends. The abrupt changes in the vegetation trends can be seen due to cyclones, forest fire or urbanisation in the particular area.

Trend slope can be classified into different classes, for example: slope values (> 0): considered as significantly increasing in the vegetation trend, slope values (< 0): considered as slight decrease or significantly decreasing trend (Lin, Q., 2012). Forkel, Matthias, *et al.*, (2013) classified significant trend slope into six different trend classes, if: (slope < 0 and $p \leq 0.05$): significant negative trend; (slope < 0 and $0.05 < p \leq 0.1$): non-significant negative trend; (slope < 0 and $p > 0.1$): no trend with negative tendency; (slope > 0 and $p > 0.1$): no trend with positive tendency; (slope > 0 and $0.05 < p \leq 0.1$): non-significant positive trend; (slope > 0 and $p \leq 0.05$): significant positive trend. J.Y. Kim *et al.*(2015) conducted study on Chilika Lake, which reveals that average greenness rate of change (GRC) for the entire lagoon was -0.057 indicating overall gradually decreasing NDVI trend from (1998 – 2014). The NDVI over the lagoon can be decreased due to the higher salinity present in the lagoon (Pattanaik, A.K., 2007). Goswami *et al.*, (2017) recently carried out a land use and land cover study on Chilika Lake and its surrounding regions by using Landsat time series data from 1988 to 2017 and they observed some changes such as decrease in area of barren ground, grass and water while there is increase in area of shrubs and forest.

We conducted our study on northern sector of Chilika Lake and its surroundings regions to identify vegetation trend and some hotspot changes which are happening for past four and half decades. Trend analyses performed using long term satellite data will be useful for detecting these dynamic changes. All the available Landsat data were downloaded and processed for year 1988 to 2017. Vegetation indices (NDVI & EVI) were calculated from the available datasets and performed trend analysis. Annual mean NDVI and EVI value ranged between 0.2 and 0.8 with an average mean value of 0.4 and 0.2. The trend analysis of dense Landsat time-series has potential to reveal a sudden and gradual changes happening in the coastal ecosystem. Positive trend indicates '*greening*' and negative trend indicates '*browning*'. Our results shows the positive trend for both the vegetation indices which indicates that there is a greening trend. The trend slope for NDVI and EVI ranged from -0.043 to 0.070 and -0.016 to 0.029 respectively. Mean slope value of 0.004 and 0.003 and pvlaue of 0.03 and 0.02 recorded for both the indices which indicate the significant positive trend ($slope > 0$ and $p < 0.05$).

We observed some local changes in Chilika lagoon such as migration of mouth, weed infestation, water hyacinth and sediment transport pattern which can be seen clearly in satellite images (Fig. 7). Satellite image acquired on Dec 1988 shows that huge weed formation in northern part of the lake and presence of these weeds will reflect the NDVI and EVI values, similarly image acquired on Dec 2017 shows that floating weed is cleaned up. The migration and formation of new mouth can be seen clearly on satellite image, old mouth became inactive due to siltation which affects the flow of water into the lagoon. In September 2000 Chilika Development Authority (CDA) created a new mouth by dredging the sand bar at the distance of 13km from the old mouth.

Conclusions

In this study we performed a trend analysis by using 29-years records of Landsat data, which can be effectively used for monitoring the dynamic changes happening in the coastal ecosystem. The robust trend of multi-spectral indices (NDVI and EVI) reveals the positive i.e. greening trend over the northern sector of Chilika Lake. We identified some dynamic changes over the study region which was analysed by taking temporal images. With 30m spatial resolution and 16 days temporal resolution, Landsat data can be quite useful for performing time series analysis to detect seasonal and annual trends over decades.

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