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THREE-DECADE ASSESSMENT OF VEGETATION, WATER, AND BUILT-UP AREA DYNAMICS IN KHORDHA DISTRICT USING REMOTE SENSING

Shrabani Moharana and Bama Shankar Rath

Department of Agronomy, Odisha University of Agriculture and Technology, Bhubaneswar-751 003, India

ABSTRACT

The increasing significance of remote sensing and Geographic Information Systems (GIS) can be attributed to their extensive applicability across various domains, including urban planning, natural resource management, environmental monitoring, land use change assessment, disaster forecasting, and management. This paper presents a comprehensive evaluation of the evolving patterns of land use in Khordha District, Odisha, over a 30-year period from 1990 to 2020, focusing on key features such as vegetation, water resources, and built-up areas through the application of geospatial technologies. Satellite imagery from the Landsat 8 series was analyzed, employing various spectral indices calculated using ArcGIS 10.8.2 software. The indices—specifically the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and Enhanced Built-up and Bareness Index (EBBI)—were generated from the corresponding satellite images, followed by correlation analysis to understand the relationships among different land use categories. This study serves as a critical resource for planners and decision-makers, facilitating informed and sustainable resource management practices aimed at mitigating the over-exploitation of soil, water, and other natural resources in Khordha District. The findings highlight the importance of integrating remote sensing and GIS methodologies in land use planning and environmental conservation strategies.

Key words: EBBI, NDVI, NDWI, Remote sensing and GIS

Remote sensing and Geographic Information Systems (GIS) have emerged as robust tools for evaluating spatial and multi-temporal changes in land use patterns, with applications spanning from small-scale farms to regional and national levels. The advancement of hyperspectral and multispectral optical sensors has enhanced the geospatial capabilities for the identification and classification of land features, resource monitoring and management, and urban area mapping. These technologies facilitate informed decision-making processes. The Normalized Difference Vegetation Index (NDVI) is one of the most widely utilized and accessible vegetation indices derived from remote sensing data. It serves as an effective measure of plant functional status and correlates with photosynthetic activity, humidity levels, and the distribution of both vegetative and non-vegetative areas (Xue and Baofeng, 2017; Koskinen *et al*., 2019). NDVI provides insights into vegetation growth, spatial distribution, and the overall health of biomass. As a quick, efficient, and reliable tool, NDVI enables the delineation of vegetated from non-vegetated areas. For instance, NDVI differencing was employed to detect changes in vegetation cover using INSAT imagery in the Vellore district of Tamil Nadu (Gandhi *et al.*, 2015). Various NDVI threshold values (0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4, and 0.5) were utilized to analyze vegetation characteristics. Simulation results demonstrated the effectiveness of NDVI in identifying surface features within visible areas, providing valuable insights for policymakers. Moreover, vegetation analysis not only aids in damage assessment and humanitarian relief but can also be instrumental in predicting adverse natural disasters and developing innovative preventive measures.

Numerous studies have documented the application of NDVI in various contexts, including drought monitoring (Kim *et al.*, 2008; Yamaguchi *et al.*, 2010), crop cover assessment (El-Shikha *et al.*, 2007), and vegetation monitoring (Yang *et al.*, 2010; Lan *et al.*, 2009), as well as agricultural drought assessments at both national (Demirel *et al.,* 2010; Zhang *et al.*, 2009) and international levels (Smith and Longley, 2015). The Normalized Difference Water Index (NDWI) is another critical tool that indicates the presence of surface water bodies in satellite imagery. Satellite remote sensing offers a timely and cost-effective means of monitoring water resources, providing accurate data on water bodies (Liu *et al.*, 2016; Karaman *et al.*, 2018; Kale and Acarli, 2019).

The Enhanced Built-up and Bareness Index (EBBI) is utilized to map and differentiate between built-up areas and barren land, based on the reflectance characteristics of land surfaces. It is considered more

*Corresponding author: moharanashrabani1990@gmail.com
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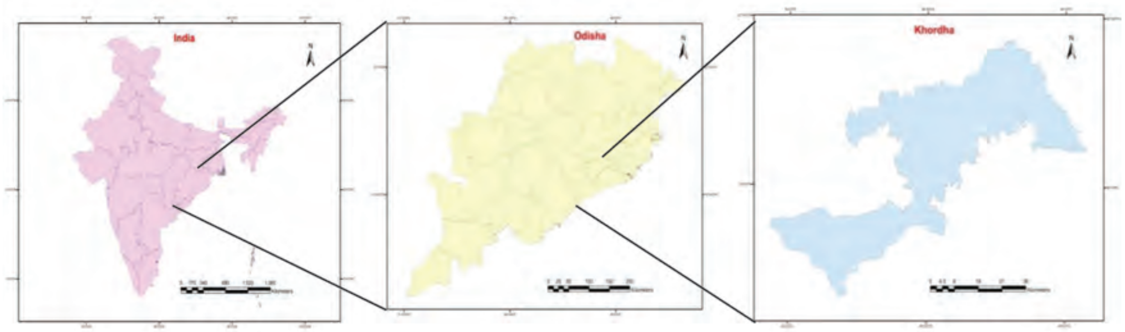

Fig. 1. Area of interest

significant and reliable than other urban mapping indices (As-Syakur *et al.*, 2012). EBBI has been validated as an effective index for analyzing built-up areas through satellite imagery over the past thirty years (Tin and Muttitanon, 2021). The present study was conducted in the Khordha district of Odisha, with the objective of mapping change dynamics related to vegetation, water bodies, and barren and built-up land coverage over the past three decades, from 1990 to 2020, utilizing remote sensing techniques.

MATERIALS AND METHODS

Study area

The present study was conducted in the Khordha district, situated within the eastern and southeastern coastal plain zone of Odisha, India. The district is geographically defined by coordinates ranging from 19°40' to 20°25' N latitude and 84°55' to 86°05' E longitude, with an elevation of approximately 42 meters above mean sea level. Covering a total geographical area of 2,813 square kilometers, Khordha experiences an annual average rainfall of 1,436.1 mm, primarily concentrated between July and September. The average ambient temperature in the district is 26.6°C, with variations between a minimum of 10.3°C and a maximum of 37.8°C. Additionally, the average relative humidity is around 76.9%, fluctuating between 28.2% and 98.4%.

Data acquisition and processing

Satellite images were collected from the Landsat series at decadal intervals from 1990 to 2020, ensuring less than 10% cloud coverage. These images were obtained from the USGS Earth Explorer website (http://earthexplorer.usgs.gov). As secondary data, Survey of India (SOI) topographic sheets at a scale of 1:50,000 were utilized to prepare base maps and facilitate remote sensing data interpretation and validation. The satellite imagery was referenced to the Universal Transverse Mercator (UTM) projection system (WGS 1984 UTM zone 45) and included two scenes of the Landsat satellite series imagery, specifically path 139, 140 and row 46, as detailed in Table 1. The acquired satellite images underwent processing within the ArcGIS 10.8.2 environment, which included radiometric and atmospheric corrections. Subsequently, the area of interest—Khordha district—was extracted from the entire scene using the "Extract by Mask" tool. A shapefile was created by clipping the area of interest following the digitization of the district boundary from the Odisha state vector layer.

2.3 Land cover spectral indices

Different land cover spectral indices, such as the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and Enhanced Built-up and Bareness Index (EBBI), can be calculated by combining the appropriate bands using ArcGIS software. This is achieved through the Spatial Analyst tools, specifically the Map Algebra and Raster Calculator functions, applying the relevant index formulas. The Landsat satellite series offers varying numbers of spectral bands: Landsat 5 has 7 bands, Landsat 7 contains 8 bands, and Landsat 8 includes 11 bands. For the analysis of NDVI and NDWI, three

Table 1. Description of satellite images used for study

Year	Satellite	Sensor	Path, row	Date of acquisition	Spatial resolution
1990	Landsat 5	TM	Path-139, 140 Row-046	13/02/1990, 23/12/1990	30m
2000	Landsat 7	ETM+	Path-139, 140 Row-046	17/12/2000, 10/12/2000	30m
2010	Landsat 5	TM	Path-139, 140 Row-046	25/04/2010, 18/04/2010	30m
2020	Landsat 8	OLI, TIRS	Path-139, 140 Row-046	14/11/2020, 09/12/2020	30m

Table 2. Formulae of NDVI, NDWI and EBBI for different landsat satellites

Spectral indices	Landsat 5 and 7	Landsat 8/9
NDVI	$\frac{\text{Reflectance in Band 4-Reflectance in Band 3}}{\text{Reflectance in Band 4+Reflectance in Band 3}}$	$\frac{\text{Reflectance in Band 5-Reflectance in Band 4}}{\text{Reflectance in Band 5+Reflectance in Band 4}}$
NDWI	$\frac{\text{Reflectance in Band 2-Reflectance in Band 4}}{\text{Reflectance in Band 2+Reflectance in Band 4}}$	$\frac{\text{Reflectance in Band 3-Reflectance in Band 5}}{\text{Reflectance in Band 3+Reflectance in Band 5}}$
EBBI	$\frac{\text{Reflectance in Band 5-Reflectance in Band 4}}{10*\sqrt{(\text{Reflectance in Band 5+Reflectance in Band 6})}}$	$\frac{\text{Reflectance in Band 6-Reflectance in Band 5}}{10*\sqrt{(\text{Reflectance in Band 6+Reflectance in Band 11})}}$

specific bands are utilized—Red, Near Infrared (NIR), and Green. In contrast, the calculation of EBBI requires the use of bands such as Shortwave Infrared (SWIR), NIR, and Thermal Infrared (TIR). The details regarding the bands, their wavelengths, and resolution for Landsat 5, Landsat 7, and Landsat 8 are provided in Table 2.

Normalized difference vegetation index (NDVI)

NDVI is employed for mapping and monitoring vegetative zones using remotely sensed data (Sonawane and Bhagat, 2017; Chen *et al.*, 2017; Shah and Siyal, 2019; Shah and Kiran, 2021). This index quantifies the proportion of vegetation by measuring the difference between the near-infrared portion of the electromagnetic spectrum—strongly reflected by healthy green vegetation—and the red portion, which is absorbed by plants (Malik *et al.*, 2019). NDVI is calculated using the following equation:

$$\text{NDVI} = \frac{\text{Reflectance in Near Infrared-Reflectance in Red}}{\text{Reflectance in Near Infrared+Reflectance in Red}}$$

The range of NDVI values spans from -1 to 1, reflecting the relative digital numbers (DN) of the Near Infrared and red bands (Sonawane and Bhagat, 2017). Negative or lower values typically correspond to non-vegetated areas, such as rocks, clouds, snow, and surface water, while positive values indicate progressively higher densities of green leaves (Shah and Kiran, 2021; Malik *et al.*, 2019).

Normalized difference water index (NDWI)

The Normalized Difference Water Index (NDWI) is effective in highlighting open water surfaces in satellite images. It is calculated by measuring the difference in reflectance between two bands, primarily the Green and Near Infrared (NIR) bands, which enables the detection of changes in water content within surface water bodies (McFeeters, 1996). Visible green wavelengths enhance the reflectance of ground surfaces, while near-infrared wavelengths amplify the reflectance of terrestrial vegetation and soil features, thereby minimizing the low reflectance typically associated with water bodies. NDWI values generally range from -1 to 1, where negative values indicate non-water areas and positive values suggest the presence of water bodies. NDWI is computed using the following equation:

$$\text{NDWI} = \frac{\text{Reflectance in Green-Reflectance in Near Infrared}}{\text{Reflectance in Green+Reflectance in Near Infrared}}$$

Enhanced built-up and bareness index (EBBI):

The Enhanced Built-up and Bareness Index (EBBI) is designed to represent areas associated with barren land and settlements. Due to similar reflectance characteristics exhibited by these two categories, distinguishing them separately can be challenging. To address this, a combined index of bareness and built-up area is utilized for mapping, based on reflectance derived from combinations of the Near Infrared (NIR), Shortwave Infrared (SWIR), and Thermal Infrared (TIR) bands. Specifically, the subtraction of the NIR band from the SWIR band yields positive values for built-up and barren pixels, while resulting in negative values for vegetated areas. Furthermore, summing the SWIR and TIR bands produces higher pixel values for built-up and bare land compared to those for vegetation. Generally, EBBI values range from -1 to 1, where negative indices indicate the presence of vegetation and positive values correspond to barren land and built-up areas. EBBI can be calculated using the following equation:

$$\text{EBBI} = \frac{\text{Reflectance in SWIR-Reflectance in NIR}}{10*\sqrt{(\text{Reflectance in SWIR+Reflectance in TIR})}}$$

RESULTS AND DISCUSSION

Temporal changes in vegetation and water resources

Vegetation, water bodies, and settlements were graphically represented using NDVI, NDWI, and EBBI, as illustrated in Figures 2, 3, and 4. The NDVI values typically range from -1 to +1, where negative values indicate low canopy cover and positive values reflect dense, healthy vegetation. In 1990, the NDVI values ranged from -0.51 to 0.68. By 2000, the maximum and

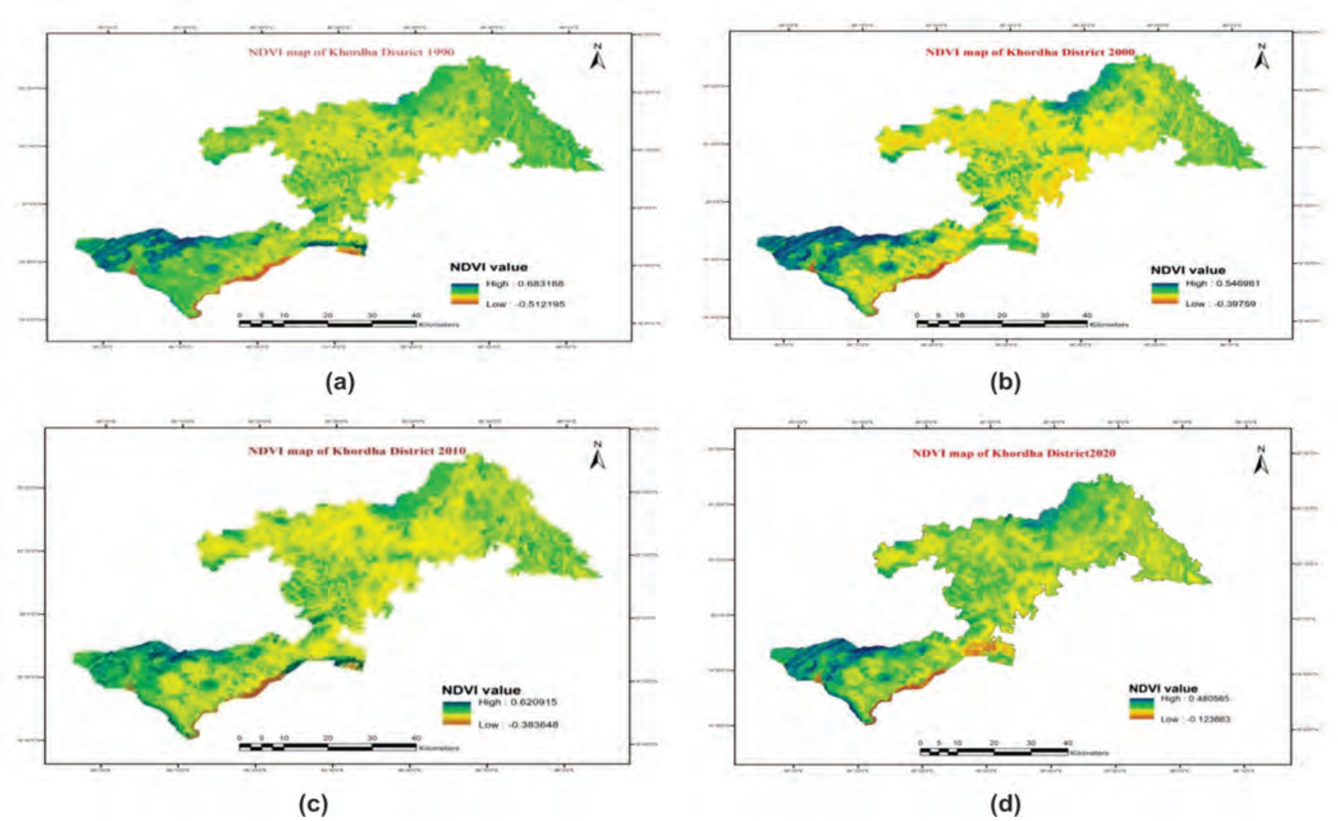

Fig. 2. NDVI maps of Khordha district for (a) 1990 (b) 2000 (c) 2010 and (d) 2020

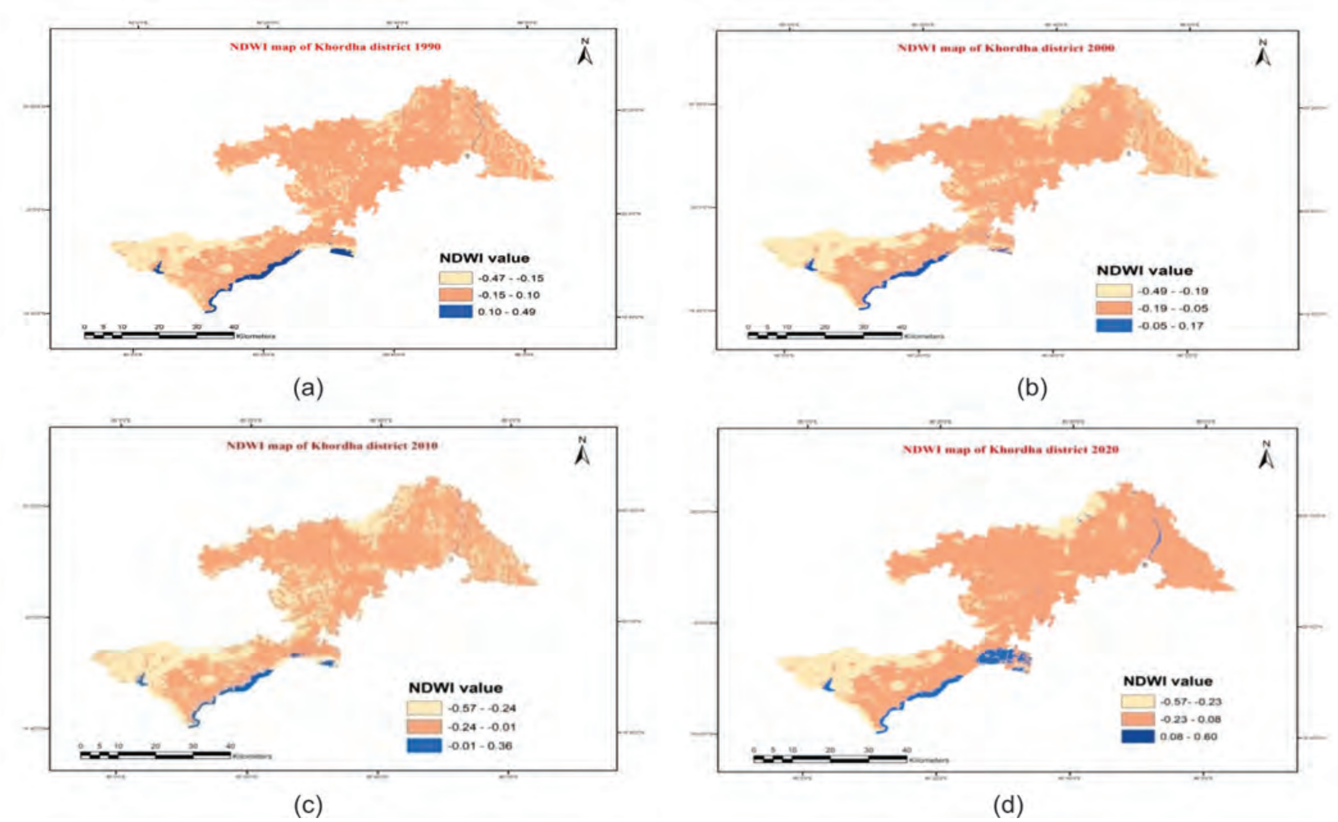

Fig. 3. NDWI maps of Khordha district for (a) 1990 (b) 2000 (c) 2010 and (d) 2020

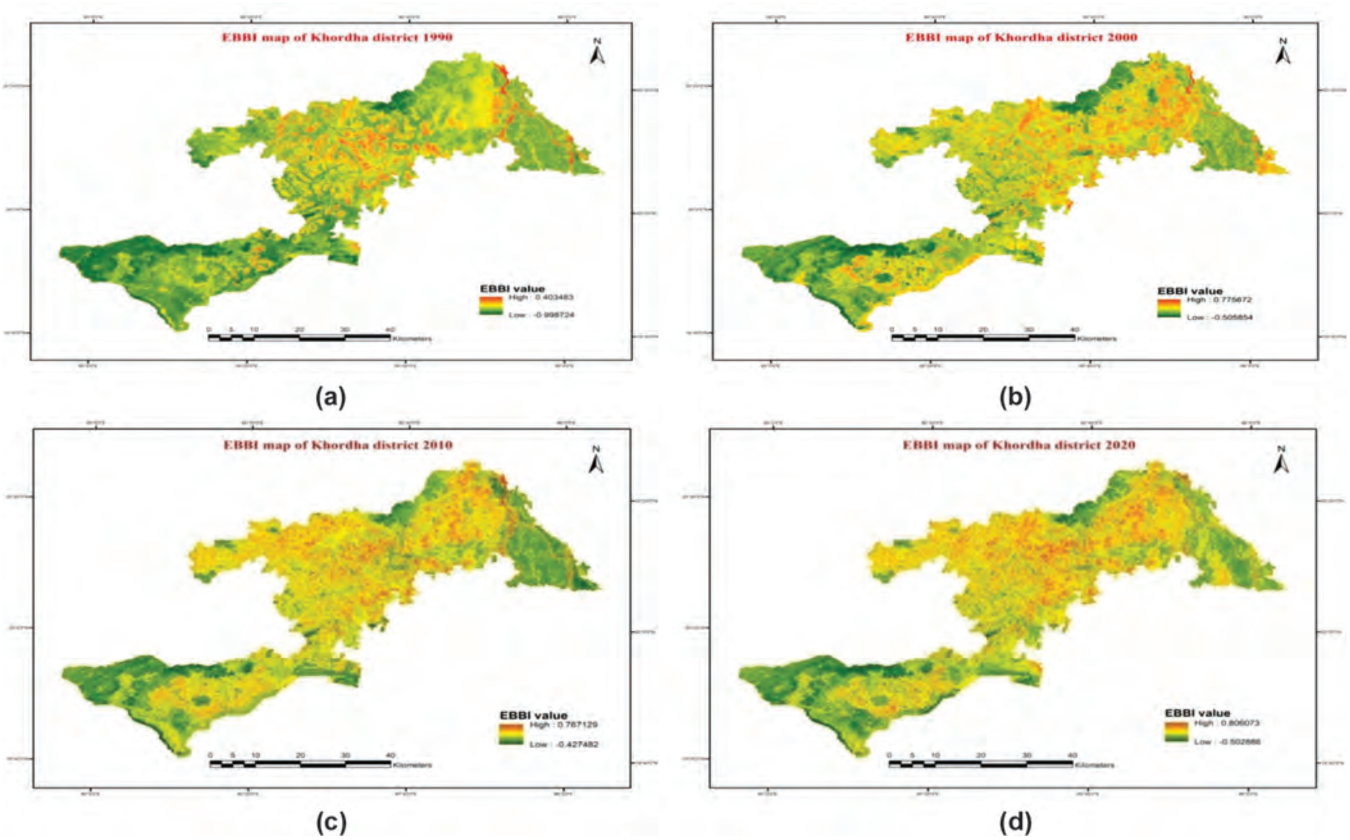

Fig. 3. EBBI maps of Khordha district for (a) 1990, (b) 2000, (c) 2010 and (d) 2020

minimum NDVI values were recorded at 0.54 and -0.39, respectively. In 2010, the values fluctuated between -0.38 and 0.62, while in 2020, they ranged from -0.12 to 0.48. As NDVI serves as an indicator of vegetation greenness, the NDVI map for 1990 displayed the highest greenness index compared to subsequent years. The second highest NDVI value was observed in 2010, followed by 2000, with the lowest NDVI recorded in 2020, attributed to a reduced amount of vegetation relative to previous years. Additionally, the timing of satellite image acquisition significantly influences the estimation of temporal variations in NDVI, as it can vary with the greenness of vegetation across different seasons.

NDWI maps for the four years, as illustrated in Figure 3, highlight the presence of surface water. The maximum NDWI value of 0.60 was recorded in 2020, followed by 0.49 in 1990. The minimum NDWI value occurred in 2000, with a measurement of 0.17. Figure 4 presents the EBBI maps for the same years. The highest EBBI value of 0.81 was observed in 2020, while the lowest value of 0.40 was recorded in 1990, indicating a significant increase in barren and built-up areas by 2020 compared to 1990. The correlation between NDVI and EBBI demonstrated a negative relationship across all four years, with the highest R^2 value of 0.261 recorded in 2000 and the lowest value of 0.048 observed in 2020, as shown in Fig. 5.

The Normalized Difference Vegetation Index (NDVI) has proven to be a robust indicator of terrestrial vegetation productivity. A notable shift in biomass content was observed between 1990 and 2020, driven by changes in vegetation patterns resulting from varying climatic conditions and land use changes. Factors such as the distribution of rainfall throughout the district and the timing of image acquisition for land use classification may have contributed to the increase in NDVI values observed in 2010. The highest NDVI values during the initial study period indicate the presence of dense vegetation; however, by 2020, these values had declined, suggesting an expansion of settlement areas characterized by sparse vegetation. The Normalized Difference Water Index (NDWI) indicates the presence of surface water bodies. Thematic maps of NDWI revealed a lower value of 0.17 in 2000, reflecting a reduced presence of water resources, while a peak value of 0.60 was recorded in 2020. Over the observation period, changes in water resources exhibited a nonlinear and non-significant trend, likely influenced by the timing of satellite image acquisition, which plays a critical role in resource mapping. Notably, the development of farm ponds for pisciculture around the periphery of Chilika

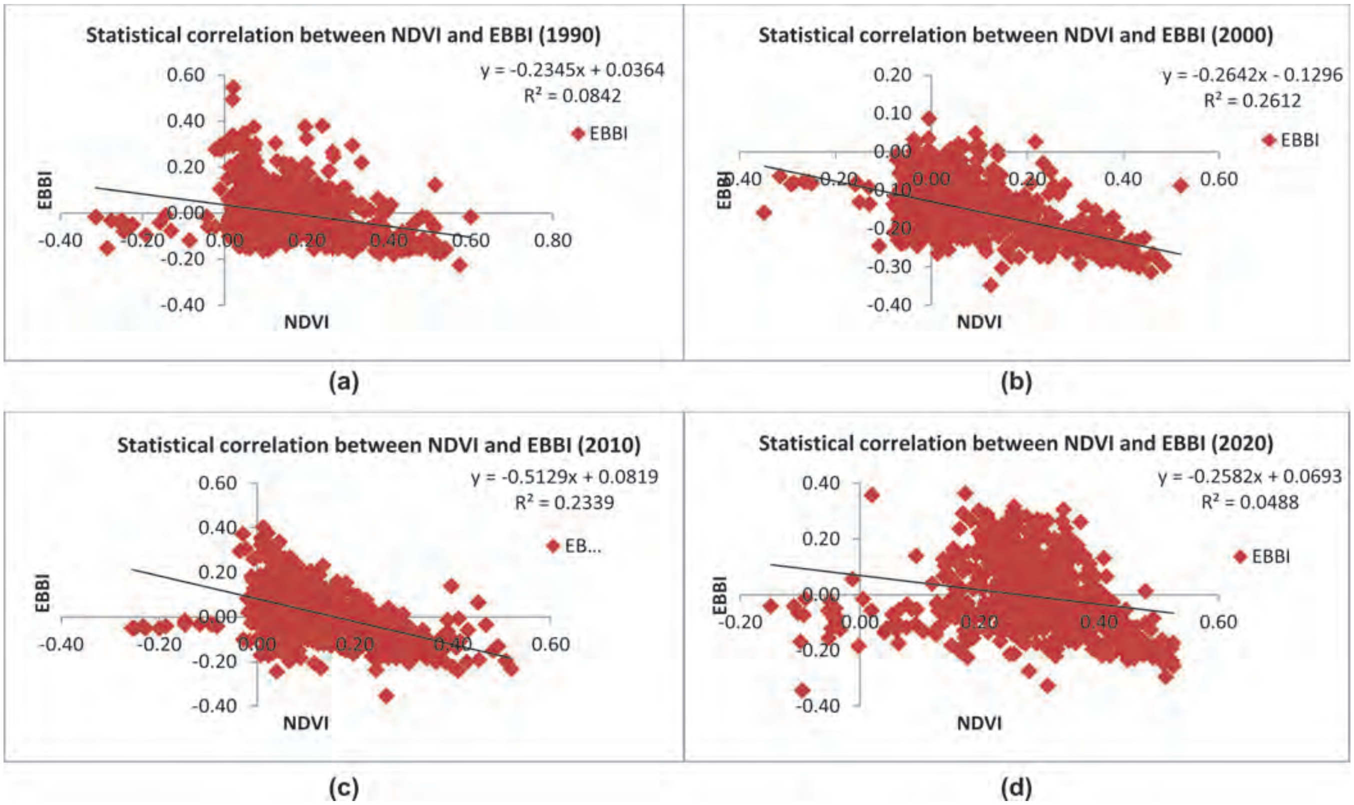

Fig. 5. Statistical correlation between NDVI and EBBI of Khordha district for (a) 1990, (b) 2000, (c) 2010 and (d) 2020

Table 3. Range of spectral indices

Indices	1990		2000		2010		2020	
	Min	Max	Min	Max	Min	Max	Min	Max
NDVI	-0.51	0.68	-0.39	0.54	-0.38	0.62	-0.12	0.48
NDWI	-0.47	0.49	-0.49	0.17	-0.57	0.36	-0.57	0.6
EBBI	-0.99	0.40	-0.50	0.77	-0.43	0.77	-0.50	0.81

Lagoon may significantly contribute to the observed increase in NDWI values in subsequent assessments.

The Enhanced Built-up and Bareness Index (EBBI) effectively identifies both built-up and barren land within a single index. The maximum EBBI value of 0.81 was recorded in 2020, while the minimum value of 0.40 was noted in 1990, indicating the highest extent of barren and built-up areas in 2020 compared to the lowest extent in 1990.

CONCLUSION

Remote sensing and Geographic Information Systems (GIS) have proven to be effective tools for conducting studies that involve the calculation of spectral land cover indices. In this study, the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and Enhanced Built-up and Bareness Index (EBBI) were calculated from satellite imagery across four years at ten-year intervals. The maximum NDVI value of 0.68, indicating dense foliage coverage, was observed in 1990, while the minimum intensity of 0.48 was recorded in 2020. On the other hand, the highest NDWI value of 0.60 was noted in 2020, with the lowest value of 0.17 occurring in 2000. Similarly, the minimum EBBI value of 0.40, alongside the maximum vegetation index of -0.99, was obtained in 1990, while the highest EBBI value was recorded in 2020. A negative correlation was observed between EBBI and NDVI across all years of the study. The variations in NDVI and NDWI values highlight the impacts of land use and land cover (LULC) changes as well as climate on vegetation and water bodies.

Assessing temporal and spatial variations in land cover spectral indices is essential for monitoring urban development and conserving natural resources in a sustainable manner. The findings from this study provide a foundation for further scientific research and hold important policy implications for mitigating the negative impacts of urbanization and industrialization. However, the timing of satellite image acquisition is a critical factor in analyzing these indices, as their implications can vary with seasonal changes. Therefore, it is advisable to capture multiple satellite images across specific time intervals or seasons to obtain a comprehensive and conclusive understanding of variations in vegetation, water bodies, and barren and built-up land.

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