Iraqi National Journal of Earth Science
www.earth.uomosul.edu.iq

Evaluation of Spatio-Temporal Forest Health of Bangladesh Using Google Earth Engine

Md. Shahadad Hossain [1*], Nobonita Shobnom [2], Umme Sumaiya Shams [3], Rezaul Roni [4]
[1,2,3,4] Department of Geography and Environment, Social Science faculty, Jahangirnagar University, Savar-1342, Dhaka, Bangladesh.

Article information

Received: 25- Aug -2024
Revised: 11- Oct -2024
Accepted: 07- Dec -2024
Available online: 01- Jan -2026

Keywords:
Forest Health,
Google Earth Engine,
Remote Sensing,
Seasonality,
Spatio-temporal Variability,

Correspondence:
Name: Md. Shahadad Hossain
Email: shahadat.46@geography-juniv.edu.bd

ABSTRACT

Bangladesh has a significantly low and steadily declining land covered in forest compared to the required one-third. Therefore, it is essential to explore the condition of the forest cover in Bangladesh. In recent years, remote sensing techniques have become increasingly popular for assessing the health of forests. The research evaluates the forest health seasonality and spatiotemporal variability. Landsat 7 ETM+, Landsat 8 OLI, and Sentinel-2 images for 2002-2021 and seven vegetation indices are used in the Google Earth Engine platform as it is widely accepted and convenient. The results reveal the time series analysis of vegetation indices; they show a maximum value of 0.8107 for SAVI in Sundarban and a minimum value of 0.0146 for NDVI in the Dinajpur and Hill Tract areas. Also, spatial variability illustrated a maximum value of 0.8107 for SAVI in Sundarban and a minimum value of 0.0146 for NDVI in the Dinajpur area. Moreover, Seasonal patterns are also identified where forest health is best observed during the monsoon season (July - October). Furthermore, the assessment indicates that the south and southeastern portions of the research region, Sundarban, and the Hill Tract area have healthier forest cover than the others. This study could be considered a comprehensive reference for managing and planning forests.

DOI: 10.33899/injes.v26i1.60201, ©Authors, 2026, College of Science, University of Mosul.

تقييم الصحة الحراجية (صحة الغابات) المكانية-الزمانية لبنغلاديش باستخدام محرك جوجل إيرث

محمد شهادات حسين [1*]، نوبونيتا شبنم [2]، أمية سمية شمس [3]، رضا الروني [4]

[1,2,3,4] قسم الجغرافيا والبيئة، كلية العلوم الاجتماعية، جامعة جاهانجيرناغار، سافار-1342، دكا، بنغلاديش.

معلومات الارشفة

تاريخ الاستلام: 25- اغسطس- 2024

تاريخ المراجعة: 11- اكتوبر- 2024

تاريخ القبول: 07- ديسمبر- 2024

تاريخ النشر الالكتروني: 01- يناير- 2026

الكلمات المفتاحية:

صحة الغابات،

محرك جوجل إيرث،

الاستشعار عن بُعد،

الموسمية،

التباين المكاني والزماني،

المراسلة:

الاسم: م د شهادات حسين

Email: shahadat.46@geography-juniv.edu.bd

الملخص

مقارنةً بالثلث المطلوب، تمتلك بنغلاديش مساحة منخفضة جداً ومتناقصة باطراد من الأراضي المغطاة بالغابات. ولذلك، من الضروري استكشاف حالة الغطاء الغابي في بنغلاديش. في السنوات الأخيرة، أصبحت تقنيات الاستشعار عن بعد شائعة بشكل متزايد لتقييم صحة الغابات. يقيّم هذا البحث التباين الموسمي والمكاني-الزماني لصحة الغابات. تم استخدام صور Landsat 7 ETM+ ، وLandsat 8 OLI ، و Sentinel-2للفترة ما بين 2002-2021، وسبعة مؤشرات نباتية، على منصة محرك جوجل إيرث (Google Earth Engine) نظراً لكونها مقبولة على نطاق واسع ومريحة. تكشف النتائج عن تحليل السلاسل الزمنية للمؤشرات النباتية؛ حيث تُظهر قيمة قصوى بلغت 0.8107 لمؤشر (SAVI) في منطقة السندربان، وقيمة دنيا بلغت 0.0146 لمؤشر (NDVI) في مناطق ديناجبور ومنطقة التلال .(Hill Tract) كما أوضح التباين المكاني قيمة قصوى بلغت 0.8107 لمؤشر (SAVI) في منطقة السندربان، وقيمة دنيا بلغت 0.0146 لمؤشر (NDVI) في منطقة ديناجبور. علاوة على ذلك، تم تحديد الأنماط الموسمية حيث تُلاحظ صحة الغابات بأفضل شكل خلال موسم الرياح الموسمية (يوليو – أكتوبر). بالإضافة إلى ذلك، يشير التقييم إلى أن الأجزاء الجنوبية والجنوبية الشرقية من منطقة البحث، وهي السندربان ومنطقة التلال، تتمتع بغطاء غابي أكثر صحة من المناطق الأخرى. يمكن اعتبار هذه الدراسة مرجعاً شاملاً لإدارة الغابات وتخطيطها.

DOI: 10.33899/injes.v26i1.60201,

Introduction

The creation of forest conditions that directly meet human needs and the resilience, recurrence, persistence, and biophysical processes that result in sustainable ecological conditions have been used to describe forest health. The spatial size also affects how we define and comprehend forest health. Forests cover roughly 30 percent of Earth's land area and play an important role in atmospheric regulation of carbon dioxide (CO_2) and oxygen (O_2) soil conservation providing habitat for many species, and providing a source of many useful products like wood and food (Xie et al., 2008; Chaturvedi et al., 2011; Rudel et al., 2005; Vega et al., 2012). On the surface of the earth, the forest essentially encompasses any natural resources, such as wood or solar energy, that can be naturally renewed through time and can be a healthy ecosystem (Sahana et al., 2015). The influence of anthropogenic and physical forces on the regions that encompass the majority of these surfaces has steadily increased in the preserved habitats over the last few decades. The primary driver of anthropogenic habitat fragmentation, however, is a rising population that requires more land for residence, agriculture, urban habitat expansion, the construction of more roads and railroads, and industrial activities (Carroll et al., 2004). In forested ecosystems, the hydrological cycle or surface force equilibrium actively contributes to the regulation of the biosphere (Rogan et al., 2002). Most forests are fragmented in wealthy countries, while on the other side of this fragmentation trend, the area covered by forests is growing at an alarming rate in other emerging nations (Talukdar et al., 2019). Forest health primarily defines the origin of forest conditions that depend on nature and humans (Kayet et al., 2019). The monitoring of forest products and assessing changes in ecological function are crucial assessments of the factors in forest health (King, 2000). The effects on forest health are mostly caused by the reduction of changes in both temperature and carbon dioxide. Because temperatures rise in the warmer season, forest persecution increases in the cooler season. The decline in forest health is caused by invading species in addition to an increase in temperature (Nandi and Sarkar, 2021). Density and fragmentation models are useful for assessing the health of a forest in a given area. Several studies have used the Landsat TM data analysis guide for mapping and analyzing forest canopy density, whose model can help in assessing forest degradation (Jaiswal et al., 2002). If a forest is in good shape, it could be a reliable indicator of the local environment (Allen et al., 2010). Both abiotic stresses, notably drought (Macpherson et al., 2017) and biotic disturbances, such as logging and fires (Lausch et al., 2017), are rising within the world's forests. The effectiveness and efficiency of a city's ecosystem are directly linked to the condition of its forests (Xiao and McPherson et al., 2002).

Land use, land cover, and vegetation mapping for both urban and rural forests have made extensive use of remote sensing data (Erikson, 2004; Xiao et al., 2004; Pouliot et al., 2002; Ustin and Xiao, 2001). Forward the resolution data from the Advanced Very High-Resolution Radiometer (AVHRR) (Tucker et al., 1985) and the Moderate Resolution Imaging Spectroradiometer (MODIS) (Huete et al., 2002) provide comprehensive findings. Researchers have devoted a great deal of time and resources to studying and creating novel approaches to silviculture (Moore et al., 2017; Watt et al., 2017), tree breeding programs (Klapste et al., 2017; Li et al., 2015), nutrition in forests (Maggard et al., 2017), and remote sensing techniques for better forest management to increase productivity in the world's plantations of trees (Watt et al., 2015; Watt et al., 2016; Pearse et al., 2017). Spatio-temporal portraits of medium-to-long-term (years to decades) vegetation dynamics are from space-based remote sensing instruments. The article explains that common vegetation indices like the Normalized Difference Vegetation Index (NDVI) can pick up on seasonal fluctuations in the amount of fractional cover and leaf area index (LAI) across different forest types, which contributes to the emphasis on structure (Wang et al., 2017). A study demonstrated that deforestation prevention policies and management strategies benefit from a better understanding of forest spatial patterns and the processes that shape them (Fuller et al., 2006). The ability to monitor seasonal or annual variations in tree health and trace the spread of disease is another focus of this study. In addition, it offers data on tree health that is crucial for analyzing the environmental, social, and economic benefits that urban forests provide to their communities (Xiao and McPherson, 2005).

National grasslands and forests must be in good condition if we accomplish our mission of helping people and conserving the environment. The Forest Service strives to maintain, enhance, and restore healthy forest conditions in the nation's forests and grasslands. According to the World Bank Country Climate and Development Report in 2022, Bangladesh is one of the most susceptible countries to climate change, which may prove to be crucial in maintaining healthy forests in the future. A healthy forest protects coastal communities from bad weather and sea level rise, in addition to absorbing greenhouse gases and managing water flows. They provide access to healthy habitats for migratory plant and animal species, too. The significance of vegetation in preserving the ecological biota and environmental balance must be understood. As a result, to evaluate vegetation status, it is necessary to consider ecological dynamism, enough soil nutrients, plant health, as well as effective coping mechanisms and management measures that can assist in reducing risks and sustaining forest health (Allen et al., 2010). Consequently, healthy forests can perform their functions more effectively than unhealthy ones. It is crucial to safeguard and maintain forests to provide integrated and sustainable drainage and sustainable management of agroforestry features.

An important facet of environmental policy and resource allocation is the assessment and evaluation of forest health. The root reasons for the detrimental effects on the health and vitality of forests differ from location to location, and it is difficult to gauge their scope and longevity. It is challenging to understand how these components interact with one another, as well as how they affect the health and vitality of forests. Wide-ranging indirect effects could have social, economic, and environmental implications. The main issues facing Bangladesh's forest resources are the fast-growing population's exponentially expanding consumption and dependence on forest products and services, as well as the weak enforcement of forest laws. Expansion of industrialization, tobacco cultivation, and land grabbing for the real estate industry, i.e., housing, and other new industrial expansions include different chemical and garment industries (Sal Forest), ship breaking and shrimp cultivation (Planted Mangrove), and so on. An increase in encroachment and illegal deforestation in forests is another reason for the diminution of the forest area. Following that, this exploration aims to evaluate the forest health along with seasonality and spatio-temporal variability to achieve: a) assessing the forest health from 2002 through 2021, b) identifying the spatio-temporal variability, and c) evaluating the seasonality of forest health, which are set as objectives.

Study Area

The present study has been done in Bangladesh, which is a South Asian country located between latitudes 20″34′ and 26″38′ North and longitudes 88″01′ and 92″41′ East. It is situated on the Bay of Bengal, east of India, and is surrounded by the Indian states of Tripura and Mizoram to the east, West Bengal to the west and north, Assam to the north, Meghalaya to the north and northeast, and West Bengal to the west and northwest. Its border with Myanmar (Burma) is shared to the southeast (Chowdhury, 2014). As our research area, we have selected five areas from the different regions of Bangladesh. These sample sites are: Sundarbans in the southern region and coastal area, Hill tracts in the southeastern region, Lawchara in the northeastern region, Madhupur in the central-northern region, and Dinajpur area in the northwestern region (Fig. 1) (Rahman, 2012).

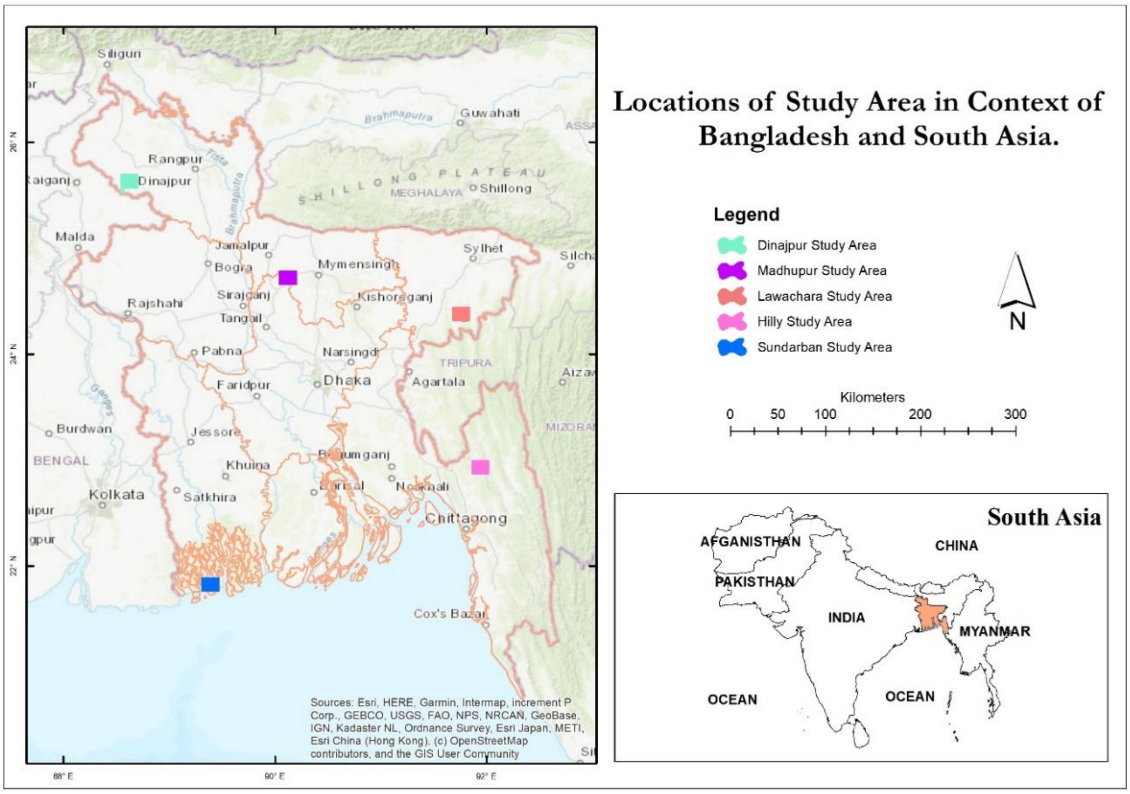

Fig. 1. The study area of Bangladesh with five sample locations of forest cover.

Materials and methods

Data type and sources

To analyze mapping and track deforestation, intra-annual availability of cloud-free land satellite data is required. The Landsat missions are equipped with a multispectral passive optical sensor that measures radiation from the Earth's surface on several arbitrarily broad electromagnetic channels known as spectral bands. The Copernicus Sentinel-2 mission comprises two identical satellites orbiting in the same orbit. Each satellite of Sentinel-2 is equipped with a cutting-edge wide-swath high-resolution multispectral imager with 13 spectral bands to provide a new viewpoint on our land and vegetation. TM, OLI, Sentinel and Blue, red, NIR, SWIR1, and SWIR2 are all similar across all frequently used spectral strips. Vegetation-sensitive bands (Table 1).

Table 1: Vegetation sensitive bands that are used in the analysis.

Landsat 7	Landsat 8	Sentinel-2
Band 1 - Blue	Band 2 - Blue	Band 4 – Red
Band 2 - Green	Band 3 - Green	Band 8 – NIR
Band 3 - Red	Band 4 - Red	
Band 4 - Near-Infrared	Band 5 - Near Infrared (NIR)	
Band 5 - Short-wave Infrared	Band 6 - SWIR 1	
Band 6 - Thermal	Band 7 - SWIR 2	
Landsat 7	Band 10 - Thermal Infrared (TIRS) 1	

Imaging of Landsat TM (Path-136, 137, 138, Row-43, 44, 45), OLI (Path-136, 137, 138, Row-43, 44, 45), and Sentinel-2 is used through Google Earth Engine. The number of imagery accessible each year in the study region, as in the other tropical covers, is restricted; nonetheless, at least one cloud-free Landsat image is available every season. The images had been geometrically rectified in Level and atmospherically corrected in the Solar Spectrum using the radio-transmission approach of the second satellite signal simulation. Their key advantage over higher-resolution imaging is that they may be used as archive data for an extended period of time. Images with greater than 10% cloud coverage are avoided and not included in the research (Mozgeris and Balenovic, 2021; Calders et al., 2020).

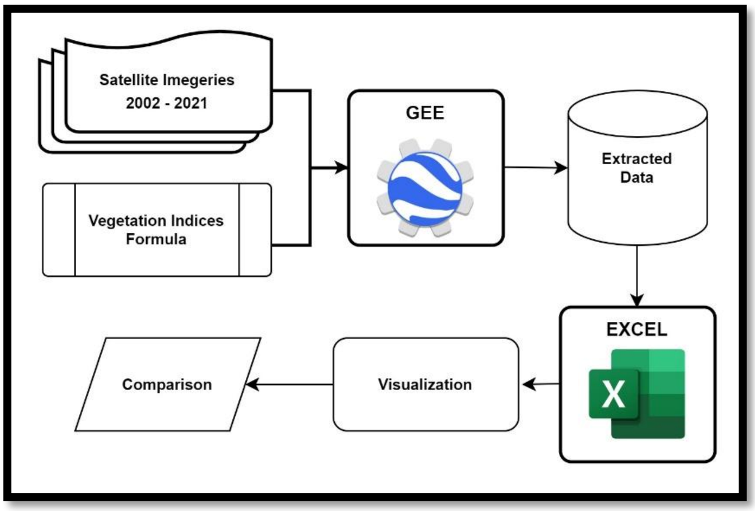

Fig. 2. A detailed flowchart of the method.

The key goal of this study is to evaluate how the sample areas of Bangladesh have changed over time. This section explains the overall methods utilized to collect and process data in achieving the aim of the study. As previously indicated, the Google Earth Engine (GEE) hosts satellite imaging data and provides computational services via a simple web-based interface. The Earth Engine Code Editor is used in this study to access this facility through interactive JavaScript coding. From 2002 to 2021, GEE satellite imagery from Landsat 7 and Landsat 8 was used. Then, the data are filtered to remove any digital photos with clouds, fog, or haze. The GEE computing module is then provided with the shortlisted and cleaned dataset, which is responsible for recognizing the forest cover initially. Following that, using pixel counting, the minimum, maximum, mean, and standard deviation values of vegetation indices are extracted as datasets. Next, extracted datasets are imported to MS Excel to filter, rearrange, combine, and make graphical representations. The meaningful visualization of the vegetation indices data helps to better understand the condition of the vegetation health, pattern, and trends to discuss causes and consequences. Figure 2 summarizes the entire procedure.

Vegetation indices

To evaluate the forest health of Bangladesh, seven VI were initially analyzed (Table 2), namely the Normalized Difference Vegetation Index (NDVI), Normalized Difference Moisture Index (NDMI), Greenness Index (GI), Soil-Adjusted Vegetation Index (SAVI), Perpendicular Vegetation Index (PVI), Enhanced Built-Up and Bareness Index (EBBI), and Leaf Area Index (LAI). These indices are used to produce the health status and vigor of a forested area. The vegetation indices were measured using reflectance values at various wavelengths to increase information relevant to vegetation while considering environmental conditions and shadow.

Table 2: Vegetation indices used in this analysis.

Vegetation Index	Equation	Reference
NDVI	$\frac{NIR-Red}{NIR+Red}$	(McDaniel,1982)
NDMI	$\frac{NIR-SWIR}{NIR+SWIR}$	(Dutta, 2020)
GI	$((0.2728 * \text{Blue}) - (0.2174 * \text{Green}) - (0.5508 * \text{Red}) + (0.7221 * \text{NIR}) + (0.0733 * \text{SWIR1}) - (0.1648 * \text{SWIR2}))/100$	(Yuan, 1996)
SAVI	$\frac{NIR-Red}{NIR+R+0.5} * (1.5)$	(Ren, 2018)
PVI	$\frac{\sqrt{(0.355\,NIR-0.149\,RED)^2-(0.355RED-0.852NIR)^2}}{100}$	(Rajan, 2009)
EBBI	$\frac{SWIR-Red}{10 * \sqrt{(SWIR+TIR)}}$	(Baranwal, 2022)
LAI	0.57 * exp (2.33 * NDVI)	(Bajocco, 2022)

Google Earth Engine (GEE)

Google Earth Engine, the platform adopted for this research, is a cloud platform that hosts a multi-petabyte database of satellite images and geographic information, as well as planetary-scale analytic capabilities. Utilizing GEE aids in minimizing the pre-processing and data-obtaining procedures, which would otherwise demand significant computing power and large data storage capacity (Kong et al., 2019). The technique presented in this paper requires the collection of spatiotemporal data over a period of 20 years. Multi-petabyte datasets are easily accessible and are mostly pre-processed on Google Earth Engine. Second, high-performance computing resources enable users to utilize a machine-learning technique to obtain verified results. Data extraction for this analysis is based on the collection of Landsat, Sentinel data and integrated vegetation indices. Selected imagery, vegetation-sensitive bands, and index equations are arranged into a GEE Image Collection object. We applied "reducers," a sophisticated feature in GEE that allows us to compute at the pixel level across a stack of images or inside a specific region of space. We utilized the EE. Reduce method to compute descriptive statistics such as minimum, maximum, mean, and standard deviation. Finally, the data are saved to CSV files and evaluated with the MS Excel program. Although applying the formulas for vegetation indices for various satellite band combinations during data extraction presented certain challenges, we made an effort to reduce these. For instance, while evaluating the greenness index with Landsat 8, we can choose SWIR1, SWIR2, or Landsat 7, which utilize the SWIR band.

Statistics

Data collection and analysis are phases in the statistical analysis process, which is used to find patterns and trends. It is a technique for reducing bias from data evaluation by numerical analysis (Candiago et al., 2015). In this work, we have generated statistics for the indices for assessing forest health in the study region. We have presented comparison graphs of vegetation indices using the extracted data as well, which help us in understanding how they change over time. The difference in scale ratio, however, prevented us from including LAI in this comparison. As we know, vegetation indices such as NDVI, NDMI, GI, PVI, SAVI, and EBBI vary from -1 to +1, while LAI goes from 1 to 4.5. To evaluate seasonality, a quarter graph is produced. We have also conducted trend analysis by linear regression to understand spatial variability and time series analysis, which reveals changes in forest cover over time in various places.

Seasonality

The temporal profiles of the vegetation indicators for the five sites under investigation are displayed in Fig. 3. The average VI values are plotted month by month. The seasonal VI fluctuation between dry and rainy seasons, as well as the appearance of green vegetation, is measured between January and December. The resemblance can be observed in the NDVI, NDMI, and GI indices. The Normalized Vegetation Index (NDVI) measures the amount and how notably the vegetation on the surface has grown. While the Greenness Index (GI) provides information on the quality of the greenery since the green area is covered with grasses, trees, and different plants, the Normalized Moisture Index (NDMI) reveals the moisture level in the vegetation (Brando et al., 2010). If we look at the lines of NDVI, NDMI, and GI, we can see that their values rise and show the maximum value from August to November, gradually decrease and show a mid-range from December to February, and afterwards display the lowest value from March to July. In contrast, PVI and SAVI show a similarity, where PVI is used to represent the level of soil brightness, and SAVI is used to correct NDVI for the effects of soil brightness where vegetation cover is low. As shown by the X and Y lines, the values are lowest from September to January, grow to a mid-range from February to May, and are highest from June to August. Particularly with respect, EBBI has a line that counts both built-up and bare space. Since there is little variation in this line, seasonality is not given considerable weight.

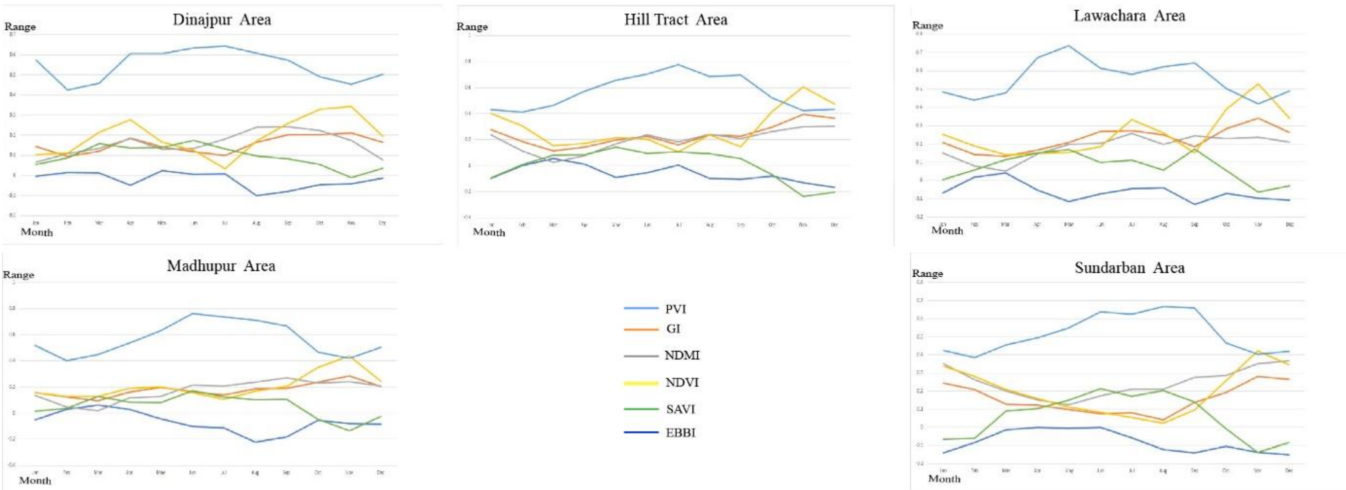

Fig. 3. Comparison of the monthly mean of different vegetation indices.

Spatio-temporal variability

The variability change patterns are defined by spatial and temporal fluctuations. The spatial parameters are the locations and frequency of change, whereas the temporal parameters are the time of occurrence and length of each change event (Quiring and Ganesh, 2010). According to Fig. 4, the yearly average NDVI varies between 0 and 0.5 in different locations. In the Lawachara region, the NDVI of the vegetation-covered area demonstrates significant variations between 2002 and 2021. The NDVI of the Madhupur vegetation-covered areas has been considerably increasing since 2017, with other regions exhibiting a minimal decline. The vegetation-covered regions' annual average NDMI varies from 0.1 to 0.4. In the Sundarban region, the NDMI of the vegetation-covered area shows greater changes between 2002 and 2014. The GI lines appear to vary from -0.1 to 0.4, while the EBBI lines appear to range from -0.2 to 0. The GI and EBBI of the Dinajpur and Hill Tract region remain relatively stable over time, although variations are observed in other locations. PVI values vary from 0.4 to 0.7, whereas SAVI values range from -0.5 to 0.3. All of the sample locations showed little fluctuation in PVI, while the Sundarbans region showed a modest rise from 2019 to the present. SAVI showed a linear trend across all of the zones, with the hill tract recording the lowest value in 2007.

However, the variations didn't reflect a consistent pattern as we used satellite data from two separate periods; the inaccuracy is related to the discrepancy in the wavelength scale of the bands.

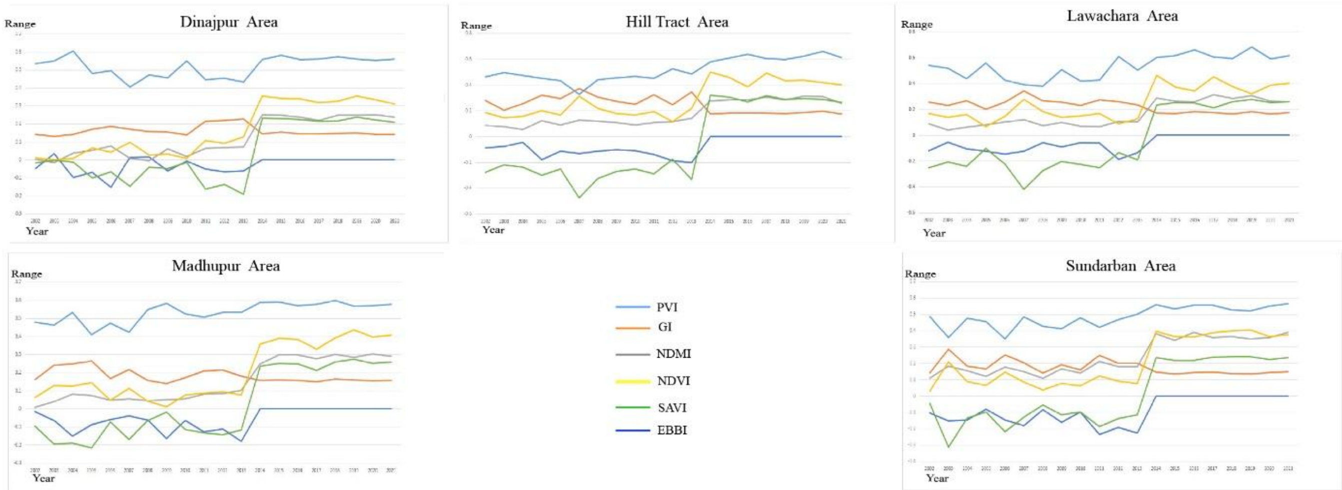

Fig. 4. Comparison of the yearly mean of different vegetation indices.

Results

Seasonality

The findings of the graph (Fig. 5) provide a good understanding of the seasonal variance. Several vegetation indices, including NDVI, GI, SAVI, and PVI, demonstrate good variability for all of the study sites. It is also interesting that these indices exhibit maximum values from July to October, during the monsoon season, minimum values from November to February (winter), and medium values from March to April (the pre-monsoon season). As we inspect the EBBI lines, we can observe that a parallel scenario is portrayed rather than much of a tendency toward growth or deterioration. Therefore, EBBI's seasonality is of little real consequence for any location.

We can bring to light some intriguing points if we carefully observe the NDMI curves. Although NDMI does not show much variation for all the sites, its major shift is observed in the Dinajpur region. This assists us in comprehending how effectively this measure reflects seasonality in geographical areas with less forest cover.

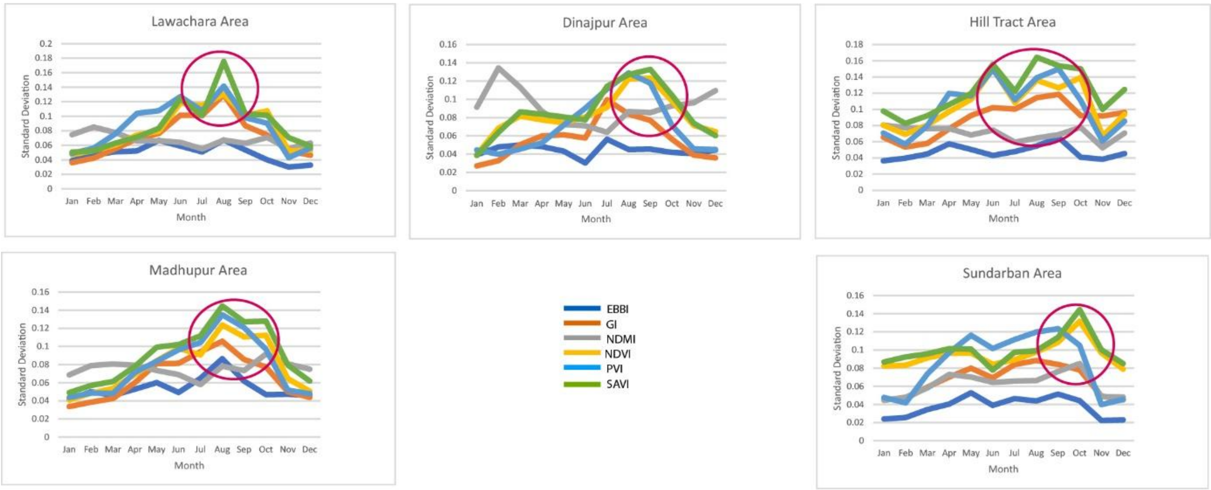

Fig. 5. Seasonal variability of different vegetation indices.

Spatio-temporal variability

For the Spatio-temporal evaluation of vegetation indices (Fig. 6), trend lines are generated using linear regression models to show how they vary over time, along with y-intercepts as statistical measures. Here, we will observe how each vegetation index has evolved for all five sample areas over the past 20 years.

We begin by reviewing EBBI, which has significantly decreased across all locations. The Sundarban Mangrove Forest has had the lowest decline, whereas the Dinajpur area has experienced the highest. The best-fitting line is detected for the Dinajpur region with a value of 0.7447. Second, we find a significant drop in GI as well. The Hill tract region is indicated by the best-fitting line with a value of 0.8. However, GI is least deteriorated in the Dinajpur region and is most degraded in the hill tract. Then, during the course of the time, all NDMI lines exhibited a modest rise. Dinajpur has the best-fitting NDMI line, with a value of 0.5562 and it has also shown a little growth compared to other areas. The NDVI patterns show a mixed situation. It increases slightly in the Dinajpur and Sundarbans regions, while exhibiting a minor decline in Lawachara, Madhupur, and the Hill Tract. However, the best-fitted line is identified for Lawachara with a value of 0.3918.

PVI and SAVI demonstrate a somewhat similar dropping tendency across all the geographic areas, as can be seen. The Sundarban mangrove forest is represented by the best-fit curve for PVI and SAVI, with values of 0.4695 and 0.8107, respectively.

Finally, we'll concentrate on LAI's illustrations. As we know, the Leaf Area Index (LAI) involves measuring how much leaf material is there in a forest cover. In all regions, LAI is going up concurrently. But with several 0.592, the Dinajpur region demonstrates the best-fit line.

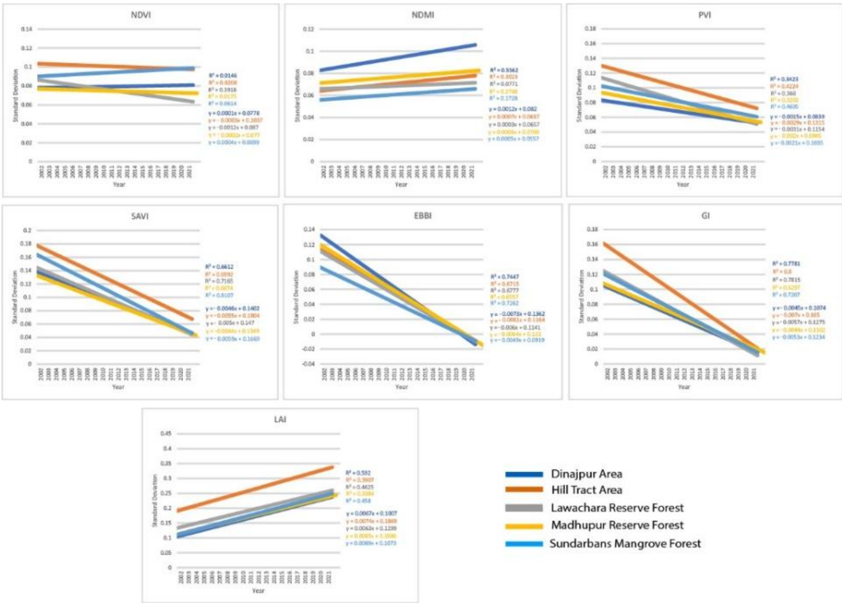

Fig. 6. Spatial variability among the areas based on different vegetation indices.

Trend analysis

We have presented the time series analysis trend of all vegetative indicators for each specific sample location for the 20 years from 2002 to 2021, according to Figure 7. We will be able to understand the past and the present condition and make predictions about how it could be in the future from this. Initially, if we investigate the vegetation indices in the Dinajpur region. We can discover that NDVI and NDMI are marginally rising while the remaining indices, such as GI, PVI, SAVI, and EBBI, are somewhat falling. The perfect fit line among them is given by GI with a value of 0.7781. As we can see in the second graph, the hill tract region's NDMI and NDVI exhibit very mild increases and decreases, respectively, whereas the trends for GI, PVI, SAVI, and EBBI reflect a considerable decline. SAVI’s value of 0.6992 indicates that this region's line of best fit.

The patterns in the vegetation indices for the Lawachara and Madhupur regions are quite comparable to those in the Hill tract regions. However, the best-fit line for Lawchara is shown by GI and SAVI for Madhupur, whose values are 0.7815 and 0.6674, respectively. The last part is the Sundarbans, where all the areas covered by the indices follow the pattern of the indices, but significantly, NDVI is only rising in this area. However, the best fit in this region shows a value of 0.8107.

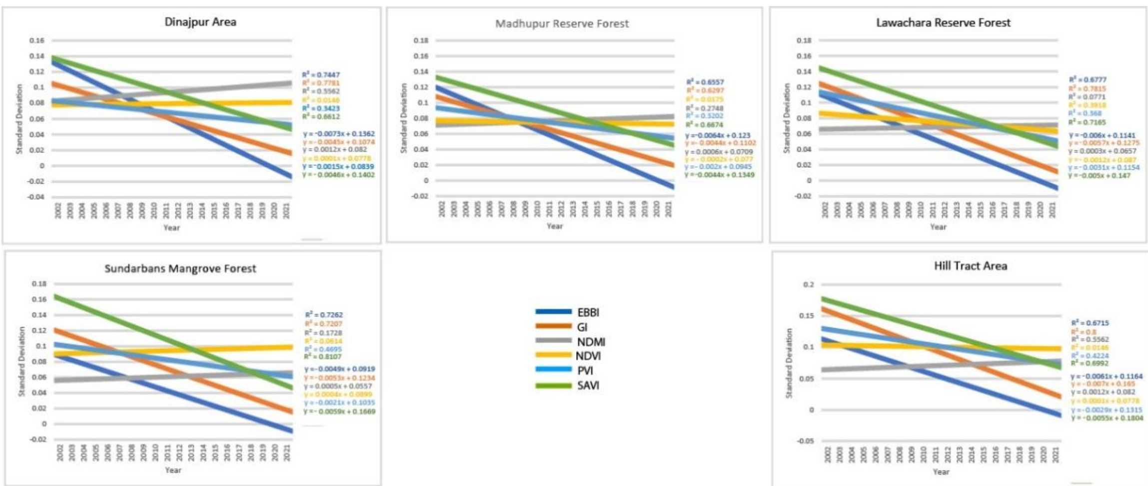

Fig. 7. Time series analysis of vegetation indices: 2002-2021.

Discussion

To determine the Bangladesh forest health status and how it has evolved, we have used seven vegetation indicators in this article. Seasonal trends and any indicators that exhibited strong sensitivity to vegetation were also discovered. In our inspection, we identified seasonality in the condition of the forest cover in Bangladesh, where the monsoon season lasts from July to August. During this time, there is a lot of rain, which improves the forest's health. According to our data, the months of July to October have the largest NDVI, GI, PVI, and SAVI values, while March to April have the pre-monsoon season's median values.

Among the sample places in Bangladesh, our studied research region, Hill Tract, Lawchara Reserve Forest, and Sundarban Mangrove Forest, are in reasonably good condition and have not changed significantly over the years. However, the state of the Madhupur Reserve Forest and the Dinajpur region has more or less degraded, and the time series analysis shows a significant diminution.

First, we observe high points of SAVI, PVI, NDVI, and GI for seasonality in the Dinajpur region. While EBBI continues a flat line and the NDMI shows somewhat fluctuation. For spatio-temporal variability, NDMI and LAI represent an increase, while PVI, SAVI, EBBI, and GI turn downwards. In time series analysis, all the indices climbed except for the NDVI.

Next, in Lawachara Reserve Forest, our investigation has found inflated seasonality lines for SAVI, PVI, NDVI, and GI, while the other two lines remained horizontal. The remaining data in the variability analysis show a downswing, but the LAI and NDMI show modest increases. However, trend analysis shows that leftovers are smooth while SAVI, PVI, GI, and EBBI decrease for this site.

Thirdly, the Hill tract region is identified in this study as having peak values in periodic analysis for SAVI, PVI, NDVI, and GI. Regarding spatiotemporal variability, PVI, SAVI, EBBI, and GI appear to decline, while LAI, NDMI, and NDVI seem to rise. In terms of on-time interval assessment, the rest decrease, while SAVI, PVI, GI, and EBBI show an increase.

Fourthly, the sporadic inspection of Madhupur Reserve Forest shows an improvement in all vegetation indices. For the LAI, NDMI, and NDVI, spatiotemporal data demonstrate an upturn, while the spare depicts a downturn. When compared to the rest, the time-period inquiry displays a growth for the NDVI and NDMI.

Lastly, this study has found that all vegetation indices—aside from EBBI—had higher values in the Sundarban Mangrove Forest area. In the context of spatiotemporal findings, PVI, SAVI, EBBI, and GI are diminished, while NDMI, NDVI, and LAI are intensified. When it comes to time series investigation, the NDVI and NDMI exhibit significant values, while the others are alternative.

We have acknowledged that all indices that reflect sensitivity, but are dependent on the amount of forest cover, are used when it comes to categorizing vegetation sensitivity bands. Except for EBBI, the other indices exhibit substantial reflectance in places with higher forest cover, although in areas with less forest cover, the relevance of EBBI has also been noted. However, considerable inconsistencies in accuracy have been noted due to the difference in the wavelength of the bands, due to the usage of data from two satellites at identical times.

Conclusion

The current study attempted an integrated approach for rapid satellite-based monitoring of changes in the forest region. This study demonstrates the ability of Landsat time series data acquired between 2002 and 2021 to identify anomalies, temporal trends, and confirm the pattern of changes over time. Vegetation indices in forest health evaluation demonstrated their sensitivity in our research locations, and seasonal patterns were observed. Additionally, we note both positive and negative trends in the spatiotemporal analysis for various locations.

The primary drawback of Landsat data is its intra-year and inter-year availability, which means that seasonal variation in vegetation conditions is unlikely to be assessed. Thus, an integrated method is used, which combines coarse spatial resolution satellite data (Landsat) with high spatial resolution satellite data (Sentinel). During the investigation, we discovered that using data from two satellites at the same time highlights discrepancies. It is advised for future research to conduct scrutiny to reduce the discrepancies.

The assessment revealed a spatiotemporal distribution of changes (physical and stress-induced) across Bangladesh's forest cover, and the methodologies used in this study might be easily applied to extract first-hand knowledge when conducting field verifications.

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