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APPLICATION OF LINER SPECTRAL MIXING MODEL IN FRACTIONAL VEGETATION COVER MAPPING - A CASE STUDY ON PART OF JUNGLE MAHAL REGION, WEST BENGAL, INDIA

[1]Ratnadeep Ray, [2]Sakti Mandal, [3]Ayan Dutta
[1]Department of Remote Sensing and GIS, Vidyasagar University, Midnapore (West),West Bengal,
[2]Department of Geography, University of Calcutta, West Bengal,
[3]Department of Field Operation, NSSO, Kolkata, West Bengal, India.

ABSTRACT
Linear Spectral Mixing Model (LSMM) is the most modern image statistical technique for feature identification by collecting spectral end-members from a digital data set having a fuzzy nature or mixel (mixed pixel) problem. For Landsat-5 TM, the instantaneous field of view (IFOV) is large enough that pixels comprise mixtures of these features. This inevitably means more feature cover types are included within one pixel and therefore more mixing of material spectral signatures. Sub-pixel mixing in remote sensing dictates that pixel reflectance cannot be simply interpreted in terms of properties of a single feature cover type. Accounting for sub-pixel variations in earth surfacial feature types is therefore an essential step for analyzing pixel reflectance in such heterogeneous regions. So in connection of sub-pixel analysis LSMM is the most ideal way to unmix the spectral signature of the features from a fuzzy and heterogeneous data set. It assumes that there is no interaction between the photons reflected by the individual pixel components and will be able to determine the purest pixels of the features. In this present study for Fractional Vegetation Cover (FVC) mapping of the Jungle mahal region of western part of West Bengal, the Dimidiate Pixel Model (DPM) having the sub-pixel decomposition capacity has been used where the conventional normalized difference vegetation index (NDVI) method has been altered and for determining the pure vegetation and soil pixels (vegetation and soil spectral end-members) following the principles of LSMM the Minimum Noise Fraction (MNF) transformation has been applied. Whole the process has been experimented over the satellite images of the concerned study area for the year of 2000 and 2010 and the actual ground reality of the forest status has been visualized successfully.

KEY WORDS: Dimidiate pixel model (DPM), NDVI, MAVI, Minimum Noise Fraction (MNF), Jungle Mahal

INTRODUCTION

Vegetation is a general term for the plant community on the ground surface, such as forests, shrubs, grassland and agricultural crops, and it can intercept rainfall, alleviate runoffs, prevent desertification and conserve soil and water. It plays an important role in energy exchange, biogeochemical and hydrological cycling processes on the land surface as an "indicator" for studying global changes (Kutiel *et al.,* 2004; Steffen, 2003). Fractional vegetation cover (FVC) refers to the percentage taken by the vertical projected area of vegetation (including leafs, stem and branches) in the total statistical area (Jing *et al*., 2010; Godínez-Alvarez *et al.,* 2009, Anatoly *et al*., 2002; Purevdor *et al*., 1998; Bonham, 1989). It is an important parameter for describing the surface vegetation, a comprehensive quantitative variable for plant community on ground surface, and a basic data for characterizing ecosystems, playing an extremely crucial role in the study of regional ecosystems (Jing *et al.,* 2010; Godínez-Alvarez *et al*., 2009; Steffen, 2003; Shoshany *et al*., 1996; Brazel and Nickling, 1987). For example, vegetation cover is one of the most common parameters used in assessing the relationship between vegetation and soil erosion. In general, soil erosion decreases with an increase in vegetation cover (Wen *et al*., 2010).

In terms of the state-of-art and development trend in the research on the FVC estimation, the methods roughly include ground survey, remote sensing and a combination of the two (Tammervik *et al*., 2003; Gutman and Lgnatov, 1998). Ground survey is a conventional method for monitoring the FVC. Early in the 1970s Muller and Ellenberg (1974) conducted a systematic research on the general method for ground survey of the FVC. Dymond *et al*. (1992) then measured the FVC of grassland by raster point sampling; Elvidge and Chen (1995) measured the FVC of shrubs and woodland by the photo random point method; Senseman *et al*. (1996) measured the FVC by the resection method; and Purevdor *et al.* (1998) used color digital images acquired by a digital camera to measure the FVC by counting the green pixels in the image.

Remote sensing provides the possibility for large scale or even global monitoring of the FVC (Anatoly *et al*., 2002; Wang *et al.,* 2002). Some methods for retrieval of the FVC using remotely sensed data have been developed, and the main ones include empirical, vegetation index, sub-pixel unmixing models (Zhou and Robson, 2001; Choudhury, 1987; Asrar *et al.,* 1992), and linear spectral mixture models (Wu and Peng, 2010). The linear regression models were applied in many cases. For instance, in an area of semi acid soil, Graetz *et al.* (1988) estimated the FVC of the sparse grassland using the linear regression model based on the Landsat TM band 5 and the measured data of the FVC. Dymond *et al*. (1992) estimated the FVC of the degraded grassland in New Zealand utilizing the

SPOT data on the basis of having built the non-linear empirical relation between the surface FVC and the normalized difference vegetation index (NDVI). Wittich and Hansing (1995) established the empirical model between the FVC and NDVI for different land cover types, and calculated the FVC using the NOAA's Advanced Very High Resolution Radiometer (AVHRR) data. Purevdor *et al.* (1998) built four non-linear models by applying the empirical model, to assess the FVC in Mongolia and Japan's grassland areas. In addition, by establishing a quadratic polynomial relation between the FVC and vegetation index, grassland FVC can be more accurately estimated using AVHRR data. North (2002) conducted linear regression using the ERS-2 along Track Scanning Radiometer (ATSR-2) data with four bands (555 nm, 670 nm, 870 nm and 1630 nm) in relation to the FVC and Leaf Area Index (LAI). The results showed that the linear mixed model combining four bands was more effective than the simple vegetation index in estimating the FVC. The empirical model relies on in situ measurement data in specific regions, and the measured result is fairly accurate only if the study area is small. The accuracy will be substantially reduced in large scale application and monitoring as there will be many constraints.

The basic idea of vegetation index method is that by an analysis of the vegetation types and their distribution patterns in the pixels, a conversion between vegetation index and the FVC is established for direct extraction of the FVC information, provided that the vegetation index being used is proven to be well correlated to the FVC. Using AVHRR data, Quamby *et al*. (1992) established a mixed linear conversion model between vegetation index and the FVC, suitable for estimating the FVC in the agricultural area. More than 40 types of vegetation indexes have currently been defined (*e.g.* perpendicular vegetation index (PVI), normalized differential vegetation index (NDVI), soil-adjusted vegetation index (SAVI), modified soil-adjusted vegetation index (MSAVI), transformed soil adjusted vegetation index (TSAVI), and vegetation condition index (VCI)), all have found wide application in areas like environment, ecology and agriculture (Li et al., 2010; Boles *et al*., 2004; Bannari *et al.,* 1995; Leprieur *et al*., 1994; Dunean *et al*., 1993; Verstraete et al., 1993). Compared to the regression model, the vegetation index is of a greater practical significance, as it does not need ground quadrate measuring over large areas, and once verified, the model can be applied to large areas to formulate universally applicable calculation method for the FVC. However, this method may be less accurate than the empirical model in estimating the FVC in certain localities, and an accurate conversion relationship between vegetation index and the FVC is usually difficult to be determined.

The pixel decomposition method has been increasingly studied and used to derive the FVC in recent years. The pixel decomposition method can be regarded as an improvement on the basis of the vegetation index method. The idea is that a pixel in the image may actually consist of several components, each of which contributes a part of the information as observed by the remote sensor. Therefore the remote sensing information (band or vegetation spectral index) can be decomposed to build the pixel decomposition model, which is used for estimating the FVC (Gutman and Lgnatov, 1998; Tammervik *et al*., 2003). The Dimidiate Pixel Model assumes that a pixel consists of only two parts: vegetation and non-vegetation, with the spectral information being just a linear synthesis of the two parts. And the ratio of the area taken by each part in the pixel will be its weight, where the percentage of the area of vegetation in the pixel will be the FVC of that pixel, and the FVC is thus estimated using this model. On the basis of the dimidiate pixel model, Gutman and Lgnatov (1998) put forward different methods for calculation of the FVC, depending on whether the pixel was homogeneous or mixed, where the mixed pixel was further divided into equal density, non-density and mixed density sub-pixels, to establish vegetation coverage models for different sub-pixel structures respectively (Jing et al., 2010; Jiang *et al*., 2006; Gutman and Lgnatov, 1998).

For successful and accurate result of FVC using Dimidiate Pixel Model, there is a need to determine the pure vegetation and soil pixels. Conventionally that is done using field derived data. But may not be accurate as the field derived data is suffering from spatial, temporal and seasonal variability in reflectance property. So the principle of Linear Spectral Mixing Model (LSMM) vis-à-vis Minimum Noise Fraction (MNF) transformation can be ideal to get the purest pixels of interest as spectral end-member from a two dimensional feature space. the LSMM is an excellent approximation technique suitable for handling the spectral mixture problem, mainly because: (1) it does not require extensive training data, (2) it produces a set of maps, one for each class types concerned, and (3) it was extensively applied to extract the abundance of various components within the mixed pixels of satellite data of similar environments (Roberts et al., 1993; Ustin *et al.,* 1996; Cochrane and Souza, 1998; Shanmugam, 2002).

The surface biophysical parameters retrieved using remotely sensed data has become the principal means for measuring and monitoring vegetation coverage (Neigh *et al*., 2008; Chen, 1999; Price, 1992), although currently multispectral remote sensing data is mainly used in extraction of the FVC of large areas or on a global scale. This study attempts to discuss the potentiality and usefulness of Multispectral data in building the pixel decomposition model, for monitoring and analyzing the vegetation coverage.

STUDY AREA

The Jungle Mahal portion of the Midnapore and Jhargram subdivision under Midnapore district, West Bengal has been consulted in the present study. The study area is extended up to $21^0 45'$N to $22^0 40'$N latitudinally and $86^0 44'$E to $87^0 30'$E longitudinally (Fig.1). This region is mainly modified by the joint action of Kangsabati and Subarnarekha rivers. This is a neighbouring area of Bihar and Orissa. This very upland is of 2029 sq. k.m. and the lands look wavy in this area. Some small ranges and 'depression' are found here. It's a part of Chhotonagpur plateau, which is formed with laterite. Hydro-geologically, the study area has been classified as: younger alluvium, older alluvium, fluvio-deltaic sediment overlained by secondary laterite (double profile), fluvio-deltaic sediment overlained by primary laterite (in situ), Platform margine conglomerates and basement crystalline complex (metamorphites). In the extreme north, some hills can be seen, which are 82 mtr. to 223 mtr. in height. The land sloping is from north-west to south-east. In its hilly surface some rivers and streams course with their move. Among them, some rivers meet the flow of Kangsabati in the north, and some of them meet the Subarnarekha. Among them, the major one is Dulung, which is on the right side of the Subarnarekha. It is originated in Binpur region and meets the Subarnarekha in Sankrail block. The Subarnarekha may be called the controlling river this upland region. This river comes from Bihar and entered into Gopiballavpur-I block of this district and heads towards east and then flows like a natural border of Bengal and Orissa in the western part of Dantan-I block. Soil surface of this western region is dry, non-fertile and unsuitable for habitation and cultivation. Soil type inpaschim Medinipur district can be divided into sixteen categories, represented as coarse loamy typic haplustalfs, coarse loamy typic ustifluvents, fine aeric ochraqualfs, fine loamy aeric ochraqualfs, fine loamy typic paleustalfs, fine loamy typic ustifluvents, fine loamy typic ustochreptas, fine loamy ulti paleustalfs, fine vertic haplaquaepts, fine vertic ochraqualfs, loamy lithic ustochrepts, loamy skeletal lithic ustochreprs, residential area, rocky outcrops, and very fine vertic haplaquepts In lower hilly areas bush and 'dwarf' sal trees are found. Blocks like Binpur-I and Binpur-II, Jhargram, Sankrail, Jamboni, Gopiballavpur-I & II, Keshiary, Dantan-I are totally or partially included in this region.

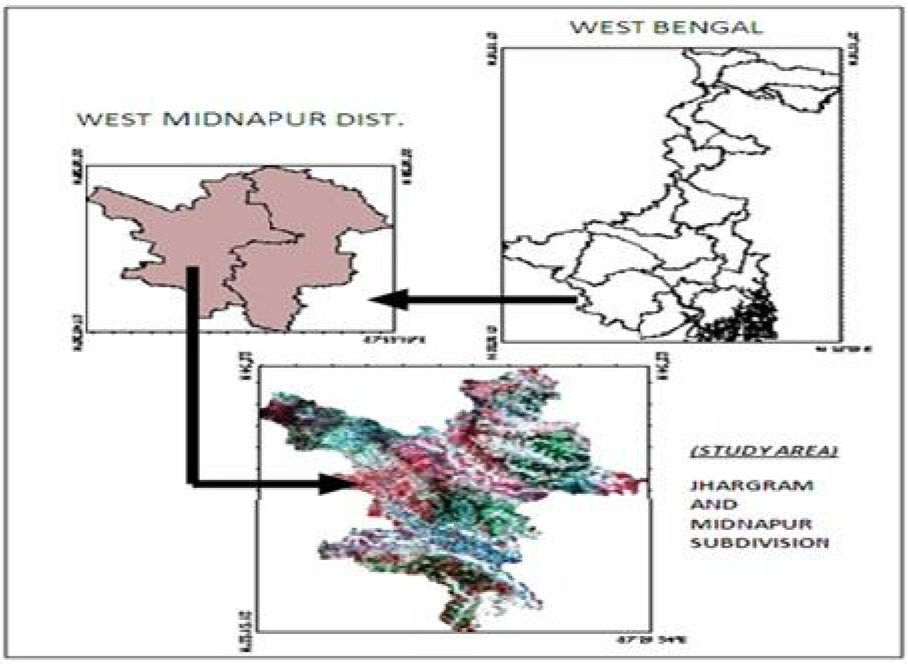


FIGURE 1 Location map of the study area

MATERIALS AND METHODS

In this present study LANDSAT ETM+ and TM digital data (P/R 138/45 and 139/45) of the year of 2000, 8th November and 2010, 12th November respectively has been used and has been processed in the TNT mips Pro environment.

Radiometric preprocessing

The use of multi-temporal satellite data at a large scale using TM and ETM+ possesses a number of challenges including geometric correction error, noise arising from atmospheric effect, errors arising from changing illumination geometry, and instrument errors (Homer et al., 2004). Such errors can introduce biases in forest classification and change analysis.

To reduce the noise due to influence of the atmospheric and illumination geometry, we used the techniques developed for the National Land Cover Database of the United States (Homer et al., 2004). Each image was normalized for variation in solar angle and Earth-sun distance by converting the digital number values to the top of the atmosphere reflectance (Chander and Markham, 2003). Considering the relative uncertainty of algorithms currently available, atmospheric correction was not performed. Only first-order normalization conversion to at satellite reflectance was performed. This conversion algorithm is ''physically based, automated, and does not introduce significant errors to the data'' (Huang et al., 2002). Finally, mosaics were created for each decade with no further radiometric normalization.

Dimidiate pixel model (DPM) and fractional vegetation cover (FVC) estimation

DPM is basically a sub-pixel decomposition model for FCV estimation. Dimidiate Pixel Model assumes that a pixel consists of two components: pure vegetation and non-vegetation, so the reflectance (R) of any pixel can be presented as:

$$\mathbf{R= (R_v+R_s)} \qquad (1)$$

Where, R_v is the is the reflectance of pure vegetation while Rs is the reflectance of non-vegetation or soil pixel. Linearly decomposing S into Sv and Ss, the proportion of vegetation area in the pixel (fc) is the FVC of that pixel, and accordingly the proportion of soil area will be **(1 – fc)**. Assuming the spectral response received by the all-vegetation "pure" pixel is R_{veg}, the information contributed by vegetation in the mixed pixel is R_v, and the spectral response contributed by vegetation in the mixed pixels can be expressed as the product of R_{veg} and fc:

$$R_v = fc * R_{veg} \quad (2)$$

Similarly, assuming the remotely sensed information received by the "pure" soil pixel is S_{soil}, and the information R_s as contributed by soil in the mixed pixel can be expressed as the product of R_{soil} and 1 − fc:

$$R_s = (1-fc) * R_{soil} \quad (3)$$

Based on equations. (2) and (3), the spectral response of a mixed pixel can be derived:

$$R = fc * R_{veg} + (1-fc) * R_{soil} \quad (4)$$

Equation (4) can be understood as linearly decomposing S into R_{veg} and R_{soil}, whose weights are the proportion of area taken by them respectively in the pixel, that is, fc and 1 − fc.

In the case elements other than vegetation and soil are included, such as water body, Equation (4) should be modified by the multicomponent mixed model. In the case of a mixture of only vegetation and soil (dimidiation of a pixel), the FVC can be derived by modifying Equation (4) as:

$$fc = (R - R_{soil}) / (R_{veg} - R_{soil}) \quad (5)$$

Where R_{soil} and R_{veg} are the spectral responses from pure soil and pure vegetation pixels, respectively. The model has a fairly sound theoretical basis, and is widely applicable regardless of the geographical constraints. In addition, a major advantage of the dimidiate pixel model is that the impacts from atmosphere, soil background and vegetation type are reduced. R_{soil} contains the soil information including the contribution to remotely sensed data by elements like the type, color, brightness and moisture of soil, while R_{veg} contains the vegetation information including the contribution to the remotely sensed data by elements like type and structure of vegetation. In fact the dimidiate pixel model is a linear stretch based on the two regulatory factors of R_{soil} and R_{veg}, whereby the impacts on remotely sensed data by atmosphere, soil background and vegetation type are reduced to the minimum. Therefore, FVC can be estimated by Eq. (5).

In DPM, remotely sensed spectral response is well related linearly to the FVC. Conventionally for FVC (horizontal density) measurement NDVI has been used to show the vegetation nature and coverage. But it is experienced that in case of floristic research, NDVI is sensitive to the soil background noise and the vegetation information will be faulty. That is why to identify the vegetal coverage and nature without the noisy influence NDVI is sometime replaced by the SAVI (Soil adjusted vegetation index) where an 'L' factor has been used.

In this present study the NDVI method has been replaced by a modified proposal for DPM. For identifying the vegetation fraction both vegetation and soil information is needed. For getting the vegetation information MAVI (Modified advance vegetation index) (Ratnadeep Ray, 2012) is seen very effective, where NIR response has been enhanced by applying a power function and to get soil information a BI (Bareness index) has been used. Those two indices can be calculated as:

$$MAVI = [\{(\rho NIR+L) * (256 - \rho RED)\} * (\rho NIR - \rho RED)]^{(1/3)} \quad (6)$$

(Where, ρRED = Reflectance value of Red band of TM5 Sensor, ρNIR = Reflectance value of Near-infrared band of TM5 Sensor, L= Coefficient, varies with the vegetation cover, Here L=2.)

$$BI = [(Band5+Band3)-(Band\ 4+Band1) / (Band\ 5+Band\ 3) + (Band\ 4+Band\ 1)] \quad (7)$$

Finally these two (equations 6 & 7) rasters has been synthesized on principle component basis (PCA) and the output will carry the principle components of both of soil and vegetation and will comprehensively reflects the vegetation type, canopy pattern and growth status in per unit pixel, is determined by elements like the FVC (horizontal density) and LAI (vertical density), and is also correlated to the FVC. Inserting that joint product raster (PC) of MAVI and BI into equation. (8), we can have the following approximation:

$$fc = (PC - PC_{soil}) / (PC_{veg} - PC_{soil}) \quad (8)$$

In equation (8), the PC for "pure" vegetation pixel and for "pure" bare soil needs to be determined for retrieving the FVC information from remotely sensed data.

Determining the PC_{veg} & PC_{soil}:

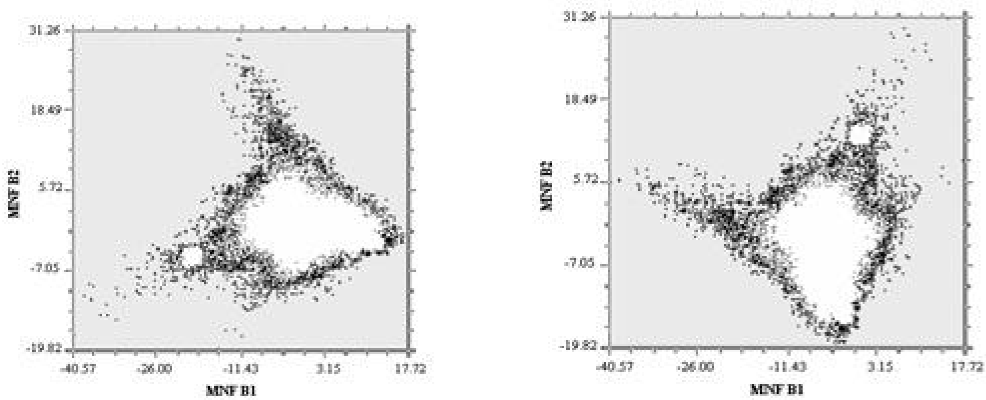
In this present study DPM is used for FVC extraction with the challenge to identify the pure vegetation and soil pixel from the mixed spectral environment. Ideally PC_{soil} should be around zero for the bare surface. However due to the atmospheric impact and the changes in surface soil moisture, PC_{soil} may change with time. In addition, PC_{soil} may also change with space depending on conditions like soil moisture, roughness, soil type and color. Therefore it is not practical to think of a fixed and ideal PC_{soil} value, as the value will have to change even for the same scene of imagery. For easy adjustment, it is not necessary to know the actual PC_{soil} value.

PC_{veg} represents the maximum value of all the vegetation pixels. Depending on the vegetation type, the seasonal change of the canopy, the interference of the foliage background, as well as wet ground, snow and fallen leafs, the determination of the PC_{veg} value is similar to that of the PC_{soil}, as the PC_{veg} value will also change with time and space. Therefore, it is not advisable to think of an ideal PC_{veg} value either.

So here spectral end-member selection may be ideal for determining pure soil and vegetation pixels because they are drawn from the population of data points to be analyzed and in the same scale of measurement. These end-members principally pure reflectance spectra that are derived by a specific target material with no mixing with any other materials. The use of reflectance end-members from spectral libraries built from field survey is not practical because they can suffer mainly from spatial and temporal variability in reflectance properties. There are different approaches for selecting spectral end-members from an image including PCA (Principle Component Analysis), PPI (Pixel Purity Index), MNF (Minimum Noise Fraction) etc. The present study uses spectral end-members identified from the feature space of MNF bands of the given Landsat ETM+ and TM digital data following the Linear spectral mixing modeling (LSMM) principle.

RESULTS & DISCUSSION

In order to successfully apply the LSMM, it was very essential to accurately estimate the spectral end-members for each component of soil and vegetation. The end-members can be assumed as the purest pixels of a given data set. These end-members were determined from the image through different approaches like the MNF transformation or two dimensional spectral plots of Red and NIR bands. If those spectral plots either from two spectral bands or two MNF transformation bands have been given a true geometric shape, the end –members should be collected from each of the apex. In this present study for end-members selection MNF transformation approach has been used instead of two dimensional scatter plots of two spectral bands because the scatter plots of LANDSAT TM and ETM+ showed an asymmetrical patterns of distributions not allowing the selection of appropriate spectral end-members. The MNF transform is one of the often-used methods for reducing redundancy of information between image bands and assisting selection of accurate and reliable end-members (Rainey et al., 2003). The spectral end-members for vegetation and soil were derived from the scatter plot of MNF B1 and MNF B2 shown in figure.2 A and B. The selection of first two coherent MNF bands was that they were found to contain 96% of the total statistical variance in TM and ETM+ image data set.



(A) **(B)**

FIGURE 2 A and B Identification of spectral end-members from the feature space of MNF Band 1 (B1) and Band 2 (B2) for the images of year of 2000 and 2010.

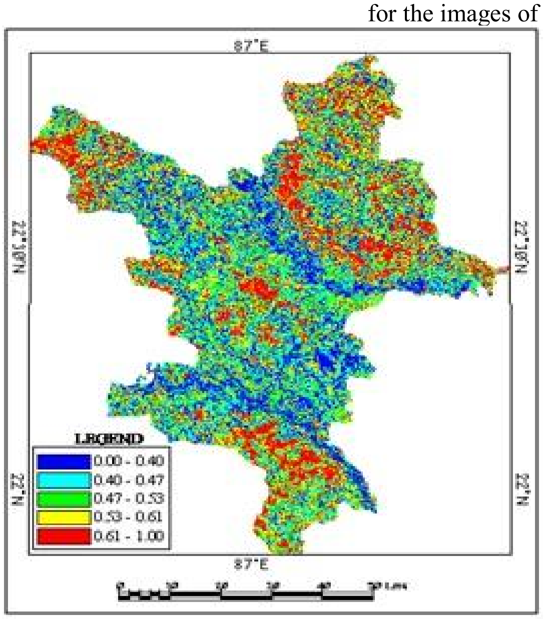


FIGURE 2. FVC map of 2000

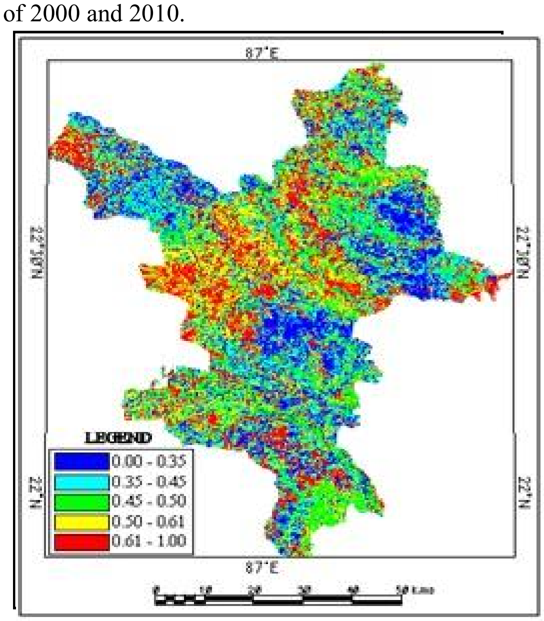


FIGURE 3. FVC map of 2010

After determining the pure vegetation and soil pixels, above-mentioned dimidiate pixel model was implemented by programming in the TNT mips Pro environment. The FVC maps (Fig. 3 and 4) as of 2000 and 2010 of the study area have been obtained using this model. The FVC maps of the study area have been level sliced into five zones and FVC values accordingly have been compared (Fig.4 and Table.1) to visualize the changing scenario.

Zones	FVC (2000)	FVC (2010)
1	0.0 – 0.40	0.0 – 0.35
2	0.40 – 0.47	0.35 – 0.45
3	0.47 – 0.53	0.45 – 0.50
4	0.53 – 0.61	0.50 – 0.61
5	0.61 – 1.0	0.61 – 1.0

TABLE 1. FVC values of each zones

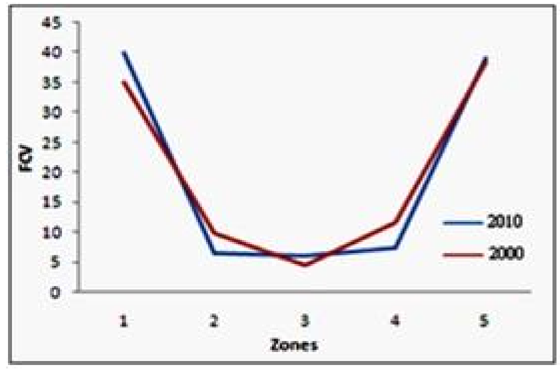
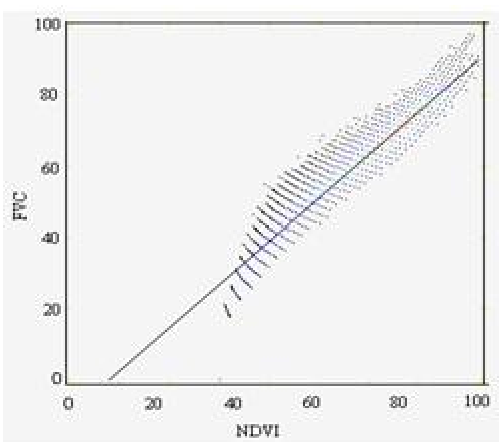


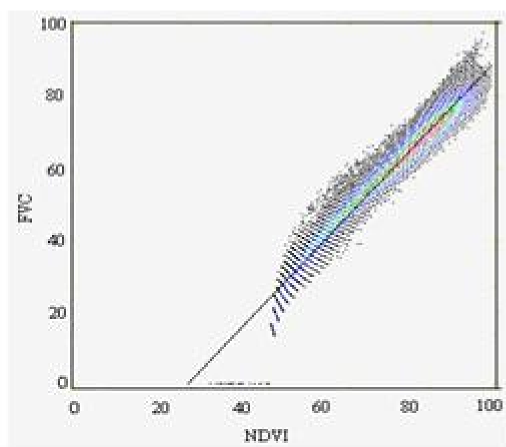
FIGURE 4. Trend of FVC (zone wise) from the year of 2000 to 2010

The area under investigation is in generally suffering from land degradation, soil loss and anthropogenic influences. The extensive metamorphism and weathering is continuously altering the soil characteristics of the area. All these effects affect the dense forest cover over here. It is seen from the figure 2 and 3 that the FVC is deteriorating in nature for the case of gully heads. The dense jungle of 'Sal' and 'Eucalyptus' is going to be 'dwarf' and also the rill channels as well as gully floors are also suffering from the same deterioration which mainly promotes the land degradation. But on the other hand in the inter-fluve area of the Kangsaboti and Subarnarekha river, the vegetation is seen to be grown where the FVC value is approximately 0.5 to 1.0. Besides this if it is zone wise accounted (Fig.4), the decreasing nature of FVC will be seen for the zone 2 and 4.which is 6.6% and 7.5% respectively.

As per different literature NDVI can be considered as a standard environmental index though some interference of soil background noise can be experienced. Many studies have attempted to correlate vegetation indices (NDVI) to the fractional coverage of vegetation and soil (e.g. Carlson and Ripley, 1997; Shanmugam, 2002) because NDVI is an indicator sensitive to chlorophyll activity and to the density of vegetation cover (Duncan et al., 1993). The NDVI value in a given pixel ranges between 0 and 1, where 0 represents 0% vegetation, while 1 represents 100% vegetation in that pixel. So in the respect of present study the FVC outputs generated by a modified thinking, can be correlated with the NDVI to assess the accuracy level. Figure.5 A and B shows the correlation between the proportion of vegetation fractions derived from DPM following the LSMM principle and NDVI in study site for the year of 2000 and 2010. It appears that vegetation fraction values increase with increasing NDVI values. It exhibits a positive correlation between vegetation fraction with NDVI, with the squared correlation coefficient (r^2) respective of 0.92 and 0.96. This positive relationship indicates the correctness of applicability of LSMM and the reliability of the derived sub-pixel proportions of vegetation.



(A)



(B)

Figure 5 A and B Validation of LSMM result – Vegetation fraction correlates very well with NDVI (A denotes relationship for 2000 having r^2 of 0.92 and B denotes relationship for 2010 having r^2 of 0.96)

This study assessed the reliability of the LSMM results by comparing model-derived fraction estimates with field derived fractional cover estimates as well as image-derived quantities. In order to compare the fraction estimates of each continuous field (end-member) from each of the three study sites, the first step involved converting the output from the LSMM to the percent covers of the different end-members. In real situations, it was not often that such pixels contained just one dominant class. To handle sub-pixel mixture problems, LSMM was therefore used to determine proportional estimates of vegetation cover in each pixel of the imagery.

The LSMM is a physically based image analysis model that supports repeatable and accurate extraction of quantitative sub-pixel information. The main advantage of application of this model is that vegetation cover types occupying from a whole to a small fraction of an image pixel could be detected. The LSMM did not rely on the detection or identification of pixel clusters with similar reflectance spectra. Rather, it was able to consider each pixel individually and assess the presence and proportion of select end-members. LSMM produced fraction images that were pixel-by-pixel measures of the percent composition for each end-member in the linear spectral mixture modeling. Fraction images produced with LSMM appeared to be an effective means of vegetation cover and other associated other cover types in such ecosystem. The findings showed that the LSMM was able to generate more accurate areal estimates of the end-member classes, matching closer to the field data estimates. In contrast, the LSMM proved to maintain higher accuracy in feature extraction and provided a more realistic representation of the landscape as it estimated continuous fields of forest cover, as opposed to the patchy and discrete nature of traditional per-pixel information extraction techniques from a fuzzy data set.

CONCLUSION

This paper presents an approach to giving better estimation of the parameters for the dimidiate pixel model, to achieve better retrieval of the FVC information in the concerned study area, and demonstrated the usefulness of the LSMM in the monitoring of vegetation dynamics from a fuzzy data set. We also examined the advantages of the LSMM in dimidiate pixel model for FVC retrieval.

In real situations, it was not often that such pixels contained just one dominant class. To handle sub-pixel mixture problems, LSMM was therefore used to determine proportional estimates of vegetation and soil cover in each pixel of the imagery. It has the ability to produce fractions representative of sub-pixel components directly related to vegetation cover types and relative area. Higher accuracy in estimating woodland vis-à-vis vegetation cover composition and proportional cover provided higher quality data for use in other application studies and input into biophysical, biogeochemical and other ecosystem models. Although the application of the LSMM offers the advantages of simplicity and ability to apply the model over large areas using reference reflectance end-members data, the model might also make overly simplified assumptions. However, linear mixing does not apply to cases where the composite occurs at a scale that is fine relative to the IFOV of the sensor (Zhu and Evans, 1994). Since mixing would occur before radiation reaches the sensor, the components of the composite would not be able to be estimated using the LSMM approach. However, it should be noted that non-linear mixing is likely only to occur when component surfaces arise in highly dispersed patterns. Owing to the nature of the woodland vis-à-vis vegetation cover and scene characteristics, the LSMM has been judged to be adequate for this purpose of the study.

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