SPECTRAL EVALUATION OF VEGETATION FEATURES USING MULTI-
SATELLITE SENSOR SYSTEM (TERRA ASTER, LANDSAT ETM+ AND IRS 1D
LISS III) IN MAN MADE AND NATURAL LANDSCAPE

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Abstract - The selection of wavelength region and number of bands is research problem for remote sensing experts for utilization of data provided by the sensor system. In the present study an initiative is taken to evaluate Terra-ASTER, Landsat ETM+ and IRS-1D LISS III for optimum band selection and classification accuracy. The entropy, Brightness Value Overlap Index (BVOI), Optimum Index Factor (OIF) and spectral seperability analysis i.e. Euclidean Distance (ED), Divergence, Transformed Divergence (TD) and Jafferie Matuse (JM) distance and accuracy of MLC classification was carried out. The Terra-ASTER was found the best after evaluating the aforesaid parameters. The present paper explains the different methods and their significance for spectral evaluation of vegetation.

Key Words: Spectral resolution, vegetation, satellite, Aster, Landsat, LISS III

INTRODUCTION
Remote sensing is an excellent integration of science and technology, which promises to ensure sustainable use of resources; natural, economic and human. The growing number of earth observation satellites and the continuing improvements of their remote sensing systems provide mankind with unprecedented global capacity for systematic monitoring of the earth's surface. Large amount of remote sensing data is generated every day, but only a small fraction is used for production of information. The remote sensing sensors or instruments used for the purpose of earth observations record information in a definite range of electromagnetic spectrum of the radiation. The determination of the optimal combination of spectral intervals providing the maximum information with the minimum number of intervals is of principal importance. Kondratyev et al., 1973 found short wave infrared region is the most suitable for discrimination of natural formations while selecting the spectral intervals with maximum information content using spectral brightness coefficient and spectral albedo. Hoffer et al. (1975) and Coggeshell et al. (1973) reported that near infrared portion of the spectrum, and to a lesser extent the middle infrared region has been shown to be of greatest value for differentiation among vegetation types, both from aerial and satellite remote
sensing. Improvement in the crop discrimination by inclusion of MIR data has been demonstrated using ground measurements (Rao et al., 1978; Ungar and Goward, 1983; Horler et al., 1984), airborne sensors (Kumar and Silva, 1977; Kumar, 1980; Townshend, 1984) and space borne data from Landsat TM (Chen et al., 1986).

For the purpose of vegetation mapping and feature discrimination, it is very important to know the spectral bands or combination of bands in single satellite sensor system or multisatellite system. The spectral band combination not only affects vegetation separability but also governs the accuracy of classification. An algorithm was developed by Sheffield (1985) for Landsat TM in which best three bands are selected with high individual variance, from the visible, near infrared and short wave infrared regions. Kritikos et al. (1986) studied the separability of spectral signatures for classifying the forest types. Classification with multivariate information increases the accuracy for land use/land cover when multiple channels are properly selected (Ma and Olson, 1989).

Another important parameter is the wavelength regions used. The wavelength regions with higher overlap decrease the classification accuracy. The spectral channels with smaller overlap should be combined and selected for an efficient classification (Ma and Olson, 1989). The extent of intermixing of features depends upon many other factors viz., spectral response of the particular class, spectral, spatial and radiometric resolution of the sensor. The efficient methods are required for reducing dimensionality and selection of the only those bands which contain the useful information regarding the features of interest. The bands selected should be un-correlated to the extent possible, since correlated bands give redundant information, which does not help in improving the discrimination.

**STUDY AREA**

For the present study two different types of landscapes were taken viz., *first* a manmade landscape and *second* a natural landscape. The agricultural fields and settlements nearby Jwalapur town of Haridwar district 78° 30’ to 78° 7’ 30” E and 29° 51’ 30” to 29° 55’ 45” N was selected as manmade landscape. It contains Agricultural fields, urban and rural settlements, canals and plantations. The Motichur range of Rajaji National park was selected as natural landscape (78° 7’ 30” E to 78° 12’0” E and 30° 0’ 0” N to 30° 3’ 0” N). This is mostly dominated with sal forest with mixed forest types in undulating topography. These selections were made carefully so that both types of landscapes could be represented well.
MATERIALS AND METHODOLOGY

For the present study Terra-ASTER, Landsat ETM+ and IRS –1D LISS III dataset has been used. The specifications and the details of dataset are given in Table 1. Four methodologies were applied to meet the aforesaid objectives. The first three methodologies were for the spectral evaluation of the three satellite data used and for determination of information content, variance and spectral overlap among the classes present in the natural and manmade landscape. The fourth methodology is for selection of spectral band combinations with highest separability of classes using divergence matrices. These band combinations are selected for the classification and subsequently accuracy assessment.

Insert Table 1

Selection of band triplets with highest information content & entropy

Spectral band selection is the process of determining the band or combination of bands that achieve the best discrimination among cover types (San Migual-Ayanz & Biging, 1997). The method used in the present study is based on the principal component analysis of the satellite data. It has taken correlation and variance-covariance between different bands of the sensors into consideration. Determinant was calculated for all the possible band triplets from the 3×3 variance-covariance sub-matrix for that band triplet. The value of the determinant for a particular band triplet corresponds to the volume of the ellipsoid for that band triplet. Then entropy was calculated for each band triplet with the help of following formula:

\[ S = \frac{N}{2} + \frac{N}{2} \ln (2\pi) + \frac{1}{2} \ln |M_s| \] (Sheffield, 1985)

(1)

Where, S is entropy,

- N is subset of data and
- Ms is N×N variance-covariance matrix.
Fig. 1a. The variance-covariance ellipsoid; Fig. 1b High correlation bands; Fig. 1c Low correlation bands ($\sqrt{\lambda_1}$, $\sqrt{\lambda_2}$ and $\sqrt{\lambda_3}$ are principal axes) (Adopted from Sheffield, 1985)

Restacking of the bands of Landsat ETM$^+$ dataset was done prior to computation. The thermal band (band 6) was stacked as band 7 and the original band 7 (SWIR) was stacked as band 6 for convenient coding.

**Optimum Index Factor (OIF)**

OIF is used to know the best band combination for feature discrimination, developed by Chavez et al. (1984) for Landsat TM. However, it is applicable for any multispectral data set. It is based on the amount of total variance and correlation between and within various band combinations. The number of possible combinations of three bands within the map list is determined using $N^3 = \frac{N!}{(3! \times (N-3)!}$ (Where, N is the total number of bands) For each combination of three bands, the OIF is calculated using the following formula:

$$OIF = \frac{Std_i + Std_j + Std_k}{Corr_{ij} + Corr_{ik} + Corr_{jk}}$$

Where, $Std_i$ = standard deviation of band $i$

$Std_j$ = standard deviation of band $j$

$Std_k$ = standard deviation of band $k$

$Corr_{ij}$= correlation coefficient of band $i$ and band $j$

$Corr_{ik}$= correlation coefficient of band $i$ and band $k$

$Corr_{jk}$= correlation coefficient of band $j$ and band $k$

The OIF values are ranked for best band combination. The C language was used to carry out the entire exercise.

**Brightness Value Overlap Index (BVOI)**

The range of brightness values or digital number for any cover type, in one spectral channel, is not unique. The brightness value ranges of different cover types may overlap. Such overlaps make it difficult to assign to a specific cover type pixels having brightness values in an overlap zone. In order to have a fast and simple procedure for selecting the optimum number from the total number of channel available, a measurement of degree of overlap...
among classes was desired. The degree of overlap is measured by determining minimum and maximum brightness values of each cover type from sample data of each spectral channel. The accumulative percentage of all pixels having brightness values ranging from the minimum to maximum for each cover type was computed for each spectral channel. For BVOI the average of the accumulative percentages of all spectral channels for each target was determined (sum diagonal values and divide by the number of spectral channel). The total accumulative percentage for any one spectral channel was divided by the total of averages for all spectral channels for each cover type. This is the BVOI value for that spectral channel. The sum of the averages of all the spectral channels for each cover type was divided by the number of cover types. This value is then the BVOI for given dataset. Mathematical expression for aforesaid description is as follows:

\[
F_{j,k} = \sum_{i=1}^{N_{j,k}} f(x_{i,k}) 
\]

\[
F_{aj} = \frac{1}{M} \sum_{k=1}^{M} F_{j,k} 
\]

\[
F_{ta} = \sum_{j=1}^{N} F_{aj} 
\]

Where, 
- \(x_{i,k}\) = (i)th brightness value within a class of spectral channel (k),
- \(f(x_{i,k})\) = number of pixels with brightness value \(x_{j,k}\),
- \(N_{j,k}\) = the range of brightness values within the class (j) of spectral channel (k),
- \(F_{j,k}\) = accumulative frequency for class (j) of channel (k),
- \(M\) = Number of spectral channels,
- \(F_{aj}\) = average accumulative frequency over all the spectral channels of class (j),
- \(N\) = Number of the classes in the dataset, and
- \(F_{ta}\) = total average accumulative frequency over all the classes

\(F_{o}\) was defined as the accumulative frequency for the whole dataset of a single channel, which always equaled 100 percent, and \(F_{tk}\), was defined as the total accumulative frequencies over all classes of channel (k).

If overlap does not exists among any classes of channel (k), then

\[
F_{tk} = \sum_{j=1}^{N} F_{j,k} = F_{o} = 100 \text{ percent} 
\]

If overlap exists among any classes of channel (k), then
The degree of the overlap among classes was determined as
\[ \text{BVOI} = \frac{F_{bk}}{F_{ta}} \text{ for channel (k), and} \]
\[ \text{BVOI} = \frac{F_{ta}}{N} \text{ for the data set} \]

**Spectral Separability Analysis**

Signature separability is a statistical measure of distance between two signatures. Separability can be calculated for any combination of bands that is used in the classification, enabling the user to rule out bands that are not useful in the results of the classification.

**Euclidean Distance**

Euclidean spectral distance is distance in n-dimensional spectral space. It is a number that allows two measurement vectors to be compared for similarity. The spectral distance between two pixels can be calculated as follows:

\[ D = \sqrt{\sum_{i=1}^{n} (d_i - e_i)^2} \]

Where,
- \( D \) = spectral distance
- \( n \) = number of bands (dimensions)
- \( i \) = a particular band
- \( d_i \) = data file value of pixel \( d \) in band \( i \)
- \( e_i \) = data file value of pixel \( e \) in band \( i \)

**Divergence**

Divergence is a measure of the separability of a pair of probability distributions that has its basis in their degree of overlap (Richards and Jia, 1999). It is one of the first measures of statistical separability used in the digital image processing of remotely sensed data, and is still widely used as a method of feature selection (Swain and Davis, 1978; Mausel et al., 1990). The formula for computing Divergence (\( D_{ij} \)) is as follows:

\[ D_{ij} = \frac{1}{2} \text{tr} \{(C_i - C_j)(C_i^{-1} - C_j^{-1})\} + \frac{1}{2} \text{tr} \{(C_i^{-1} - C_j^{-1})(\mu_i - \mu_j)(\mu_i - \mu_j)^T\} \]

(Swain and Davis, 1978)

Where, \( i \) and \( j \) = the two signatures (classes) being compared
- \( C_i \) = the covariance matrix of the signature \( i \)
\[ \mu_i = \text{the mean vector of signature } i \]
\[ tr = \text{the trace function} \]
\[ T = \text{the transposition function} \]

**Transformed Divergence**

Transformed Divergence (TD\(_{ij}\)) can be calculated using the following formula:

\[ TD_{ij} = 2000 \left\{ 1 - \exp \left( \frac{-D_{ij}}{8} \right) \right\} \]  

(10)

\( i \) and \( j \) = the two signatures (classes) being compared

\( D_{ij} = \text{Divergence} \)  

(Swain and Davis, 1978)

The transformed divergence gives an exponentially decreasing weight to increasing distances between the classes (Jensen, 1996). The scale of the divergence values can range from 0 to 2000.

**Jefferies-Matusita Distance**

The JM distance has a saturating behavior with increasing class separation like transformed divergence. However, it is not as computationally efficient as transformed divergence (Jensen, 1996). Jefferies-Matusita (JM) Distance can be computed using the following formula:

\[ \alpha = \frac{1}{8} (\mu_i - \mu_j)^T \left( \frac{C_i + C_j}{2} \right)^{-1} (\mu_i - \mu_j) + \frac{1}{2} \ln \left( \frac{\|C_i + C_j\|/2}{\sqrt{|C_i| \times |C_j|}} \right) \]  

(11)

(Swain and Davis, 1978)

\[ JM_{ij} = \sqrt{2(1 - e^{-\alpha})} \]  

(12)

Where, \( i \) and \( j \) = the two signatures (classes) being compared

\( C_i = \text{the covariance matrix of the signature } i \)

\( \mu_i = \text{the mean vector of signature } i \)

\( \ln = \text{Natural logarithm function} \)

\( |C_i| = \text{the determinant of } C_i \)
Classification Algorithm

The best band combinations were selected from spectral separability analysis and maximum likelihood decision rule of supervised classification was used for feature discrimination. The maximum likelihood decision rule is based on the probability that a pixel belongs to a particular class. It quantitatively evaluates both the variance and covariance of the category spectral response patterns when classifying an unknown pixel. The basic equation assumes that these probabilities are equal for all classes, and that the input bands have normal distributions. Under this assumption, the distribution of a category response pattern can be completely described by the mean vector and covariance matrix. Given these parameter, the statistical probability of a given pixel value being a member of a particular class can be computed. In essence, the maximum likelihood classifier delineates ellipsoidal “equiprobability contours” in the scatter diagram. The shape of the equiprobability contours expresses the sensitivity of the likelihood classifier to covariance. The algorithm for the Maximum Likelihood Classifier is as follows:

\[ D = ln(a_c) - [0.5ln(|Cov_c|)] - [0.5(X-M_c)T(Cov_c^{-1})(X-M_c)] \]  

Where,

- \( D \) = weighted distance (likelihood)
- \( c \) = a particular class
- \( X \) = the measurement vector of the candidate pixel
- \( M_c \) = the mean vector of the sample of class \( c \)
- \( a_c \) = percent probability that any candidate pixel is a member of class \( c \)
- \( Cov_c \) = the covariance matrix of the pixels in the sample class \( c \)
- \(|Cov_c|\) = determinant of \( Cov_c \)
- \( Cov_c^{-1} \) = inverse of \( Cov_c \)
- \( ln \) = natural logarithm function
- \( T \) = transposition function

Training Stage

A training set is a set of pixels selected to represent the potential class. The data file values for these pixels are used to generate a parametric signature. It is important that training sample be representative of the class that is to be identified. The selection of training samples depends largely upon the knowledge of the data, study area and the class to be extracted. The training signatures in the present study are selected according to ground truth. About 60 signatures are taken for each dataset. The selected signatures are used for the spectral
separability analysis of the dataset. The best band combinations came out from the analysis is used for the classification, taking the previously training signature in the classification process.

**Accuracy Assessment**

Accuracy assessment is a general term for comparing the classification to geographical data that are assumed to be true, in order to determine the accuracy of the classification process. Usually, the assumed-true data are derived from ground truth data. Reference pixels are points on the classified image for which actual data are known. The reference pixels are randomly selected (Congalton, 1991). For natural landscape 40 reference points are selected from field using GPS, similarly, for manmade landscape total 33 points are taken. Overall accuracy was computed by dividing the total correct (sum of the major diagonal) by the total number of pixels in the error matrix and kappa statistics of the classified outputs (Congalton and Mead, 1983; Rosenfield and Fitzpatrick-Lins, 1986; Congalton, 1991). The \( K_{hat} \) statistics was computed as:

\[
K_{hat} = \frac{\sum x_{ii} - \sum (x_{i++} \times x_{+i})}{N^2 - \sum (x_{i++} \times x_{+i})}
\]  

(14)

**RESULTS**

Seven classes for manmade landscape *viz.*, wheat, sugarcane, poplar, fallow/degraded, settlement, water, dry riverbed and ten classes for natural landscape *viz.*, dense Sal, young Sal, low density Sal, moist mixed, dry mixed, dry vegetation (seasonal), lantana, scrub, water and dry riverbed were separated out from the classification of the datasets used in the study.

**Calculation of Determinant and Entropy**

ASTER data of manmade landscape had shown maximum determinants and entropy in the case of band triplet 234 (R, NIR and SWIR) and in the case of natural landscape band triplet 134 (G, NIR and SWIR) possessed the maximum entropy. This refers to the band triplets, having most of the information content. In both the cases band 3 (R) and 4 (SWIR) were present holding unique information about the land cover. The band 3 of forest is present up to rank 16 continuously, means that NIR band of ASTER data is highly informative. While in the case of Landsat ETM\(^+\) data set of manmade landscape and natural landscape the band
triplet 345 (G, R and SWIR) had shown to be containing highest entropy with highest information, showing that G, R and NIR are the spectral regions important for information extraction. In the IRS-1D LISS III data of manmade landscape and natural landscape are showing that entropy of the band triplet 234 (R, NIR and SWIR) is maximum containing information highest than other band triplets. The entropy values for different datasets are showing that ASTER data contains the highest amount of entropy that is information content is highest for both the manmade and the natural landscapes. In manmade landscape the highest entropy content has been found in band combination 234 i.e. 26.28, than comes Landsat ETM+, its band combination 345 contains the entropy 19.88 while LISS III data have shown the lowest entropy i.e. 17.64 in the band triplet 234. In natural landscape also the performance of ASTER data has been found to be better than the other two datasets. Its best band triplet 234 has shown the highest entropy value of 23.77. Landsat ETM+ came on the second with the entropy 17.32 in the band triplet 345. LISS III is with the lowest entropy; its best band triplet 234 contains the entropy value 15.41.

**Optimum Index Factor (OIF)**

Optimum Index Factor (OIF) is one of the measures of the variance in the satellite data. The results from the OIF analysis are showing that ASTER data in the case of the manmade and natural landscape is having the highest variance and hence least correlation between the bands. In manmade landscape the best band combination of the ASTER data 239 is showing the value of OIF as 482.75 while Landsat ETM+ showing that of 300.97. LISS III had shown the lowest values of the OIF. Its best band combination 234 had shown the OIF values of 99.29. In natural landscape the ASTER data showing the OIF value of 66.95, which the highest amongst all the three datasets used. Here also the Landsat ETM+ comes to second; its best band triplet 367 contained the OIF value as 34.37. In the case of LISS III data the OIF value is lowest in its best band triplet 234 *i.e.*, 24.57. The OIF values are clearly indicating that ASTER data is the performance of ASTER data is the best having the lowest correlation between the band, hence the separability of the feature is also highest, while LISS III have shown high correlation between the bands, so with the poor separability of the features. Landsat ETM+ data is in between these two sensors, better than LISS III but poorer than ASTER.
**Brightness Value Overlap Index (BVOI)**

In manmade landscape of ASTER data the BVOI values are found to be less in bands 1, 2 and 3. In band 3 the BVOI value is found to be 0.65 which least value of BVOI amongst all three datasets of manmade landscape. In Landsat ETM+ data of the same area bands 3 and 4 have shown lower BVOI values- 0.86 and 0.72 respectively, while in LISS III data all the bands the BVOI values are more than one. The BVOI outputs of the three datasets of manmade landscape are showing that band 3 of ASTER has the least overlap of the classes, followed by band 4 of ETM+. There is very high overlap of the classes has been found in LISS III data. In case of ASTER data of natural landscape the results are showing that spectral channel 4, 7 and 8 contains the least BVOI value means that in these channel the overlap among the vegetation class is the least. The BVOI values from ETM data of natural landscape are showing that spectral channels 2, 3, 5 and 6 are the wavelength regions where the spectral overlap amongst the vegetation classes is less than other channels. The LISS III data of natural landscape has shown that spectral channel 4 is having the minimum overlap amongst all the four channels, having BVOI value of 0.95. In this case also BVOI values for the three datasets have shown the similar trend. ASTER data is with the least overlap of the classes while LISS III with the maximum overlap of the classes, and ETM+ is in between the two datasets.

Insert table 2

**Spectral Separability Analysis**

It has been found from spectral separability analysis all the three datasets for the manmade landscape that ASTER data with band combination of spectral bands 123468 contains the highest value of all the measures of spectral separability i.e. Euclidean Distance (291.72), Divergence (2133.37), Transformed Divergence (2000.00) and Jefferies-Matusita Distance (1414.10). While the Landsat ETM+ data with the band combination 23457 came on second with values- Euclidean Distance (103.69), Divergence (784.681), Transformed Divergence (1999.59) and Jefferies-Matusita Distance (1410.73). In case of LISS III data the separability analysis has shown that it spectral separability of the features has very poor in comparison to other two sensors the best band combination (234) of this sensor has shown low values of separability measure i.e. Euclidean Distance (85.89), Divergence (346.61), Transformed Divergence (1968.94) and Jefferies-Matusita Distance (1392.45). Amongst the all three datasets of natural landscape it has been found that ASTER is the best sensor showing highest
value of the all spectral separability measures. The best band combination in ASTER is 123456, which have shown the values of separability measures as follows- Euclidean Distance (223.61), Divergence (866.39), Transformed Divergence (1997.97) and Jefferies-Matusita Distance (1410.48). The separability measures of Landsat ETM+ have shown values next to that of ASTER. The combination of spectral bands 23457 was found to be best with values- Euclidean Distance (67.90), Divergence (788.75), Transformed Divergence (1982.91) and Jefferies-Matusita Distance (1394.78). Here also the LISS III data has shown poor separability of the classes. Even its best band combination i.e. 234, is showing values of separability measures much lower than that of the other two sensors- Euclidean Distance (55.86), Divergence (532.14), Transformed Divergence (4952.68) and Jefferies-Matusita Distance (1382.28).

Insert table 3

Classification

Using the data set of manmade landscape seven land use/land cover types were identified and mapped. Wheat (Triticum aestivum) is one of the major crops in the study area representing the Rabi (winter) crop. Sugarcane (Saccharum officinarum) is the largest sown rabi crop of the area. Poplar (Populus deltoids) is cultivated as a part of Agro-forestry plantation. Most of the plantation was found to possess young trees of poplar. A large part of the study area was left as fallow for future agricultural practices. There was large area also under degraded land mainly on the sides of roads, canals and riverbed. The degraded land was comprised of mainly sparse vegetation (Acacia catechu and Dalbergia sisso) and some grasses (mainly Saccharum munja). Some of the land is also found to be degraded in the interior part of the villages. The class settlement comprised of town area of Jwalapur and a number of villages. The class water is represented by the settling chamber constructed for the treatment of the sewage of Jwalapur town and the water presented in the canals. Some of the ponds were also found in the rural areas. The dry riverbed which was extracted out in the classified data was of Ranipur Rao which is the seasonal stream having water only in rainy season.

On analyzing the dataset of natural landscape around ten classes were mapped. Sal (Shorea robusta) is the dominant species in the study area. The class dense sal is represented by the forest area covered by sal having density more than 70%. It the largest class among all the cover type mapped. There are also few patches of young sal. In this cover type the crown
cover is less however number of trees per unit area is very high and the trees were of younger age. The low density sal is the area covered by very sparse growth of sal and interspersed by grasses mainly *Saccharum munja*. The density of sal was found to be less than 20%. The topography in this cover type was highly disturbed. Moist mixed forest was found mainly on the flat areas near perennial drainages and low-lying areas with high humidity. The important tree species found was *Albizia procera*, *A. lebbek* and *Emblica officinalis*. Dry Mixed vegetation was mainly found on the ridges in the study area. The tree species, which represented this cover type, was *Acacia catechu*, *Aegle mormelos*, *Ailanthus excelsa*, *Ziziphus xylocarpus*, *Z. mauritiana* and *Butea monosperma*. Dry vegetation (seasonal) comprises of plantations of teak (*Tectona grandis*) and some other vegetation, which remain dry in this season (March-April). Due to leaf fall teak class could not be separated out and got mixed with other vegetation, which was also leafless. Lantana (*Lantana camara*) could also be mapped in few parts. The scrub is represented by forest blanks, sparse shrubs and degraded forests. A high degree of soil erosion was also found in these areas. Water was found in the river channels and small streams. Motichur rao, which was the largest river stream of the study area found to have less water, as it is a seasonal river. The dry riverbed was mainly composed of boulders and sand.

**Accuracy Assessment**

The overall accuracy in case of manmade landscape was also found to be highest in the ASTER data (band combination 123468), which was 93.94% with Kappa coefficient 0.9291. The band combination 23457 of Landsat ETM+ was with the overall accuracy of 84.85% and Kappa coefficient of 0.8272. Here also LISS II (band combination 234) had shown the lowest accuracy comparing to the two other datasets, the overall accuracy was 81.82% and Kappa coefficient of 0.7868. The classified output of ASTER data (band combination 123456) of natural landscape is found to be with the highest overall accuracy of 95% and Kappa coefficient of 0.9442, followed by Landsat ETM+ (band combination 23457) with overall accuracy of 87.5% having the Kappa coefficient of 0.8606. The band combination 234 of LISS III of the same landscape was found to be with minimum overall accuracy (72.5%) and with minimum value of Kappa coefficient *i.e.* 0.6927.

Insert Table 4
DISCUSSION & CONCLUSION

With the advent of newer and advanced remote sensing sensors, the scientists have a lot of choices of satellite data for accurate mapping and assessment of natural resources. At present when lot many sensors are available it is important to evaluate the sensor systems and their spectral regions for discrimination of vegetation features. The number of bands present in a particular sensor and the spectral regions used in it are the some of the crucial factors which decide the usefulness of the data for different applications, including vegetation related studies. The selection of spectral wavelength region i.e. spectral bands and the sensor system is the research problem for remote sensing expert to suggest the best spectral regions and satellite sensor for the discrimination of the vegetation features in different landscapes viz., manmade and natural.

Using JM distance as a measure of separability, Chen et al. (1986) found that in ranking of the best three band combinations, TM 5 was placed higher than TM 7, while in best four-band combination, both TM 5 and TM 7 were included. Higher sperability was observed in studies on crop estimation in Haryana, India in MIR band of TM (Dadhwal et al., 1996). Moreover, choice of spectral bands and spectral bandwidth according to information content plays significant role in vegetation discrimination through remote sensing (Roy, 1989). San Miguel-Ayanz and Biging (1997) reported that since the TM imagery presents a better spectral resolution than the SPOT imagery, there are more choices in the band selection process, which allows a better separability between the classes being discriminated in each iteration.

A study on crop plant discrimination using Landsat TM data had shown that overall classification accuracy for the band combination 2,3,4,5 was found to be 96.94% as compared to 86.93% for band combination 1,2,3,4 (Sharma et al., 1995). The visible and near infrared bands in combination with middle infrared band enhances dimensionality, spectral separability and classification accuracy of the data (Oza and Sharma, 1990). Roy et al. (1988) had done a comparative study of IRS-1A LISS II, Landsat-TM and SPOT-1, and reported that Landsat-TM had shown improved separability of vegetation type due to higher spectral resolution.

Four methodologies were applied for the spectral evaluation of the three satellite sensors viz., ASTER, Landsat ETM+ and IRS-1D LISS III for manmade and natural landscape. The
purpose behind using so many parameters is to test the datasets from all the aspects and to suggest the appropriateness of the data for future use. The first three methodologies are basically for the spectral evaluation of the bands with reference to information content, variance-covariance and spectral overlap among the land use/land cover classes. While the last methodology is for spectral separability analysis of the datasets and evaluation of there classification accuracy. It was found that the higher spectral resolution decreases the overlap among the cover type in a particular dataset and as spectral resolution lowers the overlap among cover type increases which means lesser separability. It can be inferred from the present study that spectral resolution plays a very important role in discrimination of vegetation features. ASTER data which is with the highest number of the bands amongst the satellite data used had shown highest classification accuracy while LISS III data with lowest number of bands had shown lowest accuracy, while Landsat ETM+ stood in between the two sensors.

In the present study all the three datasets are extensively examined and tested for their vegetation discrimination capabilities using well-established methodologies. All the parameters viz. entropy, variance, cover type overlap, spectral separability and accuracy assessment applied on the datasets revealed that spectral resolution definitely plays role in the performance of the data as far as discrimination of features is concerned both in natural and manmade landscape with desirable accuracy. All the parameters tested had given the same conclusion that ASTER is the best dataset while ETM+ and LISS III came on second and third respectively. As far as the radiometry of the satellite sensors concerned the present study shows that radiometry may have some influence on separability of the features but not much as the spectral resolution. ASTER and Landsat ETM+ both have radiometric resolution of 8-bits but their information content, variance, cover type overlap and spectral separability were found to be very much different from each other, both in manmade and natural landscape. The spectral resolution had shown a great influence for vegetation feature discrimination and classification accuracy.

REFERENCES


### Table 1. Satellite data specifications

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Bands</th>
<th>Spatial Resolution (m)</th>
<th>Sensor Technology</th>
<th>Swath</th>
<th>Revisit</th>
<th>Orbit</th>
<th>Quantization</th>
<th>Launch Date</th>
<th>Acquisition Date</th>
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<td>60</td>
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<td>705 km</td>
<td>Sun-synchronous</td>
<td>December 18, 1999</td>
<td>31 March 2001</td>
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<td>Equatorial orbit crossing 10:30 a.m. ±15 min.</td>
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<td>0.76-0.86</td>
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<td>2.185-2.225</td>
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<td>2.235-2.285</td>
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<td>8.475-8.825</td>
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<td>16 days</td>
<td>10.95-11.65</td>
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<td>10.40-12.50</td>
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<td>Scanning mirror</td>
<td>70</td>
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<td>185 km</td>
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<td>April 15, 1999</td>
<td>01 March 2001</td>
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<td>0.525-0.605</td>
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<td>2.08-2.35</td>
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<td>10.40-12.50</td>
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<td>Linear array</td>
<td>142</td>
<td>24 days</td>
<td>817 km</td>
<td>Sun-synchronous</td>
<td>September 1997</td>
<td>01 March 2001</td>
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<td>1, 2, 3</td>
<td>148 km for bands 1, 2, 3 and 148 km for band 4</td>
<td>Inclination= 98.69°</td>
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Table 2. Comparison of Entropy, OIF and BVOI for various sensors

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<th>Entropy</th>
<th>Natural</th>
<th>Manmade</th>
<th>OIF</th>
<th>Natural</th>
<th>Manmade</th>
<th>BVOI</th>
<th>Natural</th>
<th>Manmade</th>
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<td>Terra – ASTER</td>
<td>23.77</td>
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<td>IRS – 1D LISS III</td>
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<td>17.64</td>
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NB: Band Combination in parenthesis

Table 3. Best average seperability measures for various sensors

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<tr>
<th>Sensor</th>
<th>Euclidean Divergence</th>
<th>Transformed Divergence</th>
<th>Jeffries-Matusita</th>
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<tr>
<td>Terra – ASTER</td>
<td>223.61 (37.34)</td>
<td>1997.97 (1999.98)</td>
<td>1410.48 (1412.54)</td>
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<tr>
<td>Landsat ETM</td>
<td>67.90 (10.85)</td>
<td>1982.91 (1992.58)</td>
<td>1394.78 (1352.99)</td>
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<td>IRS – 1D LISS III</td>
<td>55.86 (6.22)</td>
<td>1952.68 (572.45)</td>
<td>1382.28 (1000.24)</td>
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NB: Minimum Value in parenthesis

Table 4. Comparison of Accuracy

<table>
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<th>Sensor</th>
<th>Best Band Combination</th>
<th>Overall Accuracy</th>
<th>Kappa Coefficient</th>
<th>Best Band Combination</th>
<th>Overall Accuracy</th>
<th>Kappa Coefficient</th>
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<tr>
<td>Terra – ASTER</td>
<td>123456</td>
<td>95%</td>
<td>0.9442</td>
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<td>93.94%</td>
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<td>Landsat ETM</td>
<td>23457</td>
<td>87.5%</td>
<td>0.8606</td>
<td>23457</td>
<td>84.85%</td>
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<td>72.5%</td>
<td>0.6927</td>
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<td>81.82%</td>
<td>0.7868</td>
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