The Jahangirnagar Review: Part II: Social Science, Vol. XLV, 2021
Printed in December 2021, ISSN 1682-7422 © Jahangirnagar University

Effect of Variation of Vegetation Species (Rubber and Natural Forest) on Enhanced Vegetation Index (EVI)

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Abstract: The Enhanced Vegetation Index (EVI) is one of the most adequate and popular indices to monitor the vegetation cover. However various types of environmental and topographical factors can produce hindrance in the EVI values. Like all other factors the species variations and characteristics have also an effect on EVI values. To find out the effect of vegetation species on EVI values the Landsat OLI image acquired from a forest dominated area with species variations from the central part of Bangladesh named Madhupur forest. To calculate the EVI values the arithmetic combination of three bands (Blue, Red and NIR) are used in QGIS environment besides for mapping purposes and for extraction of EVI values from processed raster the ArcMap 10.6 software are also used here. The output of the study indicate that high dense rubber *(Ficus elastic)* forest gives the highest EVI value like 0.62 and for moderate and low dense rubber forest the values are in between 0.44 to 0.54 where the high dense natural *(Shorea robusta)* forest gives the lowest EVI value like 0.05 and for moderate and low dense natural forest the values are in between 0.23 to 0.26. Which clearly stated that, the species characteristics and its variation has a direct impact on EVI values.

Keywords: EVI, Landsat OLI, Spectral bands, Vegetation species, Vegetation characteristics.

Introduction

The vegetation classification, phonologic information and biophysical derivation of radiometric and structural vegetation parameters are important concepts to understand different species in particular forest. Owing to monitoring these issues, the Vegetation Index (VI) is considered the suitable way, that is defined as arithmetic combination of two or more bands which are directly related to the spectral characteristics of vegetation (Huete et al., 1999). For monitoring the variations in vegetation and vegetation cover, different vegetation Indices (VI) are now considered worldwide for definite results. The quantitative measure of any biomass or plant vegetation or forest or species are defined generally as the Vegetation indices. The combination of several spectral bands in Satellite imageries with particular values has is usually formed different Vegetation indices whose are segmented or multiplied by each other in order to attain the value which helps to identify the amount or vitality of vegetation (Halos & Abed, 2019). The Vegetation Index (VI) was developed to obtain the characteristics of vegetation and the land use with

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the combination of two or more particular wavelength bands – blue, green, red, and near infrared (NIR), which are vastly related to photosynthesis (Huete et al., 1999). Therefore, VIs are often applied to identify the vegetation cover and to analyze the land use and land cover changes, especially, to detect the spatial variability of different species (Matsushita et al., 2007), vegetation cover distributions in particular locations and its densities over time (Lunetta et al., 2006; Myneni et al., 1997; Saleska et al., 2007). To detect Land Use-Land Cover (LULC) dynamics, the method of EVI indices are used broadly (Ehsan & Kazem, 2013; Singh et al., 2016). Furthermore, measuring the EVI are mostly used for the assessment of the spatiotemporal characteristics of LULC, highlighting the vegetation cover (Kinthada, 2014). Though NDVI measurements are generally used to assess the spatiotemporal characteristics with vegetation cover, its principle is derived from the reflectance characteristics of photosynthesis. Due to the testing vegetation greenness with red bands signal are absorbed by plants and NIR band signals are reflected by plants. More advanced indices like EVI, EVI2, GRVI etc. were developed reduce these issues and broadly used in addition to NDVI (Phompila et al., 2015). Specially, the EVI helps to enhancing greenness signals from the ground surface including forest canopy structures with the use of blue band (Huete et al., 1999; Shishir & Tsuyuzaki, 2018). Thus EVI can reduce soil and atmospheric interference for more accuracy (Holben & Justice, 1981). The reflectance characteristics of photosynthesis is the main principle of EVI, in particular, through the test of the greenness in whole vegetation absorbed by the plants with the blue and red band signals of the sensor and reflected the near-infrared band signals (Shishir & Tsuyuzaki, 2018). The weakness of this EVI index is that in some cases its accuracy can be distorted by the atmospheric (clouds), various ground conditions over surface (soil types) (Kushida et al., 2015; Miura et al., 2001). The greenness signal including forest canopy structures is mostly enhanced by the accumulation of the EVI with the use of blue band (Ronchetti et al., 2020) and it also reduces the extra soil and atmospheric interferences consequently (Holben & Justice, 1981). Assessing any VI calibration, the topographic effect is an important environmental factor contributing to the noise in hilly areas (Dymond, 1999; Meyer et al., 1993; Smith et al., 1980; Trotter, 1998). As the effects are visible and near infrared parts of a surface's solar spectrum are comparable, these could be eliminated or weakened when NDVI is expressed as band ratio (Lee & Kaufman, 1986). Nevertheless, EVI includes a constant term titled the soil adjustment factor or canopy background L, in its denominator (Equation 1). The constant L allows the EVI assessment to include the term without a band ratios format (Matsushita et al., 2007). Different studies showed that lack of definite datasets of radiances regarding topographic effect put hindrance especially in vegetation cover of hilly region (Trotter, 1998). Again, datasets of vegetation composition, biomass and diffuse illumination contain variation because of slope, aspect, altitude etc. This type of complexity in data brings difficulties in distinguishing radiance variations. As a consequence, the spectral data variances are observed in EVI which evaluates topographic effects despite of having these factors (Matsushita et al., 2007). Remote sensing techniques can deliver accurate vegetation information with the correct selective sensors and image processing methods, those are really proficient and even cost-effective (Kamal et al., 2015). For accomplishing method, the prior component is long term medium resolution remote sensing data provided by the Landsat mission (Schultz et al., 2016). Landsat offers the longest running cross-calibrated data at medium resolution of the Earth's surface that is also consistent globally. Since the archive is developing for a longer time, several studies had been demonstrated using Landsat's capabilities for mapping forest cover and also related changes (Abdullah et al., 2015; Faruq et al., 2016; Hossain et al., 2015; Kamal et al., 2015; Schultz et al., 2016). Due to this reason the Landsat OLI satellite image are used in this study. The main aim of this study is to examine how the vegetation indices response for different vegetation species on the basis of their characteristics. All the vegetation species have their own characteristics which has also impact on all vegetation indices like EVI, NDVI, SAVI etc. This study had been conducted to find out the effect of various types of vegetation species on EVI values. For evaluating this and calculating EVI values, the electromagnetic blue, red and NIR band of Landsat 8- OLI satellite imagery had been used thoroughly.

Study Area

Madhupur tract is situated in the central part of Bangladesh which is a large upland area and the Madhupur upazila is situated in the northern part of Madhupur tract. This region contains with the overall high Land topography (M. M. Rahman et al., 2008). Only a union in the dense part of Madhupur forest is selected for conducting this study, that is placed under Madhupur Upazila of Tangail District. This forest is located in between the River Banar in the east direction and the River Bangshai in the west direction and only the forest located in the flood free central part of Bangladesh. Its landform is largely dominated by the Pleistocene Terrace area of Tangail District (Shishir & Tsuyuzaki, 2018). Madhupur forest is largely consisted of deciduous species and having characteristics of tropical with moist. About 45,565.18 acres area are associated in the total area of this forest and from these, about 2,525 acres are restricted for reserved forest. On the other hand, about 4, 304 acres are under the process to be declared as reserved forest (Hossain et al., 2015). About 129 species were found where 65 species including in trees, 15 by shrubs, 26 climbers and 23 by herbs. Sal forest is the dominant of these species, generally forms 75% to 25% of the upper canopy in the natural growth (M. Rahman & Vacik, 2010).

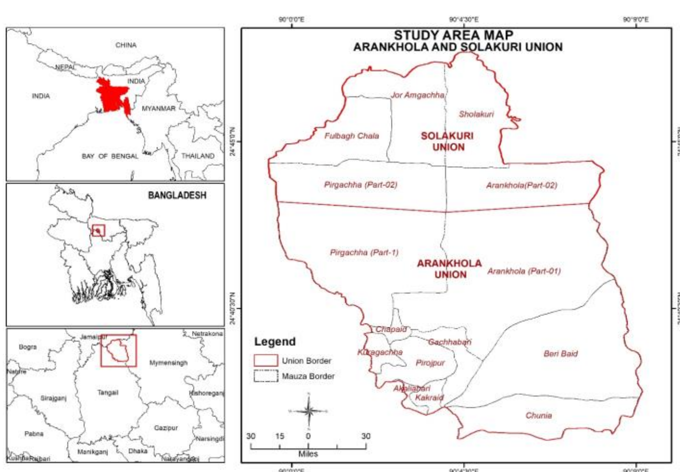

Figure 01: Geographical location of Solakuri and Arankhola Union where Madhupur forest situated

Image Acquisition

We use multi-temporal satellite image to identify the vegetation cover of the in the Madhupur forest (Faruq et al., 2016). We have downloaded the Landsat OLI Satellite Images from USGS- Global Visualization Viewer (GloVis). The image acquired during the mid of March at this time the sky is clear with only 20 to 25 percent cloud cover. From the mid-February to mid-April it is considered as spring season in Bangladesh and at the beginning of this season the leafless trees get back leaf (Banglapedia, 2021) and the mid-march it turns into the maturity which gave the highest spectral reflectance for the specific electromagnetic wave. The study area is mainly the forest dominated area so for best analysis and result in EVI values and spectral reflectance profile this image is collected which also lessen the effect of cloud and rainfall (Giri et al., 2008).

Table 1: Properties of Landsat imagery

Sensor	Year	Projection	Path-Row	Date Acquisition Date	Spatial Resolution (m)	Cloud Cover
LS 08 (OLI)	2014	UTM	137-43	17/03/2021	30	0.36

Source: (GloVis, 2021)

The Landsat Operational Land Imager (OLI) has 11 spectral bands respectively. Amongst them, the first nine spectral bands with the finest spatial resolution of 30m (except for Band 8, having 15m spatial resolution). The last bands have the spatial resolution of 100m. For fulfilling of the objective of the study, the band 2-blue,4-red and 5- NIR have been used to evaluate the EVI value. All band values are mentioned precisely in Table 2.

Table 2: Landsat OLI Bands and Their Spectral Wavelength

Bands	OLI (Landsat 8)		
	Band Name	Wavelength	Resolution
Band 1	Coastal Aerosol	0.433- 0.453	30 m
Band 2	Blue	0.45- 0.515	30 m
Band 3	Green	0.52- 0.60	30 m
Band 4	Red	0.63- 0.68	30 m
Band 5	NIR	0.84- 0.88	30 m
Band 6	SWIR- 1	1.56- 1.66	30 m
Band 7	SWIR- 2	2.10- 2.30	30 m
Band 8	Pan	0.5- 0.68	15 m
Band 9	Curus	1.36- 1.39	30 m
Band 10	TIRS-1	10.6- 11.2	100 m
Band 11	TIRS-2	11.5- 12.5	100 m

Source: (NASA, 2019)

Materials and Methods

The focus of this study is to identify the effect of various species on EVI values. EVI is mostly used to identify vegetation cover in any considered area, which uses the arithmetic combination of three bands- blue, red and NIR. These bands are related to vegetation spectral characteristics that precisely provide consistent spatial and temporal information of vegetation (Shen et al., 2009). Here in this study, we will calculate and extract the EVI values for a forest dominated area which contains two major classes of vegetation species and try find out the differences and variation of the EVI values for these two types of species.

Enhanced vegetation index (EVI) using reflection blue to develop correct signals of the background soil and reducing atmospheric effects such as scattering particles. The combination of empirical relationships for atmospheric correction has resulted in develops of vegetation index (EVI) (Mokarram et al., 2016).

For conducting preferred output, methods of image pre-processing, geometric and atmospheric corrections had been performed with QGIS 3.6.2 software. Then, the following indices were used for calculating the Enhanced Vegetation Index (EVI) in this study (Mokarram et al., 2016):

EVI = G * ((NIR – R) / (NIR + C1 * R – C2 * B + L)) …………………………… (1)

Where,

G (gain factor) = 2.5

L = 1 [Adjust of Canopy Background]

C1 = 6 and C2 = 7.5 [C1 and C2 = Coefficients for Atmospheric Resistance]

In Landsat 8- OLI:

EVI = 2.5 * ((Band 5- Band 4) / (Band 5 + 6 * Band 4 – 7.5 * Band 2 + 1)) …….. (2)

The sequence of procedures followed in this research had been indicated in the below flow chart (**Figure 02**).

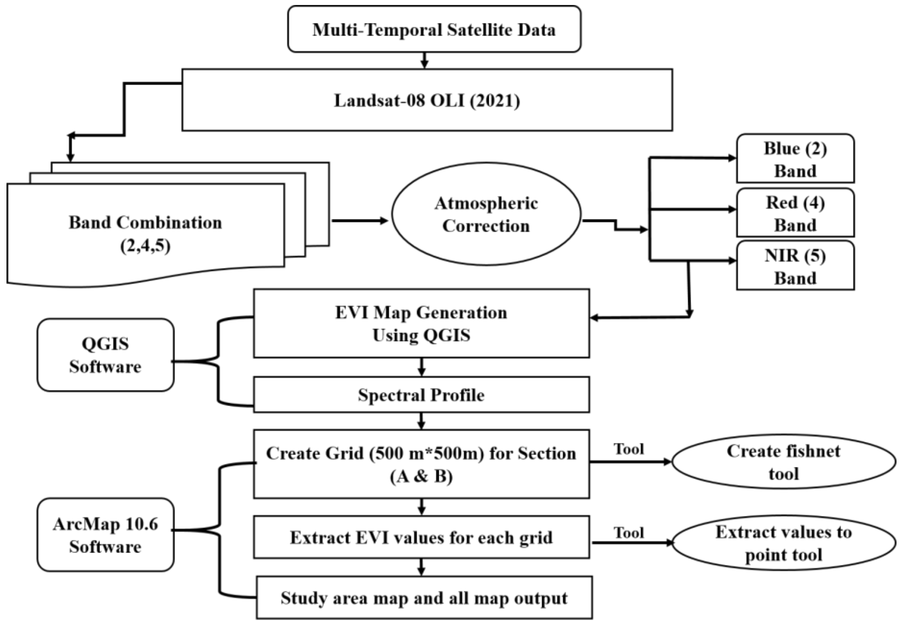

Figure 2: Flow Chart with Methodological Procedures in Definite Sequence

The multi-temporal satellite image of the Landsat OLI sensor of 2021 was used in our study. The QGIS 3.6.2 software were used for image pre-processing, atmospheric collection, EVI calculation and spectral profile drawing.

To keep this research rational and easy analysis of the data we only consider the densely forest dominated area as our study area. There are two dense area are found in the Madhupur forest one is rubber plant (Ficus elastic) dominated area and the other is natural (Shorea robusta) forest (Faruq et al., 2016). Based on the density of the forest we divided our study area into two section. The rubber plant dominated area are marked as (section a) and the natural forest dominated area are marked as (section b) (figure 03).

To make the analysis comparable we created (500*500) m grid and its midpoint of the study area where each grid containing almost 287 pixel of the image. After calculated the EVI in QGIS we extract the cumulative EVI values for each grid. The EVI values for each grid gives us the idea about the difference between the EVI values for two sections of our study area (figure 05). All of these work also with study area map and all other map output are produced using ArcMap 10.6 software.

Study Area in Landsat 08 (OLI) image

There were some modifications in the calculation of EVI and this EVI algorithm had been adopted coefficients where NIR, red, green and blue bands can present atmospherically corrected surface reflectance effectively. Here, L had been used for denominating the adjustment in canopy background, that is used for addressing the nonlinear, differential transmittance of NIR and red wavelength (Shishir & Tsuyuzaki, 2018). These parameters had improvised the sensitivity in EVI for the vegetation monitoring capability by dissociating the canopy background signal, which actually detects the atmospheric influences for removal (Huete et al., 1999).

Figure 3 shows the distribution maps of the aspect of EVI in the study area. From the considered forest area, the vegetation cover had been displayed brighter in section A and deep disappearing shadowed in section B due to the light- blocking forest canopy having the characteristics of uniform vegetation surface. Therefore, the reflectance of the A is brighter that can be clearly seen in the images accumulating EVI than the B due to spatial distribution. The reflectance values between A and B are largely different and these values have detected different vegetation covers alongside aspect area. The results shows that the variations of the reflectance in EVI values mainly caused for the species variations.

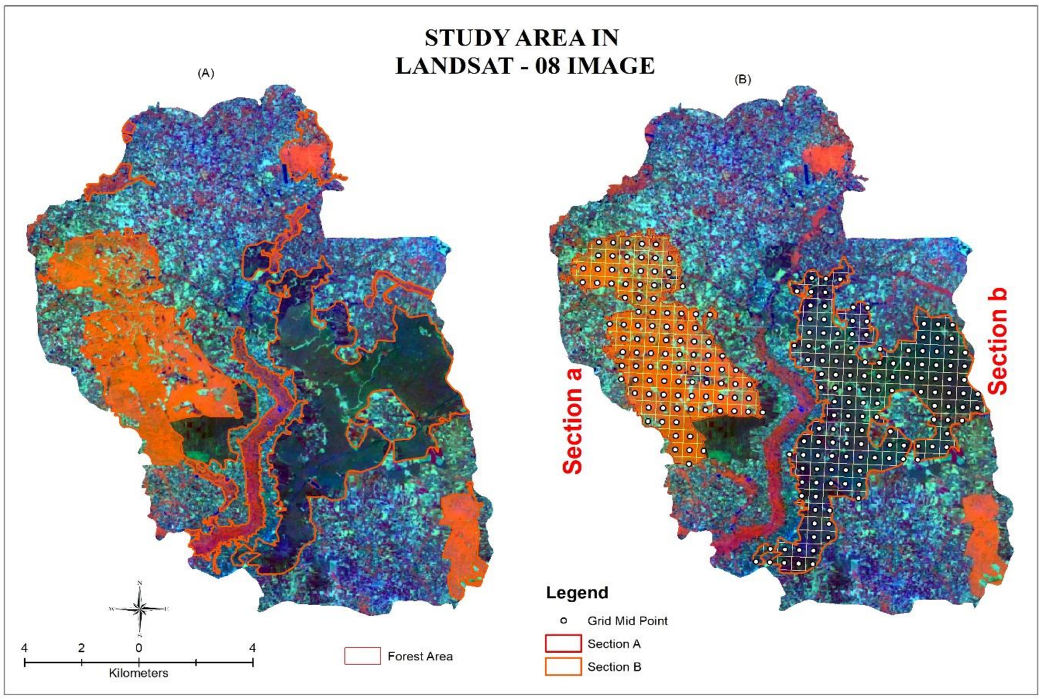

Figure 3: False color combination map of Madhupur forest. (A) Dominated forest area in Madhupur region. (B) Grid map of the two sections (a and b) of study area. Rubber *(Ficus elastic)* forest area marked as (section a) and Natural (Shorea robusta) forest marked as (section b).

EVI Map of the Study Area

The EVI values were shown in the highest range of 0.62 for Rubber *(Ficus elastic)* forest while the Natural (Shorea robusta) forest ranges of lowest value in between -0.0035 and 0.3642. The EVI separates these two vegetation covers clearly. According to (Shishir & Tsuyuzaki, 2018) research, they found EVI values between 0.37 and 0.48, which were mostly associated with respective cropland and occasionally grassland in the considered study area. Besides, EVI values were fluctuated largely over the Shorea forest and homestead vegetation. So, calculating the vegetation cover of Rubber forest and the Shorea forest (Natural) were respectively different in the EVI values. The difference is supposed to be the reflectance criteria of canopy.

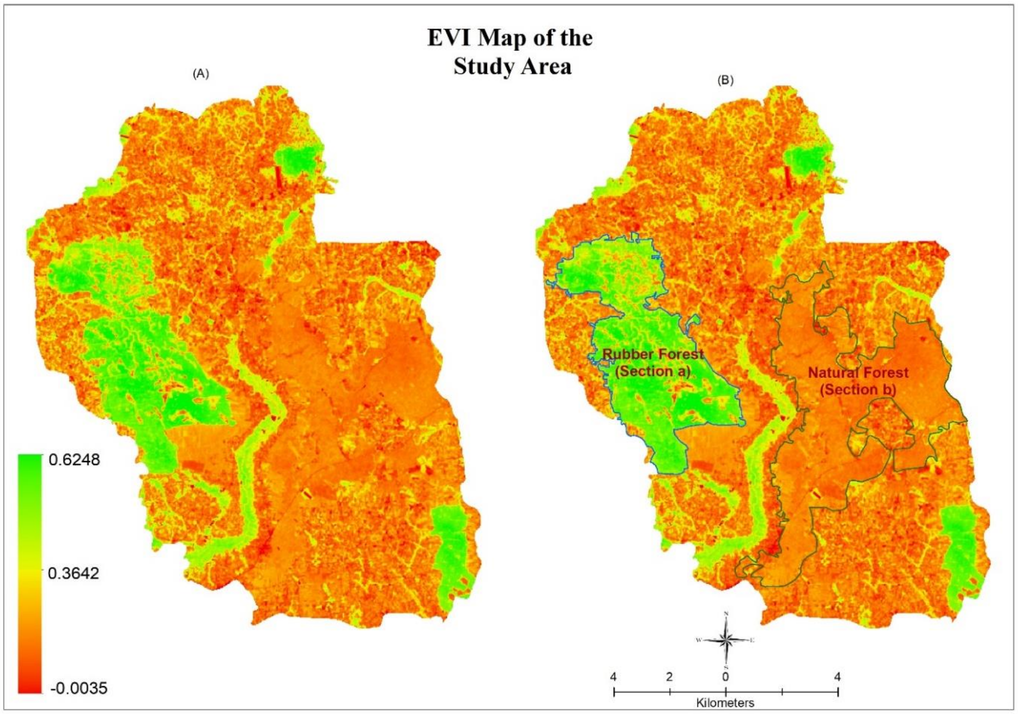

Figure 4: EVI map for the whole study area

EVI map for Rubber forest and Natural forest

For better understanding in the variation of EVI values and comparable data analysis we consider only the two highly clustered and dense forest cover area for this research. One is the Rubber (Ficus elastic) forest which is marked as (section a) and the other is Natural (Shorea robusta) forest (section b) (figure 04) which contains various types of trees.

From EVI map of this two section (figure 05) it found that the EVI values for Rubber *(Ficus elastic)* forest is very high and its values is as like as healthy vegetation. The value range for EVI is -1 to +1, and for healthy vegetation it gives high positive values close to +1 (Halos & Abed, 2019). Form the map (figure 05) the EVI values for dense rubber forest is very high like 0.62 and for moderate and low dense rubber forest the range is in between (0.62 to 0.44) which is very much similar to reality. In comparison to (figure 03) and (figure 05) we found in every grid where the density of the rubber forest is high the EVI value is also very high. That means in case of rubber forest EVI values has a close relation with the density of the forest. When the density of the rubber forest increased the EVI values also increased and vice versa.

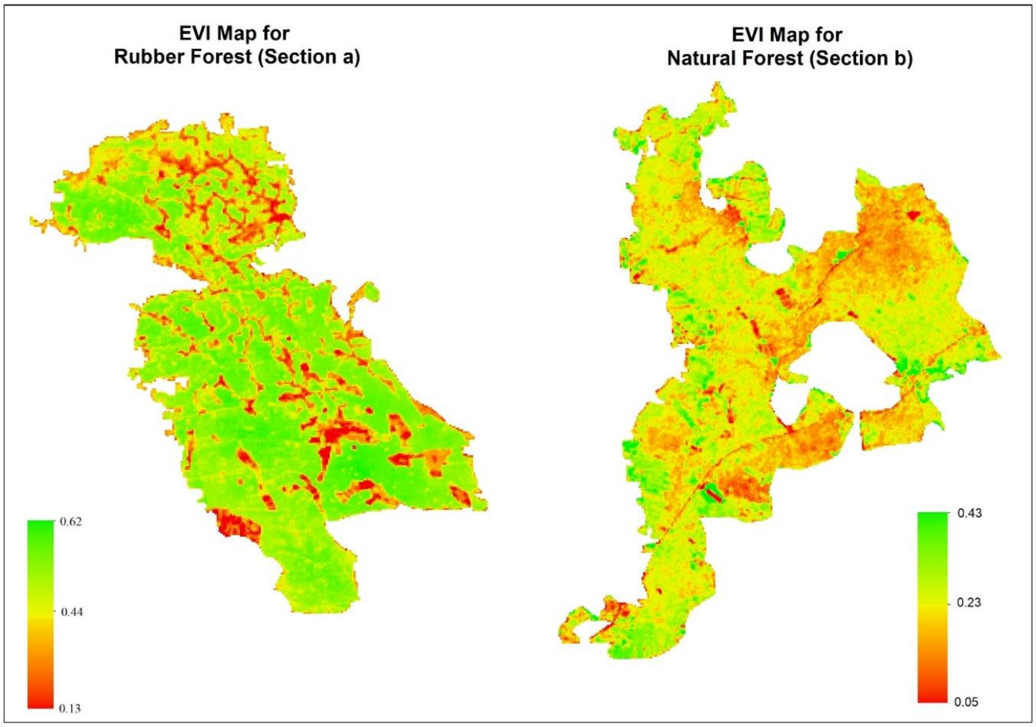

Figure 5: Generated EVI map for Rubber forest (section A) and Natural Forest (section B)

On the other hand, the density of the particular natural (Shorea robusta) forest (section B) is also similar to the rubber forest but the EVI values is not similar. From the map (Figure 05) the highest EVI value is 0.43 and lowest value is 0.05. According to the EVI value range the health vegetation means the dense vegetation will give high EVI value and the low dense vegetation will give low value. But in case of natural forest (section B) we found completely different things. And that is where the natural forest density is very high the EVI value is very low and in case of low vegetation density it gives high EVI values. In EVI map (Figure 05) for natural forest the highest EVI value is 0.43 but in reality (Figure 03) in these areas we found low vegetation density and lowest EVI value is 0.05 but in reality (Figure 03) in these areas we found it as highly dense vegetated area. Which means the natural forest of this study area did not give expected value like as rubber forest. It means the EVI values for all species is not same and the species have a direct effect on EVI values. This variation in EVI values can be happen for various reason like leaf structure, maturity, pigmentation (Roy, 1989), soil quality etc.

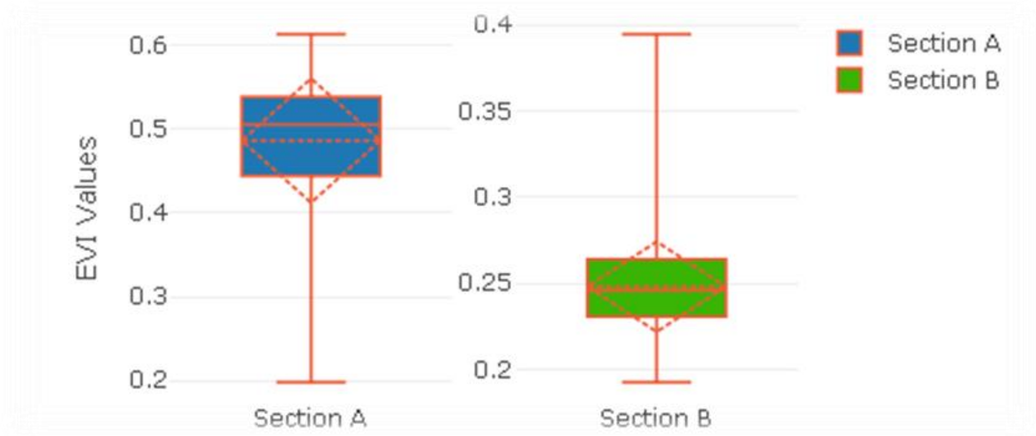

Figure 6: Boxplot for the EVI values of rubber (section A) and natural (section B) forest

The above boxplot (figure 06) shows the difference and variations between the EVI values of Rubber (Ficus elastic) forest and natural (Shorea robusta) forest. In the boxplot, section A indicates the brighter and deeper EVI values of rubber forest and section B indicates the shadowed EVI values of Natural forest, which had been extracted from the EVI map using the grid midpoint (figure 03).

For the dense and moderate rubber forest (section a) the EVI values are in between (0.44 to 0.54), the mean EVI values is 0.49, the median is 0.51 and the lower fence is 0.31. Its means the rubber forest gives high EVI values as like as the reflectance value. For the dense and moderate natural forest (section b) the EVI values are in between (0.23 to 0.26), the mean EVI values is 0.248, the median is 0.246 and the upper fence is 0.31. Here for natural forest (section b) the mean and median EVI value are almost same and there is a little variation in EVI values range among the dense and moderate forest. The boxplot clearly stated that the natural forest gives lower EVI values compare to rubber forest.

Spectral profile

To identify and monitor vegetation conditions and to map land cover changes, the different vegetation indices derived from Satellite image data are considered one of the primary sources (Teillet et al., 1997). For the identification of vegetation cover, Remote sensing techniques use passive sensors to obtain the electromagnetic wave reflectance information from canopies (Xue & Su, 2017). Accumulating the spectral reflectance of leaves, various factors can affect e.g., leaf structure, maturity, pigmentation, sun exposition, turgidity (water content), nutritional status, disease etc. Besides, anatomy of leaves and soil water content imply effects primarily and thus, these give diversifications in the spectral reflectance values in vegetation (Roy, 1989).

In this study two types of vegetation are found in the two sections (A and B) of the study area and they give different EVI values as well as reflectance values in the spectral profile. This is happening for the above-mentioned factors and it can be for the phonological development in reflectance details (e.g., the progression of a crop toward maturity) (Odenweller & Johnson, 1984).

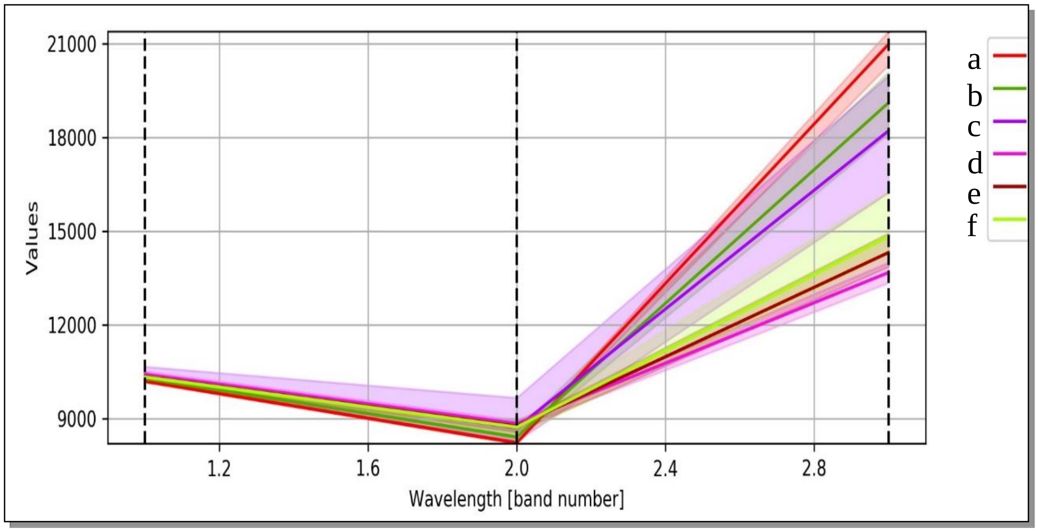

Figure 7: Spectral profile for rubber (section a) and natural (section b) forest. The legend for the profile are given at its right ride. Here high dense rubber forest (a), moderate dense rubber forest (b), low dense rubber forest (c), high dense natural forest (d), moderate dense natural forest (e) and low dense natural forest (f).

The spectral profile (figure: 07) shows that, in case of blue (band 2) and red (band 4) the reflectance value for rubber forest (section a) and natural forest (section b) are almost same. The NIR (band 5), consistently it provides high spectral response for rubber forest (section a) as like as healthy vegetation and gave the highest reflectance value but for natural forest (section b) it gave the lowest spectral value and greatest spectral separation identified compare to rubber forest (section a) (Kamal et al., 2015). Though both are the densely forest dominated area but due to leaf structure, maturity, pigmentation (Roy, 1989) and also for various other factors the spectral reflectance are different and which have a direct effect on the EVI value for both rubber (Ficus elastic) and natural (Shorea robusta) forest.

Conclusion

The EVI can classify the grassland, cropland and agricultural low land types influenced the different land use (Shishir & Tsuyuzaki, 2018). This EVI method doesn't consider the adverse effects of environmental factors such as atmospheric conditions and soil background in calculations, though these manually impacts on the reflectance. The calculation of EVI accompanies a change in orientation from horizontal direction to an inclined surface. A change in light source and sensor position can be responsive giving different values. For this reason, this study had been claimed two EVI values in different vegetation species covered in study area (Holben & Justice, 1981). The advanced quantitative relationship in vegetation indices like EVI between spatial scale and topographic effect needs further study for recommending the topographic hierarchical effect. As these characteristics are removed from EVI in applications, still the factors work on vegetation and thus EVI performs better than does the NDVI in many accumulations (Matsushita et al., 2007). The EVI responses in reflectance can be utilized more effectively in conjunction with higher spatial resolution data extracted from Satellite images of an area with rough terrain and topography. These characteristics effects on the vegetation indices having only one band ratio format in Bangladesh. To reduce both atmospheric and soil background noise simultaneously, the EVI can be constructive research method for planning forestation and divert contribution in reserved with homestead vegetations. This study can serve a counter analysis of species richness of both species at highly protected core area. The findings can provide information describing well balanced distribution undisturbed forests areas to formulate more conservation plans and to understand plant diversity.

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