Remote Sensing-Based Fractal Dimension Algorithm to Identify Land Cover Class from Time Series EVI Data

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Abstract
Identification of land cover features is a very important input for policymakers towards sustainable planning and management at local to regional scales. These land cover features can be classified based on the spectral signatures extracted from the multispectral/ hyperspectral remote sensing data; spatial structure such as form, size, texture, etc., from fine-resolution data; or annual temporal profiles in time-series datasets. Several researchers in the past classified land cover features either using two or multi-date satellite images. However, these methods have limitations due to its inability to handle high-dimensional time series data, noise, cloud, etc. The specific objective of this study is to identify land cover features using the fractal dimension technique (box-counting) from the MODIS (MOD13Q1-v5) 16-day interval with 250m spatial resolution time-series Enhanced Vegetation Index (EVI) profile at pixel level over the Jharkhand state. Mathematically, Fractal Dimensions (FD) define the complexity of a geometric shape and quantify the sharply uneven or irregular surface or edges and signified as decimal numbers. In this study, FD images using the box-counting method helped to detect land cover features broadly into five land cover classes, namely open forests, closed forests, pure agriculture, mixed agriculture, and plantations. The proposed technique can extract patterns, identify the land cover class, and characterize/classify the study area.

Keywords: Time series, EVI, fractal dimension, box-counting

Introduction

Satellite remote sensing data allows us to study the extent and place of land cover change over the ground surface. These land cover changes require quantification, and their effect needs to be understood systematically, which impacts the ecosystem's local and regional climate. The spatial structure, spectral signature, and temporal variation help the detection of land cover features or classes using remote sensing data. The land cover change detection approach is proven using one-date or multi-date satellite images, which have limitations like cloud cover, area coverage, temporal resolution, etc. Therefore, time series satellite data play a crucial role since it has the potential to detect temporal variables within a pixel, and it can used in various remote sensing applications like land cover change studies, deforestation, climate change studies, etc. Time series Vegetation Index (VI) can be acquired from multiple satellite sensors like MODIS, MERIS, AVHRR, etc. The main issue is to detect consistent temporal profiles as a reference from time series VI data for various land cover features (Chen et al., 2017; Wilson et al., 2017; Jung et al., 2015).

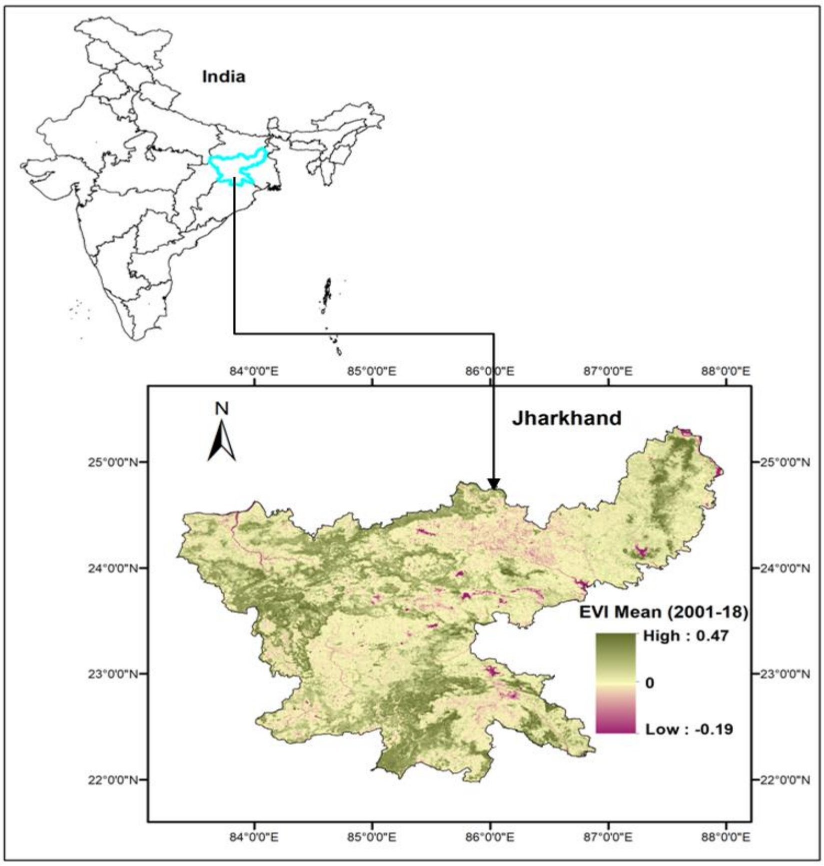

Fig. 1 Location map of Jharkhand state, India.

The changes in land use and land cover play a crucial role in the natural ecosystem, mainly due to human-induced and natural processes. There is a requirement from time to time for the characterization of landscapes for policymakers in different projects. For example, there is a requirement to know the terrain parameters for setting up power cables inside the forest. This can be achieved using satellite remote sensing data by characterizing the terrain. The vegetation index helps to identify the vegetation cover on the ground surface and land cover studies local to global scale. MODIS provides the VI data with different spatial resolutions for the land cover feature extraction. It also offers various products like Albedo, leaf area index, etc. Researchers have used these MODIS products for research and remote sensing applications (Jung et al., 2015; Chakraborty et al., 2018).

Fractal dimension (FD) is used to measure an object's complex geometry (shape) using self-similarity characteristics at various spatial scales. The FD has been implemented in multiple remote sensing applications such as forestry, geomorphology, and landscape structures (Mandelbrot et al., 1983; Sun & Southworth, 2013). Still, the FD approach has limited remote sensing time series VI data studies. B Mandelbrot first used the FD a few decades ago to study the coastline paradox to measure the shore's length. This study used FD to quantify the complex objects line coastlines (Mandelbrot B, 1967; Mandelbrot B.B, 1982). After that, various researchers used and established in the area of fractal geometry. Lam N and, Quattrochi D have showcased the FD ability and its applications to calculate the fractal dimension in geography using remote sensing satellite images (Lam & Quattrochi, 1992; Jiang & Plotnick, 1998). The same fractal dimension approach was implemented in various projects and areas like topography, ice-sheet surfaces, coastlines, etc. (Jiang & Plotnick, 1998; Rees, 1992). The current research mainly aims at forest, plantation, and agriculture classes under this study. This study uses the fractal dimension method, mainly the box-counting algorithm, to detect land cover classes from time series EVI data within a pixel. To achieve the goal, this method does not require any reference profile.

Materials and Methods

Study Area: The study area is Jharkhand state, India, between 21-25 degrees latitude and 83-87 degrees longitude (Figure 1). It has a total geographical area of 79,716 km^2. The Chota Nagpur Plateau spread across, and several rivers traverse Jharkhand state. The state's climate is diverted from subtropical to tropical, wet and dry from north to southeast. The state gets sufficient rainfall from July to September, resulting in a rich diversity of flora and fauna. The state has around 30% and 37.30% forest and cultivable areas, respectively. Waterbodies, built-up areas, wasteland, etc., account for the rest (Web Reference 1,2,3&4).

Data Used: The satellite data used in this study are time series MODIS 16-day enhanced vegetation index (EVI) data with 250m spatial resolution. MODIS product MOD13Q1-V5 with tile h25v05 acquired 23 in total for 2018 from the LP-DAAC site. Time series EVI data have inherent noise present due to cloud and atmospheric effects, which results in fluctuation (abnormal drops and peaks) in the temporal profile of the dataset. To minimize this inherent noise present in time series EVI data, the Savitzky–Golay filter is used to remove noise and smooth the raw time series EVI data (Priyadarshi et al., 2018; Priyadarshi et al., 2022).

Methodology: Cloud and atmospheric effects introduce the noise in time series EVI data, which must be removed before analysis (Priyadarshi et al., 2018). The Savitzky-Golay filter removes noise from EVI data by preserving the temporal profile and suppressing disturbances (Priyadarshi et al., 2018; Priyadarshi et al., 2022). In this study, the box-counting was used to calculate the FD of the satellite images. The fractal dimension (FD) used the concept of self-similarity to characterize and disclose the complex geometry. A fractal object has properties that remain the same irrespective of scale change, a self-similarity concept (Mandelbot and Pignoni, 1983; Kusak M, 2014; Jeganathan & Mondal, 2017). The FD has the ability to quantify changes in properties, such as length, area, volume, etc., of an object while changing the scale or at different scales. It can be defined as below

$$FD = \log (N) / \log (1/r) \tag{1}$$

Where N is the number of self-similar with r size, the log is the natural logarithm, and FD is the fractal dimension, FD having a non-integer value. The box-counting method to calculate FD is implemented in time series EVI data.

Box counting is a widely used approach to calculate the fractal dimension of an object irrespective of whether it has self-similarity properties within the object (Figure 2). In this study, the box-counting was used to calculate the FD of the satellite images.

The box-counting algorithm has been used to estimate the FD using boxes (total number) to cover the EVI annual temporal profile. The segment is characterized by finding the difference between two consecutive EVI data and storing it in an array of Ls. The box has r x r, which fit diagonally (d) for n number of times in a non-overlapping way to cover each segment. If the maximum value of Ls is less than that of a maximum of r, the last value of the array r is given by

$$r \leq \sqrt{2} \times \max(Ls)$$

For every value of r and every value of Ls, calculate n, which is given by

$$n = int\ \frac{Ls}{d}$$

Here, d is the diagonal length of the box given by d= √2×r. The remainder part of the boxes that cannot cover the segment have been ignored using the integer function. The process finds the total number of boxes needed to cover each segment by adding all n boxes, and it is an iterative approach using the r-value (range 0-1) pixel-wise. At last, the FD was calculated by finding the slope of this regression line of log(N) vs. log(1/r).

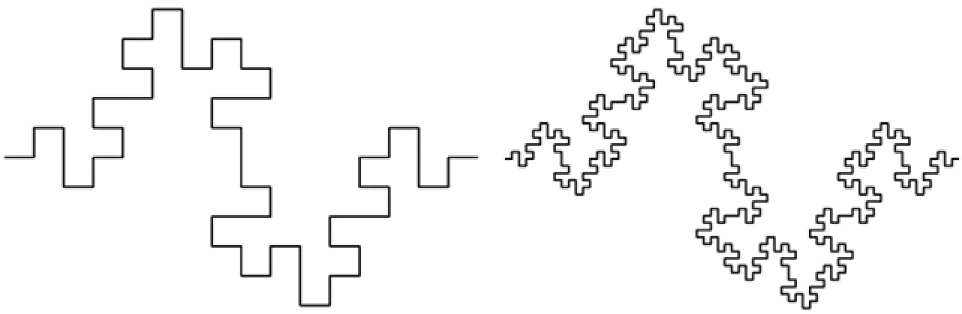

Fig. 2 Minkowski Curve with 2 iterations (left) and 3 iterations (right).

Results

The choice of the proper parameter (box size) impacts the execution of the fractal method. The box counting is subject to the slope of the linear regression line. Accordingly, starting with a larger box size would bring about less information/data for the log-log plot, which may lead to a wrong estimate of the slope and, in turn, the fractal dimension. Although there are no rules for linear regression, a minimum of five to eight data points would suffice for a reliable result (Shelberg et al., 1983). In this study, the box size minimum and maximum ranges from 0.005 to 0.2 with an increment of 0.005. Furthermore, the EVI data has been scaled in between 0 and 1. This ensures that we get, at most, a 40-maximum amount of data for the log-log plot.

Figure 3 depicts the resultant FD image of Jharkhand created by applying the box-counting method. The legends accompanying the figures provide an estimated value range for each class. Figure 3 illustrates the distribution of closed and open forests and areas of pure agriculture, mixed agriculture, and plantations. Closed forests are located between 0.90 and 1.11, open forests between 1.11 and 1.15, pure agriculture between 1.15 and 1.25 regions, and mixed agriculture between 1.25 and 1.40. Lastly, plantations lie between 1.40 to 1.50.

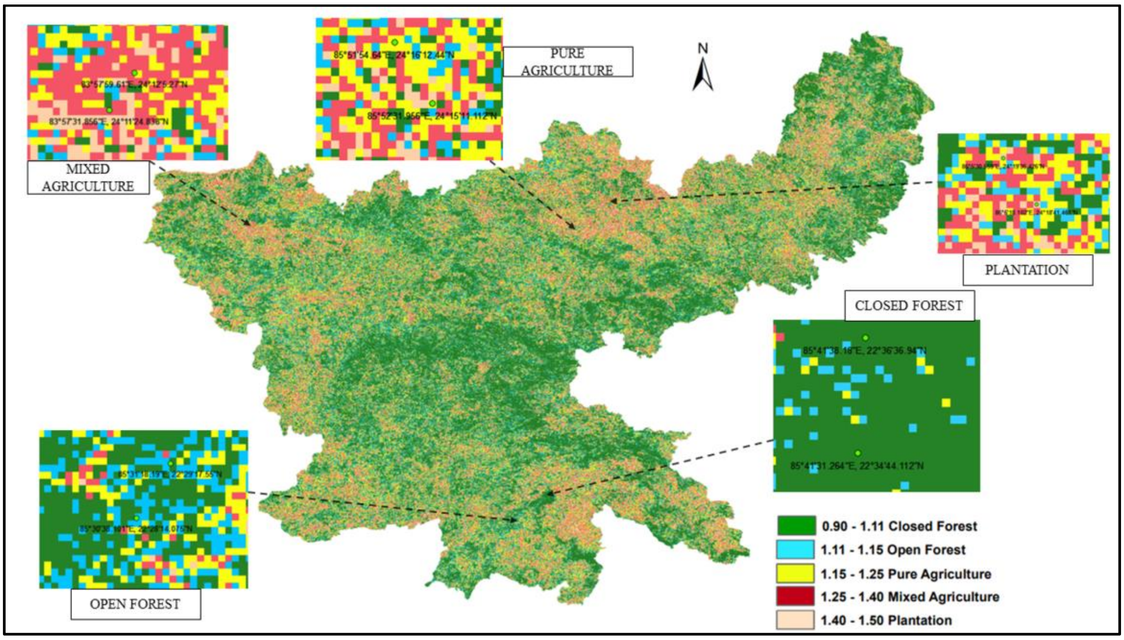

Fig. 3 FD image of Jharkhand using Box Counting Method.

Figure 3 makes it apparent that the closed forest type dominates the area. The corresponding region from Google Earth for the specified pixels for each class inside a 1Km^2 radius is shown in Figures 4,5,6,7&8, respectively. Consequently, using these results, one may identify the closed forests and open forests that can be located around these closed forest pixels. The boundary separating pure agriculture from mixed agriculture needs to be clearly defined, though. A few agricultural regions have also been designated as open forest regions. Finally, there are a few pixels that represent areas of plantations.

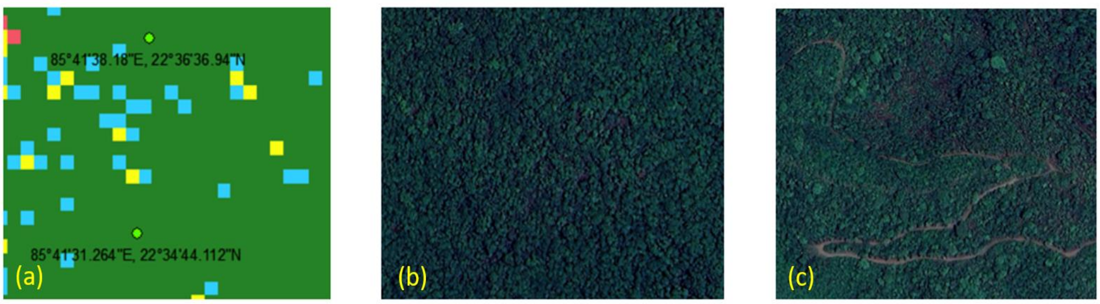

Fig. 4 (a) Closed Forest Region; (b) Corresponding Google Earth Region (85˚41'38.18''E, 22˚36'39.94''N); (c) Corresponding Google Earth Region (85˚41'31.264''E,22˚34'44.112''N).

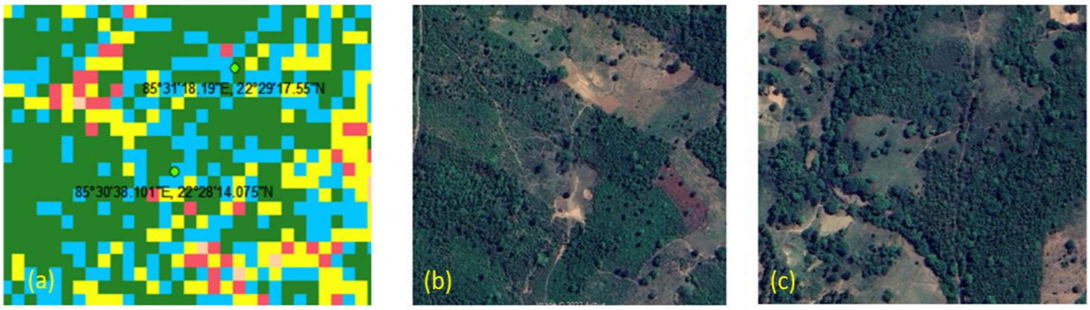

Fig. 5 (a) Open Forest Region; (b) Corresponding Google Earth Region (85˚31'18.19''E, 22˚29'17.55''N); (c) Corresponding Google Earth Region (85˚30'38.101''E,22˚28'14.075''N).

Fig. 6 (a) Pure Agriculture Region; (b) Corresponding Google Earth Region (85˚51'54.64''E, 24˚16'12.44''N); (c) Corresponding Google Earth Region (85˚52'31.956''E,24˚15'11.112''N).

Fig. 7 (a) Mixed Agriculture Region; (b) Corresponding Google Earth Region (83˚57'59.61''E, 24˚12'5.27''N); (c) Corresponding Google Earth Region (83˚57'31.856''E, 24˚15'24.838''N).

Fig. 8 (a) Plantation Region; (b) Corresponding Google Earth Region (86˚05'30.559''E, 24˚19'36.426''N); (c) Corresponding Google Earth Region (86˚06'10.102''E, 24˚18'41.461''N).

Discussion

When the FD image is compared with the map of Jharkhand on Google Earth, it is observed that there are minor errors in the estimated ranges of fractal dimensions for the classes. It was observed that individual FD calculations had produced similar fractal values for two different vegetative classes having dissimilar temporal patterns. This is because the FD is not sensitive to magnitude and phase difference in the EVI annual profile but is associated with the degree of complexity. Therefore, the inherent complexity of the two curves could be the same despite dissimilarities in the annual profile due to different land cover classes. For instance, some open forest regions lie in closed forests and pure agriculture areas. Another example, some dense forest lies in pure agricultural areas. Significantly, the noise (due to atmospheric conditions, clouds, etc.) present in the EVI data affects the quality and complexity of the annual profile.

Similarly, there is no definite boundary between where pure agriculture ends and mixed agriculture begins. This is mainly because the fractal dimension measures the randomness or roughness present in the temporal profile. Thus, it is evident that two different curved profiles may have similar fractal dimensions.

Conclusions

Ecosystem-related observations from remote sensing data offer massive potential for understanding the location and extent of local and regional land cover change. Hence, pattern extraction in the time series vegetation index to identify land cover class is helpful in LULC classification, forest fragmentation, and land cover change detection studies and provides scope to understand the vegetation cover changes at regional and global scales. The current study explored three different FD techniques for discriminating LULC features in the Jharkhand state. The box-counting method revealed that closed forests are located between 0.90 and 1.11, open forests between 1.11 and 1.15, pure agriculture between 1.15 and 1.25 regions, mixed agriculture between 1.25 and 1.40, and plantations lie between 1.40 and 1.50. The FD images helped us understand the similarities in the annual EVI profile of various land cover features. The experiments revealed that using FD images has considerably helped identify basic land cover classes and accurately detect forest, agriculture, and plantation classes. The fractal approaches evaluated in this study provide a way forward to further research on using time series satellite data-based fractal information for improved vegetation monitoring and understanding the effect of land cover mixing and other associated noises on the annual EVI profile. The method developed under this study has the ability to classify different time series data and can be extended to the national scale.

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