Modeling β Diversity and Simpson's Index Using Hyperion Reflectance in Vansda National Park, Gujarat

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Abstract:
Global biodiversity is under threat due to increasing anthropogenic activities. Pressure on biodiversity is immense especially in rapidly developing countries like India. In the present study, an attempt has been made to establish accurate relationships between Hyperion (EO1) reflectance spectra and measured β diversity index and Simpson's index of the tropical moist deciduous forest of the study area. Developed accurate models can help in mapping and assessment of diversity at larger spatial scales. The efficiency of statistical modeling techniques including Partial Least Square (PLS) regression and Multiple Linear Regression (MLR), is demonstrated in this study (with maximum R^2 of 0.74 and 0.73 for PLS and MLR respectively). A vegetation index (SR 1457/933) is introduced for β diversity estimation, yielding exceptional accuracy in model development and validation (with a maximum R^2 of 0.63).

Keywords: Biodiversity, β diversity index, Simpson's index, Partial least square regression, Multiple Linear regression, Hyperspectral remote sensing.

1. Introduction

The biodiversity of tropical forests is severely affected due to increasing levels of anthropogenic activities. Bellard et al., (2012) reported that global biodiversity is in decline, and this pattern is forecasted to remain so within the near future. Tropical ecosystems are very affluent in terms of species diversity. Therefore, it becomes extremely important to understand spatial patterns of species diversity in tropical ecosystems (Nagendra and Gadgil, 1999; Sanchez-Azofeifa et al., 2003; Loarie et al., 2007). Tropical dry deciduous forests are noted for their numerous uses. They are rich repositories of medicinal plants used as raw materials in the industry and mostly harvested from the forests (Ravikumara et al., 2022). Tropical forests, with their vast diversity, represent an ideal proving ground for the developments needed to make diversity mapping a reality (Asner and Martin, 2014). In the tropical country like India anthropogenic pressure on the biodiversity of tropical forests has increased swiftly in the last few decades due to rapid economic development along with population growth. Therefore, sound assessment of biodiversity at larger spatial scales in the tropical forest cover of India has become a pressing need.

Field-based biodiversity enumeration/estimates cover smaller regions of forest cover. Moreover, the execution of these studies for larger areas of forest cover is time-consuming, cost cost-prohibitive. However, by combining information about the known habitat requirements of species with maps of land cover derived from satellite imagery, precise estimates of potential species ranges and patterns of species richness are possible (Turner et al., 2003). Remote sensing can play a particularly important role in helping to understand where species live and in providing measures of diversity such as species richness (Geller et al., 2017).

Hyperspectral remote sensing data are capable of fairly accurate identification of different species (Nagendra, 2001; Carlson et al., 2007). Hyperspectral data is having an inherent ability to collect information at a high spectral resolution using a series of contiguous spectral bands, which can

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be used to record information regarding tree species biodiversity. Variability in hyperspectral information can be useful for discriminating tree species in landscapes including tropical forests, despite the greater complexity of such environments (Cochrane, 2000; Clark et al., 2005). Many researchers used imaging spectrometer data successfully for various biodiversity aspects of tropical vegetation (Asner et al., 2005; Carlson et al., 2007; Oldeland et al., 2010; Lopatin et al., 2016). However, most of the earlier studies were implemented using airborne imaging spectrometers or microwave remote sensing data. Very few studies such as Kalacska et al., 2007 and Chambers et al., 2009 were found to be performed on biodiversity aspect mapping using spaceborne hyperspectral data. Therefore, the proposed study sought to estimate biodiversity using spaceborne Hyperspectral data. The objective of the present study is completely apparent, that is development of the statistical models and indices for the estimation of β diversity index and Simpson's index (SI) of the tropical deciduous forest using space-borne imaging spectrometer data. β diversity was selected as a biodiversity aspect for the present study because of its universal acceptance. Simpson's index has low sensitivity to sample size (Magurran, 1988). Simpson's index is the sum of the squares of the proportions of the component species. Moreover, Legendre et al., (2005) emphasize that beta diversity is ''a key concept for understanding the functioning of ecosystems, for the conservation of biodiversity, and for ecosystem management,'.

2. Materials and methods

2.1 Study area

The present study was carried out in Vansda National Park (VNP) (20^0 51'16"-21^0 21'22"N & 73^0 20'30"-73^0 31'20" E) at Navsari District of Gujarat state in India. It contains a hilly terrain with hills of moderate altitudes from 110-360 m, an extension of the Sahyadri Range. VNP covers an area of 23.99 km^2. It chiefly consists of moist deciduous tropical types of forest (Nirmal Kumar et al., 2007). Teak (*Tectona grandis* L.) and Bamboo *(Dendrocalamus strictus* Nees.) are the dominant species of the study area. Other tree species growing in the sanctuary include, *Acacia catechu* Willd., *Terminalia arjuna* (Roxb.) Wight & Arn., *Butea monosperma* (Lamk.), *Holarrhena antidysenterica* (R.) Br, *Mitragyna parviflora* (Korth.), *Dalbergia latifolia* (Roxb.), *Anogeissus latifolia* (Wall.), *Bridelia retusa* (L.), *Albizia lebbeck* (L.), *Madhuca indica* (Gmel.), *Garuga pinnata*(Roxb.), *Pongamia pinnata* (L.) and *Ficus racemosa* (L.).

2.2 Hyperspectral image acquisition

An archived Hyperion (EO1) image of the study area was obtained (Figure 1). At the time of data acquisition, cloud cover was <25%. Pre-processing of the acquired Hyperion EO1 image was carried out using ENVI 4.6 (Excelis, Boulder, CA, USA) software. Atmospheric correction was carried out using FLAASH software (an inbuilt module of ENVI 4.6). The image was geo-registered with WGS-84 Geodetic datum (root mean square error (RMSE) 0.1 pixel).

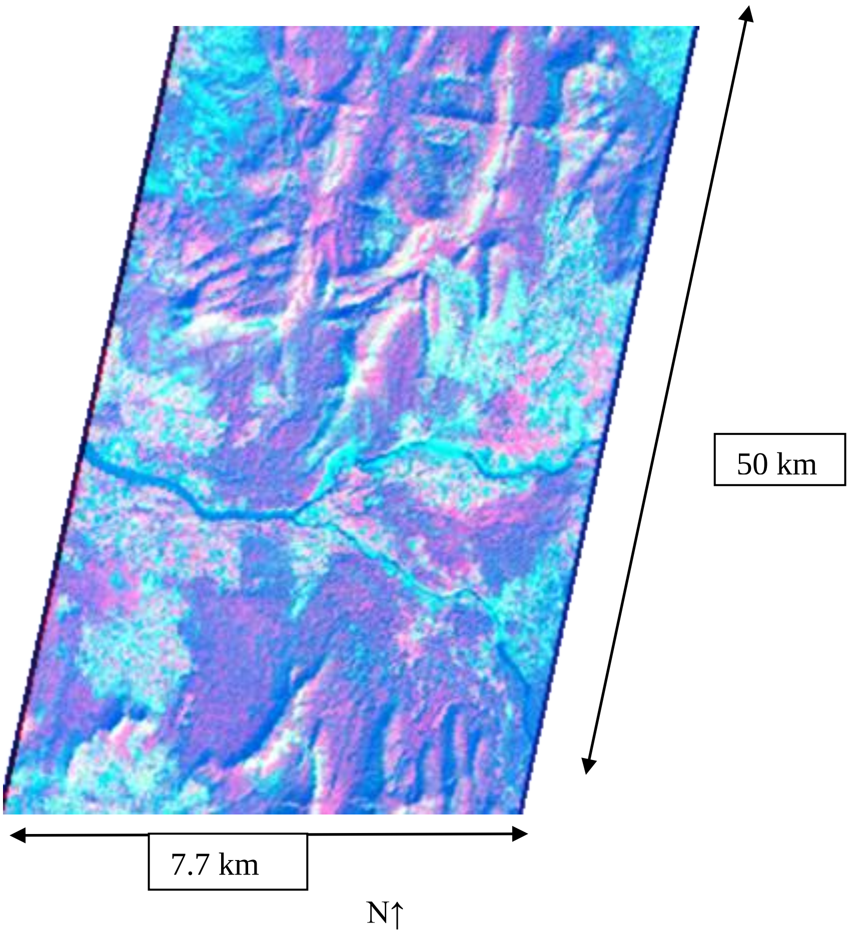

Figure 1: FCC (False color composite) Hyperion (EO1) EO1148045201101411OKZ image subset of the study area

2.3 Field data collection

An extensive field survey was conducted in the study area for the identification of important vegetation covers of trees. Quadrats of 30 × 30 m size were laid down (Quadrat size coincides with spatial resolution of EO1, 30 m). Vegetations with low density of trees (<20 trees/quadrat), moderate densities of trees (20-40 trees/quadrat), and high density of trees (>40 trees/quadrat) were identified. Ground control points (GCPs) of quadrats marked in representative vegetation were covers taken and transferred to Hyperion images of the study area. GCPs were obtained with the help of Global Positioning System receiver made by Garmin® (accuracy ± 5 m). Quadrats marked for each vegetation cover will fall in a patch size of a 3×3 pixel window. For each quadrat of β diversity, and Simpson's index was calculated using equations 1 and 2. The heights of the trees were measured by using Ravi's multimeter (indigenous equipment). The instrument works on the trigonometric principle. The diameter at breast height (DBH)of the trees was measured using a meter tape.

Measurement of β diversity (Wilson and Shmida 1984):

$$\beta = s/\alpha - 1 \quad (1)$$

Where s is the total number of species recorded in the study system, and α is the number of species found within the marked quadrate.

Measurement of Simpson's index (Verma et al., 2007)

$$SI = 1-\Sigma (pi)^2 \quad (2)$$

Where *p* is the prepositional abundance of the species.

2.4 Data analysis

The correlation coefficient (with the help of the SPSS v20 statistical analysis tool) was calculated between β diversity index, Simpson's index, and reflectance value of Hyperion EO1 spectra at each wavelength. Wavelengths showing good correlation (Correlation coefficient ≥±0.40) were used to develop indices. Indices showing the best result for quantification were identified with the help of the above exercise. The coefficient of determination R^2 was calculated for each regression analysis. Leave one out technique was used to validate results (Vyas and Krishnayya, 2014).

Multiple linear regression (MLR) and partial least square (PLS) regression were used for the extraction of relevant information from Hyperion reflectance spectra. In the present study, PLS regression analysis was tested to predict β diversity and Simpson's index using hyperspectral reflectance spectra as the independent variable. Partial least square regression and MLR analysis were performed using Unscrambler X (CAMO Software AS, Oslo, Norway).

2.5 Diversity map generation of the study area

Indices developed for the measurement of β diversity and Simpson's index was tested to develop a diversity indices map of the study area. Generated equations were transferred into the Band math tool of ENVI 4.6 for the production of the diversity map. Each wavelength of the indices was mapped to an input image band along with its mathematical expression. Output images reflect pixel-level diversity values of the study area.

3. Results

3.1 Measured indices of biodiversity and Reflectance spectra

Table 1. Measured biodiversity attributes of the study area

Parameter	Tree density per quadrate	Species richness	Beta diversity	Simpson's index
Minimum	19	7	0.22	0.79
Maximum	60	25	2.98	0.94
Mean	35	18	1.35	0.84
Standard Deviation	±13	±6	±0.93	±0.05

Altogether, 33 different tree species were identified from marked quadrates (n=21). Table 1 shows the measured biodiversity attributes of the study area. Significant variation is evident in this data. Variation of vegetation covers under high, low, and moderate density levels is apparent in the photographs of the study site shown in Figure 2. Figure 3 shows the reflectance spectra acquired from Hyperion (EO1) for three different vegetation covers (425 to 2385 nm). Reflectance spectra showed considerable variability throughout the entire electromagnetic spectrum.

Figure 2. The vegetation cover with hilly terrains of Vansda National Park.

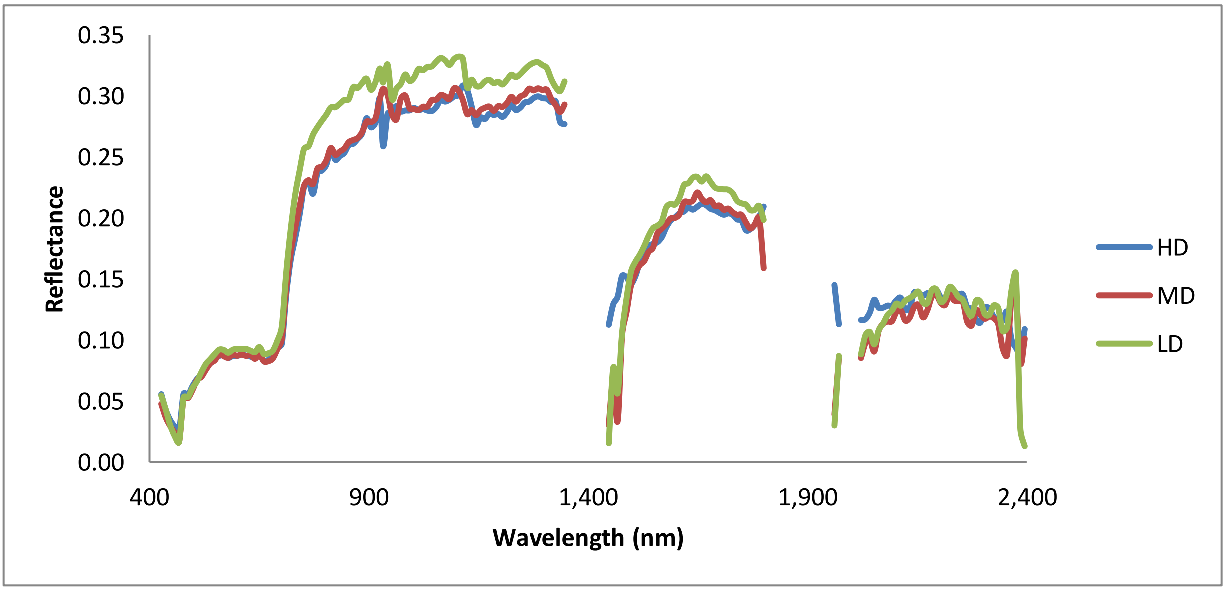

Figure 3. A Hyperion (EO1) reflectance spectra of three different vegetation covers HD (high density), MD (Moderate density), and LD (Low density).

3.2 Correlation between reflectance spectra and measured indices of biodiversity

Figure 4 (a.) and (b.) shows the correlation coefficient between calculated β diversity, Simpson's index, and reflectance spectra of Hyperion (EO1). It is apparent that, many wavelengths across the various regions of the electromagnetic spectrum are significantly correlated (correlation coefficient >±0.40) with β diversity index and Simpson's index.

Wavelengths 457 nm and 1457 nm showed a very high positive correlation with β diversity (0.64 and 0.69 respectively) whereas 933 nm showed a maximum negative correlation (-0.48). Other wavelengths such as 2375 nm (-0.40) also showed a significant correlation with β diversity. Wavelengths 732 nm and 2285 nm showed a very high positive correlation with Simpson's index (0.60 and 0.56 respectively) whereas 457 nm showed maximum negative correlation (-0.44). Other wavelengths such as 2012 nm (-0.45) also showed a significant correlation with Simpson's index.

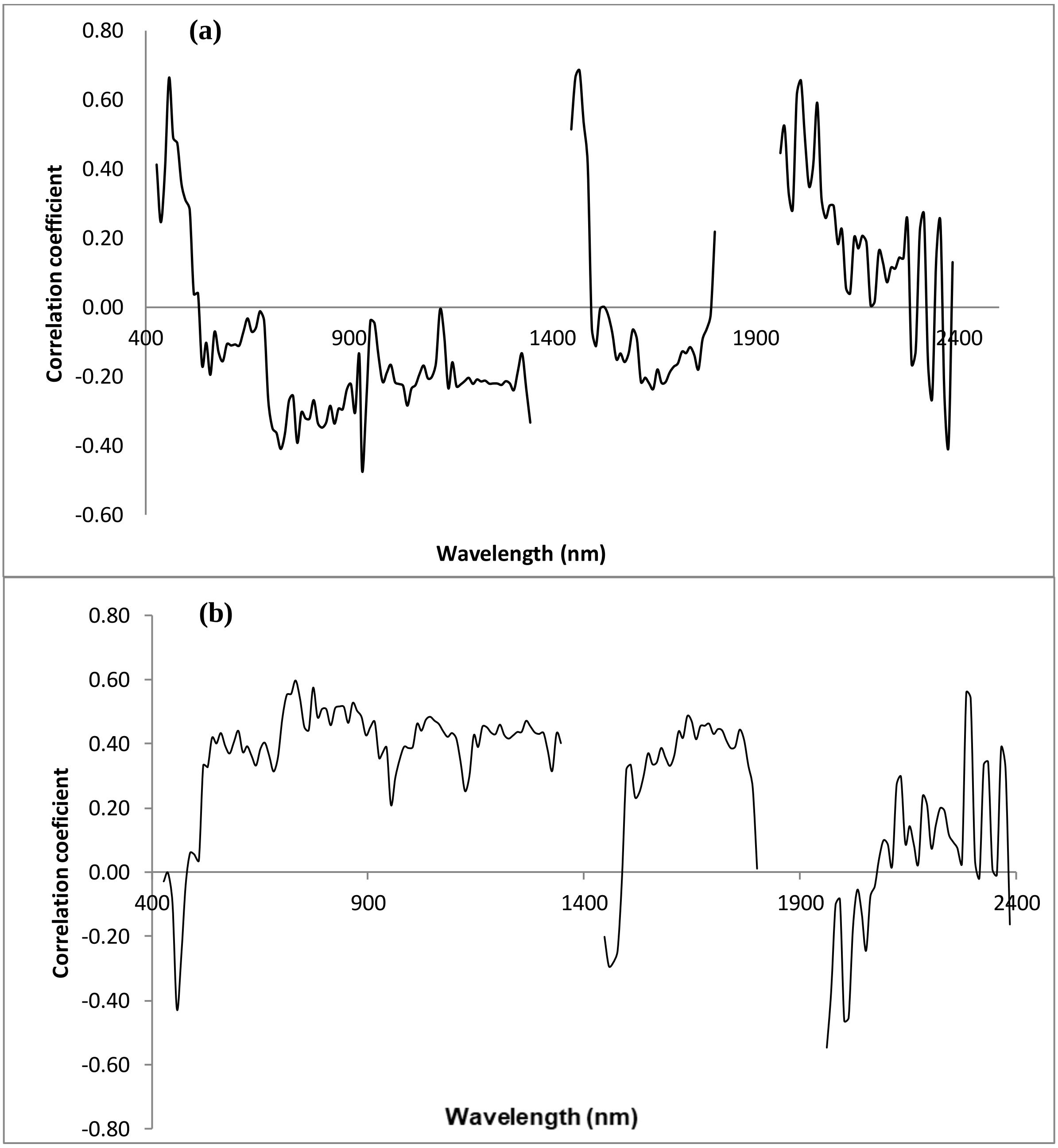

Figure 4: Correlation coefficients (a) between measured β diversity, and (b)Simpson's Index along with Hyperion (EO1) reflectance spectra

3.3 Developed indices and regression models for measurement of β biodiversity

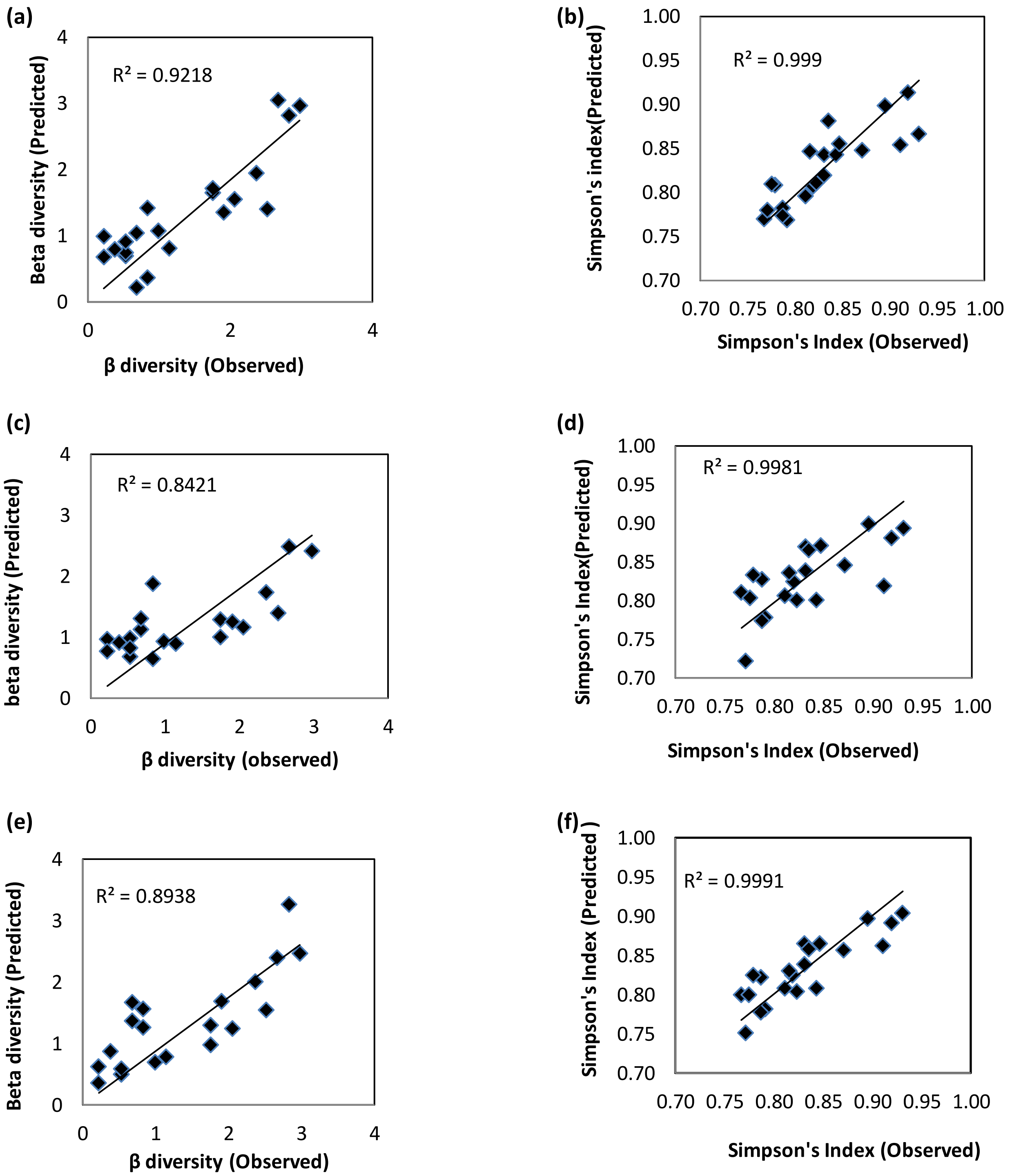

Figure 5: Cross-validation showing R^2 of prediction for developed models (β diversity and Simpson's index respectively). (a.) and (b.) PLS regression, R^2 for developed model obtained was (0.74,0.71 B diversity and Simpson's index respectively), (c.) and (d.) SR 1457/933 and SR 457/2285. R^2 for the developed model obtained was (0.63,0.51 respectively), b.) MLR R^2 developed model obtained was (0.62, 0.73 respectively).

As mentioned in paragraph 3.2 wavelengths having correlation coefficient ≥±0.40 were identified and used for the development of indices and development of regression models. Amongst all the developed indices Simple ratio (SR 1457/933) gave the best result for β diversity with R^2 of 0.63

for model development and R^2 of 0.60 for validation. MLR gave promising results when all four wavelengths (457, 1457, 933, 2375 nm) showing significant correlation were used to prepare the model for β diversity measurement (R^2 of 0.62 for the development of the model and R^2 of 0.58 for validation) (Figure 5).

3.4 Developed indices and regression models for measurement of Simpson's index

Amongst all the developed indices Simple ratio (SR 457/2285) gave the best result for Simpson's index with R^2 of 0.51 for model development and R^2 of 0.43 for validation (Figure 5). MLR gave promising results when all four wavelengths (457, 732, 2012, 2285 nm) showing significant correlation were used to develop a model for measurement of Simpson's index (R^2 of 0.73 for the development and R^2 0.60 for validation)**.**

3.4 Partial least square regression

Partial least square regression executed between measured biodiversity indices and Hyperion (EO1) reflectance spectra using different wavelength combinations (Visible 400-800 nm, NIR and FIR 800-1300 nm, SWIR 1300 to 2400 nm). Amongst all other developed models, PLS regression models with visible wavelength range gave the best results. R^2 of 0.74 and obtained for the developed PLS regression model of β diversity measurement (R^2 of 0.69 for validation). Correspondingly, for Simpson's index, PLS regression models with visible wavelength range gave the best results. R^2 of 0.71 was obtained for the developed PLS regression model (R^2 of 0.60 for validation).

3.5 Diversity map of the study area

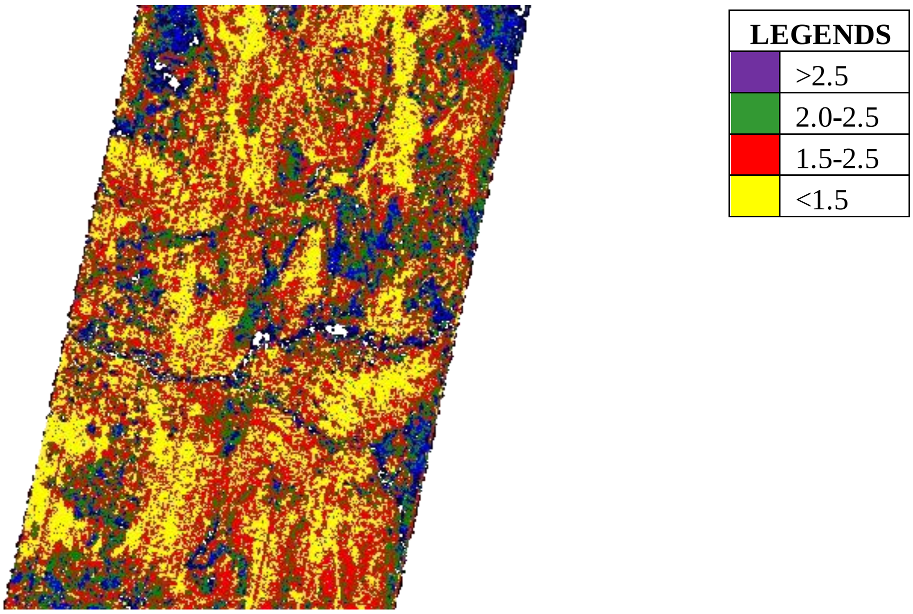

Figure 6: Biodiversity map of the study area (based on the Regression model developed for SR 1457/933 for β diversity)

A diversity map of the study area was prepared using the SR index developed for β diversity as it gave the highest accuracy for model development and validation. The diversity map generated for the study area shows the appropriate distribution and pattern of β diversity (Figure 6).

4. Discussion

In the present study, the suitability of space-borne Hyperspectral data (Hyperion EO1) was examined for the measurement of β diversity and Simpson's index of tropical deciduous forest. The discussion on the findings of this study is as follows.

Measured species richness and β diversity values are comparable with the data collected from phytosociological studies of the same forest area by Kumar et al., (2013). Moreover, β diversity and Simpson's index measures of the present study are also analogous with values obtained from various sites of tropical dry deciduous forests across India by Sagar et al., (2003); Nagendra, (2001); Roshni et al., (2022) and Lal et al., (2021).

The outcome of the present study for the estimation of tree species β diversity and Simpson's index is highly encouraging. Results obtained with all three statistical modeling techniques are very promising, as all of them were able to estimate the variance in β diversity index and Simpson's index with comparatively better accuracy. Earlier, Laurin et al., (2016); Hernandez-Stefanoni et al., (2014) and Rahmanian et al., (2023) obtained comparable or lesser accurate results of tree species richness estimation using diverse remote sensing data (R^2 0.62 to 0.64 and R^2 0.39 to 0.49 and 0.57 respectively). Ceballos et al., (2015) attained accuracy with R^2 of 0.65 for the prediction of plant richness in a deciduous Chilean forest, using hyperspectral data. In addition, Simonson et al., (2012) concluded that diversity of forest species was significantly associated with Lidar-measured vegetation height with R^2 of 0.50. Lopatin et al., (2016) found that Generalized Linear Models showed R^2 of 0.66 for total, tree, shrub, and herb richness with the help of Lidar data. Results of the present study are better than these studies, especially in terms of accuracy.

Interestingly, there are a number of wavelengths identified that showed utmost correlation with β diversity and Simpson's index (457, 933, 732, 1457, 2012, 2285, and 2375 nm). It is important to note that most of the wavelengths are biochemically very distinct. Reflectance at 433 nm is affected by variation in pigmentation (especially chlorophyll content). Whereas reflectance around 933 nm is affected by canopy water content (Vyas and Krishnayya, 2014). Cho and Skidmore (2006) found that 732 nm of NIR wavebands is sensitive towards variation in Nitrogen content. Reflectance in the range of 1457 nm changes with Nitrogen content in canopy (Carlson et al, 2007). Variation in reflectance at 2385 nm may be attributed to the change in Nitrogen content (Ustin et al., 2002). Moreover, Chrysafis et al., 2020 also concluded that a similar wavelength range is useful for modeling species richness using hyperspectral remote sensing.

Thus, it is evident that variation in biochemical parameters such as pigmentation, nitrogen, and water content in the canopy of different tree species creates adequate variation in reflectance patterns around specified wavelength regions. In the present study, these apparent variations helped a lot in the accurate estimation of β diversity index and Simpson's index. Similarly, Jetz et al., (2016) concluded that the ecosystem processes and variations in the plant's chemical, physiological, and structural properties are often directly linked to the functional biodiversity of plants. Earlier, Asner and Martin (2014) found that as species richness increases, the variability of N and N + P also increases non-linearly. In the present study, species richness measured for the study area is associated with both the biodiversity index calculated (Table 1). Asner and Martin (2014) also stated that there is a sufficient theoretical basis to link the spectral, chemical, and taxonomic diversity of tropical tree species. Results of the present study are comparable with Jetz et al., (2016) and Asner and Martin (2014).

Earlier, Vyas et al., (2013) found that reflectance at 1457 nm was responsive towards change in Leaf area Index (LAI). Costanza et al., (2007) concluded that biodiversity and Net Primary Productivity (NPP was measured as a function of Leaf Area Index) are intricately linked in complex ecosystems. This association between both attributes may be the reason behind the sensitivity of wavelength 1457 nm towards change in β diversity index.

Partial least square regression analysis using visible region of reflectance spectra obtained very accurate results for the estimation of β diversity and Simpson's index. The partial least square regression technique was found to be very useful in exploiting information in the reflectance spectra of visible regions. Earlier, Vyas et al., (2012) and Asner and Martin (2008) found that visible region can be used for accurate estimation of chlorophyll content using PLS regression. Therefore, the effect of variation in chlorophyll content is evident in the results of PLS regression analysis of β diversity. Moreover, In the present study variations in species richness along moderate, low, and high dense regions of the study area were observed. Earlier, Vila et al., (2007) concluded that wood production increased with tree species richness. Therefore, one can say that biomass content variation in the study area also creates sufficient sensitivity towards visible-NIR region (Vyas and Krishnayya, 2014). This facilitated to provide of better results for the estimation of both the biodiversity indices in PLS regression.

After the cautious comparison of the FCC image and β diversity Map of the study area, it is evident that region containing moderate or high biodiversity is situated around the water bodies as well as on the slopes of elevated regions. Less human disturbance due to elevation and high humidity in soil due to water bodies in the vicinity may have played an important role in sustaining the growth of a range of tree species in the study area.

5. Conclusion:

The present study has been able to identify regions as well as wavelengths that are sensitive towards the variation in β diversity and Simpson's index in moist tropical deciduous forests of the study area. The present study was also able to establish an accurate relationship between Hyperion (EO1) reflectance spectra and β diversity and Simpson's index with the help of three different statistical techniques. In the future, above-identified wavelengths would also be extremely important for the development of new space-borne platforms for the assessment of global biodiversity. Moreover, the importance of PLS regression analysis was re-established in the present study for the estimation of attributes in complex ecosystems. The diversity map developed in the present study will be useful for Government agencies such as the Forest Department for the proper management and conservation of forest ecosystems in Vansada National Park, Gujarat. Similar diversity maps can also be developed for the various regions of the tropical deciduous forests.

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