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SPATIAL DISTRIBUTION OF ECOLOGICAL COMMUNITIES USING REMOTELY SENSED DATA

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Abstract

In Pakistan in spite of few attempts for mapping land-cover types, satellite remotely sensed data has not been used extensively; and its potential is not being explored for providing information on mapping vegetation cover in general and ecological communities in particular. In this study, we used SPOT(Systeme Pour l'Observation de la Terre) multispectral (XS) satellite sensor data in visible and near infrared portion of the light spectrum as a surrogate for distribution of ecological vegetation groups defined by the classification and ordination methods (the most commonly used multivariate techniques used in floristic composition classification in vegetation ecology) and non-vegetation classes. The results indicate that classification of vegetation groups based on species composition identified using classification and ordination techniques to some extent resemble to those groups classified using SPOT XS data with least accuracy in comparison to non-vegetation classes which were more homogenous and spectrally separable and were classified more accurately in comparison. Two classification models i.e. supervised maximum likelihood and fuzzy supervised classification showed similar overall level of accuracies. The possibilities of lower classification accuracies and difficulties of classifying ecological communities based on the species composition using remotely sensor data are discussed.

Introduction

Satellite remote sensing (RS) has become a valuable tool for gathering information about land cover types and holds great potential for deriving timely and reliable information on the nature, extent and magnitude of land-cover (Apan, 1997; Turner, 1991), which is required for planning and implementation of conservation and management programmes (Nagendra, 2001; Zomer *et al*., 2002). During the past decade, digital remote sensing has become an increasingly important tool for mapping and monitoring and classifying vegetation resources around the globe (Cohen *et al.*, 1996). This is due to the increasing availability and understanding of remote sensing data in general (Arora, 2002) and to the greatly expanded use of geographic information systems (Roy *et al.,* 1991; Dymond *et al.,* 1996). Resource scientists and managers now require spatially explicit vegetation data over extensive geographic areas, which mean that traditional field survey techniques, even when coupled with aerial photography are useful but of limited use (Cohen *et al.*, 1996; Dwivedi *et al*., 1997). Traditional methods of vegetation mapping are time-consuming and generally uneconomical, with data collected over long time intervals, and are particularly inefficient and impractical for real-time global and regional mapping of different vegetation types and other land-cover categories (De Fries & Townshend, 1994; San Miguel-Ayanz *et al.*, 1997; Nagendra & Gadgil, 1999). Another important factor is an increased understanding that large-scale monitoring of forest conditions is practical only if digital remote sensing is included in the sampling and mapping scheme (Townshend & Walsh, 2001).

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Satellite sensors most commonly used for land-cover mapping, particularly forest types mapping include Landsat Thematic Mapper (TM) and Multispectral Scanner (MSS), airborne Thematic Mapper Simulator (TMS), Systeme Pour l'Observation de la Terre multispectral (SPOT XS) and Average Very High Resolution Radiometer (AVHRR). Among these, Landsat TM sensor data have been used extensively in forest type mapping (Stenback & Congalton, 1990; Hill, 1999). This is because of its improved spectral, spatial and radiometric resolution (Wilkie & Finn, 1996). Most of the investigations using sensor data have provided accurate classification results (Karteris, 1990; Rignot *et al*., 1997; Singh *et al*., 2002).

Although satellite remote sensing data have been extensively used for mapping and classifying land-cover classes, and are available at various spectral and spatial scales, they have not been fully exploited in Pakistan for mapping different vegetation types of ecological importance. Although a few attempts have been made using SPOT XS data (Malik *et al*., 1999, 2000). Yet the potential of remote sensing has yet to be explored in terms of providing information on ecological communities. Therefore the aim of this study is to map the spatial distribution of different vegetation groups classified using classification and ordination analysis using remote sensing techniques and assess the potential of SPT XS for mapping vegetative and non-vegetative classes.

Materials and Methods

Floristic data were collected from 90 randomly selected plots from Lohiberh study site (Malik & Hussain, 2006) from 30 field areas which were selected subjectively (Fig.1). Each field area comprised an area of 1.44 ha, which is equal to 120mx120m or 6x6 pixels of satellite sensor data (SPOT XS). Three to five randomly located points from each area were sampled based on vegetation homogeneity/heterogeneity. For each plot floristic and geographic data were collected. The latitude and longitudes were recorded for each plot using a Global Positioning System (GPS). Field information about different vegetation types and other parameters such as deforestation, urban encroachment, grazing pressure, land-use/cover patterns, general topography of the area and cultivation were also recorded. Floristic data from each plot was recorded as a percentage cover which was assessed as the vertical projection onto the ground of all the above ground parts of the individuals expressed as a percentage of the reference area. The percentage cover recorded was then partitioned to the “DOMIN” scale (Kent & Coker, 1992). Floristic data were analyzed using TWINSPAN classification and ordination analysis for plant communities classification which were used for mapping their spatial distribution (Malik & Husain, 2006). The remote sensing data obtained on 8 June 1998 by SPOT XS sensor were used and were geometrically corrected with Root Mean Square Error (RMSE) of 0.19 m. An area of original image containing the study area was subset from the full scene of the SPOT XS sensor data and was used for subsequent analysis.

The classification schemes included vegetation groups identified using hierarchical classification of floristic data and three other land-cover classes such as ‘settlements & barren-land’, ‘water bodies’ ‘land-area used for cultivation purposes and degraded land. Fuzzy supervised classification using maximum likelihood algorithm for the image classification which takes into account that there are pixels of mixed makeup, (a pixel which cannot be definitely assigned to one category) (Jensen, 1996). ‘Fuzzy convolution operation’ was performed on the fuzzy classified image, which creates a single classification layer by calculating the total weighted inverse distance of all the classes in a window of pixels. Then it assigns the centre pixel in the class with the largest total inverse distance summed over the entire set of fuzzy classification layers. This has the effect of creating a context-based classification to reduce the speckle in the classification. Classes with a very small distance value remain unchanged while classes with higher distance values may change to a neighbouring value if there are a sufficient number of neighbouring pixels with class values and small corresponding distance values. A 3 x 3 window size was used in the convolution process. The following equation was used in the 'fuzzy convolution operation' (source ERDAS, 8.6):

$$T[k] = \sum_{i=0}^{s} \sum_{j=0}^{s} \sum_{l=0}^{s} \frac{w_{ij}}{D_{ijl}[k]}$$

where
i = row index of window
j = column index of window
s = size of window (3, 5, or 7)
l = layer index of fuzzy set
n = number of fuzzy layers used
W = weight table for window
k = class value
$D[k]$ = distance file value for class k
$T[k]$ = total weighted distance of window for class k
The centre pixel is assigned the class with the maximum $T[k]$

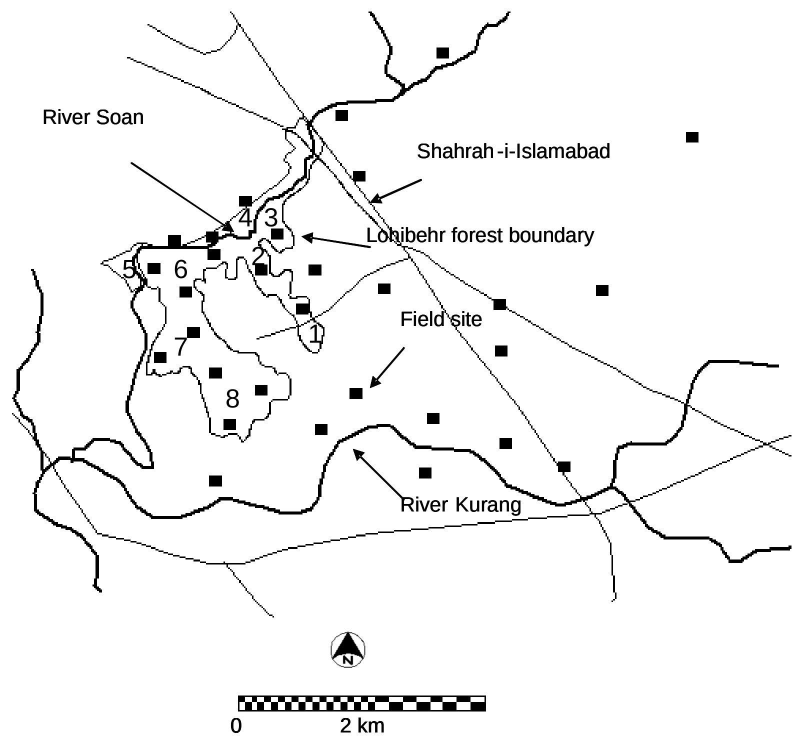

Fig. 1. Location of the field sites where floristic data were collected. Numbers inside the Lohibehr forest indicate different compartments.

Classified images obtained from each classification were assessed for their accuracy assessment.

Accuracy assessment: To assess the accuracy, an independent dataset for the vegetation and non vegetation was collected from 70 sites. Different measures of accuracy for instance 'overall accuracy', the 'confusion matrix', 'procedure's' and 'user's' accuracy; 'error of commission/omission', and the 'kappa coefficient' were examined in the error analysis. 'Overall accuracy' was calculated by dividing the number of validation pixels that were classified correctly by the total number of validation pixels for all classes. The 'error matrix' (also referred as 'confusion matrix' or 'contingency table') was used to illustrate class agreement and error in greater detail by illustrating the relationship between the independent validation sites (of the known class) and the percentage of those pixels actually classified into the various classes by the maximum likelihood classifier (Jensen, 1996; 2000; Lillesand & Kiefer, 2000). Percentages of pixels classified correctly are shown on the diagonal of the confusion matrix, while errors of 'commission' (incorrect inclusion into class-row entries) and 'omission' (incorrect exclusion from class column entries) can be seen off the diagonal (Lillesand & Kiefer, 2000). The 'procedure's accuracy' which is a measure of omission error was computed by dividing the number of correctly classified pixels in each category by the total number pixels in the corresponding column. The 'user's accuracy' which is a measure of commission error, was computed by dividing the number of correctly classified pixels in each category by the total number pixels that were classified in that category (corresponding row total). Finally, Kappa coefficients were calculated using the following equation (Lillesand &Kiefer, 2000):

$$K = \frac{N \sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} \cdot x_{+i})}{N^2 - \sum_{i=1}^{r} (x_{i+} \cdot x_{+i})}$$

where

K = Kappa coefficient

r = number of rows in the error matrix

x_{ii} = the number of observations in row i and column i in the major diagonal)

x_{i+} = total number of observations in row i

x_{+i} = total number of observations in column i

N = total number of observation included in matrix

Results

Four ecological communities were recognized from the TWINSPAN clustering and ordination method. These include *Ziziphus-Malcolmia*, *Prosopis-Chrysopogon, Capparis-Eleusine* and *Salix-Saccharum* plant community types (Malik & Husain, 2006) and are used with spectral classification of SPOT XS data.

Table 1 represents the error matrices of the fuzzy supervised classification model and Table 2 shows the accuracy totals of all the classified land-cover types. The land-cover maps produced are given in Fig. 2 and 3.

Table 1. Error matrix of fuzzy supervised classified map.

Class Name	Aca	Cap	Pros	Deg	Cul	Sac	W	Sett	Totals
Ziziphus malcolmia	8	0	2	0	0	0	0	0	10
Capparis eleusine	1	4	0	0	1	1	0	0	7
Prosopis chrysopogon	1	0	5	0	0	0	0	0	6
Degraded land	0	0	0	8	0	0	0	2	10
Cultivated land	0	1	0	0	7	1	1	0	10
Salix saccharum plant community types	0	2	0	0	1	4	0	0	7
Water bodies	0	0	0	0	0	0	8	1	9
Settlements and barren land	0	0	0	2	1	0	1	7	11
Totals	**10**	**7**	**7**	**10**	**10**	**6**	**10**	**10**	**51**

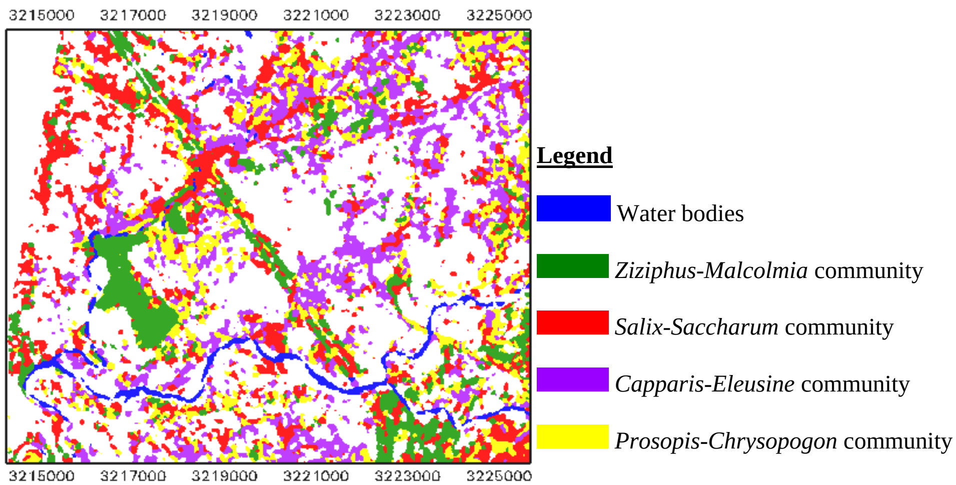

Fig. 2. Land cover maps showing the spatial distribution of vegetation classes.

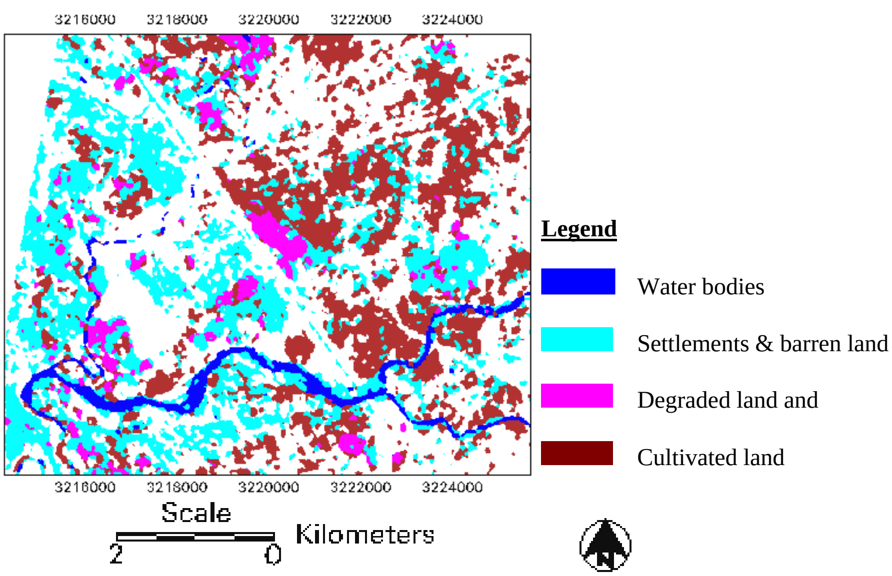

Fig. 3. Land cover maps showing the spatial distribution of non-vegetation classes.

Table 2. Accuracy total of fuzzy supervised classified map, Overall Classification Accuracy = 72.86%, Overall Kappa Coefficient = 0.70, for species abbreviations see Table 1, whereas E.O is error of omission and E.C is error of commission.

Class Name	Reference Totals	Classified Total	Number Correct	Procedure's Accuracy (%)	User's Accuracy (%)	E.O (%)	E.C (%)	Kappa coefficient
Ziziphus malcolmia	10	10	8	80.00	80.00	20.00	20.00	0.77
Capparis eleusine	7	7	4	57.14	57.14	42.86	42.86	0.55
Prosopis chrysopogon	7	6	5	71.43	83.33	28.57	16.67	0.82
Degraded land	10	10	8	80.00	80.00	20.00	20.00	0.77
Cultivated land	10	10	7	70.00	70.00	30.00	30.00	0.67
Salix saccharum plant community types	6	7	4	66.67	57.14	33.33	42.86	0.55
Water bodies	10	9	8	80.00	88.89	20.00	11.11	0.87
Settlements and barren land	10	11	7	70.00	63.64	30.00	36.36	0.60
Totals	**70**	**70**	**51**					

A total of 70 pixels were used for the calculation of the error matrix. Out of total pixels evaluated, 45 and 51 were correctly classified into the various land-cover classes using the two classification models respectively. The overall classification accuracy achieved for all land-cover classes was 65.71% and 72.68% and the overall kappa statistic was 0.62 and 0.70 for the two classifications. The Kappa statistic for the standard supervised classification ranged from 0.40 for *Capparis-Eleusine* and 0.77 for water bodies and the procedure's and user's accuracies ranged from 42.86% to 70.00% and 42.48% to 77.78% respectively. The E.Os and E.Cs for all land-cover classes were between 20.00% to 57.14%.

For the fuzzy supervised classification, *Ziziphus-Malcolmia* community type, degraded land and water bodies had the highest accuracy with a Kappa statistic of 0.77 and 0.87 respectively whereas vegetation types such as *Capparis-Eleusine,* and S*alix-Saccharum* were the least accurately identified classes with an E.C of 42.84%.

The data in Tables 1-2 also indicated that non-vegetation classes were more accurately classified as compared to vegetation classes which are due to the fact that boundaries between these classes are clearly defined and these classes are more uniform in their detail compared to vegetation classes. These factors resulted in higher accuracies.

Discussion

While analysing the SPOT XS data, wide variations in spectral response of a single vegetation type were found. This could be due to varied illumination geometry of the terrain of the study area. Careful consideration of spectral variation should be taken, especially when simple supervised classification techniques are applied (Saxena *et al*., 1992). This was accomplished by preliminary analysis of false colour composites (FCCs), topographical sheets, available vegetation maps, and by an intensive ground truth data collection. The results indicated that besides the obvious difficulties arising as a result of geographical complexities in the area, classification of plant communities could be possible by digital processing of satellite data.

A number of land-cover types were present in the SPOT XS image of the study sites. However the colour distribution of vegetation groups did not coincide well with the vegetation types recognized in the field. Instead different colour or tones could be identified within each vegetation types. Certain colours appeared to be associated with physiognomic differences between the main vegetation categories (scrub, and pine forest, open shrubby vegetation etc.), but none of the actual vegetation types could be readily identified. As far as broadly defined ground cover-types were concerned, satellite data seem to be superior to the topographic maps because the topographic maps mainly reflect physiognomic features (rock outcrops, stony sites, shrub-lands). Satellite imagery adds to this by providing more information about the luxuriance (cover) of the vegetation (Kalliola & Syrjänen, 1990).

These results indicate the usefulness of near infrared and visible red bands for the separability of different classes. The near infrared band responds to green biomass and is believed useful for species discrimination (Trisurat *et al*., 2000). Wolter *et al*., (1995) have also suggested the use of red, infrared and mid infrared bands for the separation of conifers, hardwood, and mixed coniferous hardwood classes, these bands were also found useful for detecting the presence or absence of the understorey vegetation for various degrees of canopy closure (Stenback & Congalton, 1990). Similarly, Foody & Hill (1996) also recommended the use of red, and near infrared for differentiation of different forest types. The present results are also consistent with the findings of Schmidt & Skidmore (2003).

Ground surveys revealed the presence of *Broussonetia papyrifera*, *Dalbergia sissoo*, *Prosopis juliflora*, *Eucalyptus* sp., and *Populus* sp., either in small stands or interspersed among thick *Acacia modesta* scrub in Compartments 3, 4, 6, 7 and 8 (Fig.1). With regard to species recognition, accurate differentiation was difficult within thick scrub forest of *Acacia modesta*. This is most likely due to following reasons: 1) emergence of *Prosopis juliflora, Broussonetia papyrifera, Eucalyptus* and *Populus* which are not in large contiguous areas; 2) they are in irregular, relatively small patches which are interspersed with pure *Acacia modesta* even less then the pixel size of SPOT XS imagery and 3) there is no uniform spacing. Therefore it was difficult to discriminate them on the imagery.

Barren land features have low separability from settlements and urban areas (Fig. 3), therefore it was difficult to map separate houses and buildings from bare land features on imagery as a large number of small dwellings were present and it was very difficult to assign spectral signatures. These were merged into a single class of settlements and barren land. Roads were more visible in the visible bands of SPOT XS because of their linear features. However they were not discriminated in heavily built-up areas and under thick vegetation cover. Gao & Skilcorn (1998) also pointed out that the NIR band provided more detail in the non-urban areas than in the urban areas and urban features are more readily seen in the visible red band compared to other bands. Rivers were adequately discriminated and classified but streams and nullaha were not discriminated using supervised classifications.

Although *Prosopis juliflora* and *Capparis decidua* dominated vegetation types were easily separated from the scrub forest class but they were mixed with fields, barren land with scanty scattered bushes and grasses.These factors determine the radiometric reflectance characteristics of these land-cover types. Similarly open canopy vegetation types often showed a much greater spectral variability than the more homogenous forest vegetation like *Acacia modesta* scrub forest. The spatial resolution of the SPOT XS (20mx20m) also prevented detailed studies on these vegetation types because the size of a rather homogenous object would exceed the 20mx20m to reach good classification accuracy (Kalliola & Syrjänen, 1990).

To assess the degree of correspondence between ecological classes identified from cluster and ordination analyses and those identifiable in the remotely sensed data, attention was focused on only classifications producing up 4 ecological groups. The two groups classification obtained from clustering and ordination analyses essentially separated scrub forest from flood plain vegetation. They were also easily separated from the remotely sensed data as they were spectrally as well as statistically distinct from each other. It is likely that these two classes are structurally different with different species composition with different canopy structure. These factors combined to make these two vegetation classes quite distinct spectrally from each other and from other classes such as settlements and cultivated areas.

The classification of ecological groups produced by TWINSPAN at each level were not tested using spectral classification, because the vegetation group identified using TWINSPAN division cannot be spectrally separable or ecologically similar groups could be spectrally distinct which would further lower the classification accuracy (Thomas *et al.*, 2003). For example in the present study, most of the vegetation classes obtained at the third level of TWINSPAN could be spectrally as well as ecologically distinct, but sites classified by TWINSPAN classification as degraded forest are a combination of two spectrally distinct vegetation classes, namely, group identified on the left side of the first division comprise of vegetation classes such *Ziziphus-Malcolmia, Capparis-Eleusine* and *Prosopis-Chrysopogon* where *Ziziphus-Malcolmia* is highly separable from *Capparis-Eleusine* and *Prosopis-Chrysopogon*. Similarly, if classification is tested at the Third level of division, more ecological classes could be obtained which could not be separable spectrally. It was observed that most of the spectrally separable groups were observed at different levels within the hierarchical divisions. This seems logical, in that it would be expected that spectral groupings would not correspond on a one-to-one level within hierarchy (Thomas *et al.*, 2003).

The results indicated that the vegetation groups identified from the classification of the remotely sensed data to some extent resembled those derived from the TWINSPAN, agglomerative clustering and ordination analyses. In general, using multivariate and remote sensing techniques, classification of different vegetation groups of ecological importance is possible, although some results do show lower classification accuracies. According to Nagendra (2001), 10-25 species in a relatively a homogenous stand can be directly identified using remote sensed data to provide maps with accuracies of around 60-100%.

Based on spectral and spatial resolution of satellite imagery employed and lower classification accuracies results, a three group general ecological group-based classification is recommended instead of four vegetation groups which should include *Acacia modesta* scrub, sparse vegetation characterized by *Prosopis juliflora* and *Capparis decidua* vegetation and group defined by the flood plain vegetation along with non-vegetated groups. These classification schemes could further improve the classification accuracy.

The supervised fuzzy maximum likelihood classification map produced using a convolution operation, which creates a single classification band incorporating the contextual information to estimate the most likely class for each pixel, was on the whole no more accurate than the standard maximum likelihood approach. Both classification methods had approximately the same overall level of accuracy. Similarly, studies that used the contextual classifier generally improved their accuracy by only a few percentage points (Poulin *et al.*, 2002). However, in the present study, few classes were more accurately classified using a fuzzy classification procedure. This was partly because the fuzzy classification led to a more homogenous classification that contaminated fewer isolated pixels or small clusters of pixels of any given class, thus eliminating the salt and paper noise in the classification. The results revealed an overall accuracy of 65.71% and 72.85. This indicates the poor performance of SPOT XS data for vegetation types classification. This could be due to the poor spectral resolution of SPOT XS bands, which undermines its superior spatial resolution.

Although, in this study, fuzzy supervised classification was attempted for the classification, which produced fraction images (multi-layered classification), that displayed the proportion of coverage of a particular class in each pixel (Foody *et al.,* 1996), it did not improve the classification accuracies. One possible explanation is that multi-layered classification was hardened to produce a thematic map of the area (single layer). Thus the information at subpixel level was lost while hardening the fraction images into a single layer image.

The results of this study also indicated that classification based on species composition or based on ecological groups to some extent is possible. Our results disagree with the findings of Lucas (1993) and Nilson *et al*., (1999) that digital classification of satellite multispectral data alone can not be used to determine the species composition in the forest stands and could not adequately discriminate between different forest classes. The classification accuracies of non-vegetation classes were higher than for vegetation classes in our study, which could be attributed to their spectral homogeneity, use of broad category scheme and the identification of training sites of good representative signatures used for the classification process.

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