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LINKING REMOTE SENSING AND ECOLOGICAL VEGETATION COMMUNITIES: A MULTIVARIATE APPROACH

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Abstract

In spite of few attempts for mapping land-cover types in Pakistan, remotely sensed data has not been used widely; and its potential is not being explored for providing information on mapping vegetation cover in general and ecological communities in particular. The present study was undertaken in the Lohibehr scrub forest in the Foothills of Himalaya, northeast of Pakistan. The objective of the study was ot find out the relationship between remote sensing data and vegetation communities of ecological importance using multivariate techniques such as TWO WAY INDICATOR SPECIES ANALYSIS (TWINSPAN), Principal Component Analysis (PCA) and Correspondence Canonical Analysis (CCA). Floristic data were compiled for vegetation types and Digital number (DN) values were extracted from SPOT XS image for visible and near infrared bands (NIR). Classification and ordination methods were used for the classification of floristic data and to describe the relationships between floristic species composition and DN values. Ordination analyses indicated positive correlation between floristic species composition and DN values along the first ordination axis, with the NIR. The ordination methods proved effective in summarizing basic, general structure of the plant community types and to some extent indicated correspondence with their spectral signatures. The results highlighted the potential of remote sensing data in providing information on different plant community types that could be used in planning, management and conservation of subtropical forest.

Introduction

During the past 20years, digital remote sensing has become an increasingly important tool for mapping and monitoring vegetation resources around the globe (Cohen *et al.,* 1996; Malik & Husain, 2006a), due to the increasing availability and understanding of remote sensing data in general and to the greatly expanded use of geographic information systems. Resource scientists and managers now require spatially explicit vegetation data over extensive geographic areas, which means that traditional field survey techniques, even when coupled with aerial photography are of limited use (Cohen *et al.,* 1996). Traditional methods of vegetation mapping are time-consuming and 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).

Remote sensing has been widely used in mapping and classification of vegetation types (Chavez & MacKinnon, 1994) and has considerable potential for the provision of information on different vegetation types of ecological importance (Franklin, 1994) as vegetation classification and mapping can be considered as the process of distinguishing vegetation communities that represent a realistic (although abstract) model, and displaying their spatial distribution on maps. To date, many studies have focused on issues such as forest/non-forest classification (Trisurat *et al*., 2000), particularly to monitor deforestation, but its potential to extract information about vegetation communities of ecological significance has not yet been explored in detail using remotely sensed data (Vogelmann & Moss, 1993; Key *et al.,* 2001; Malik, 2006b, c). Different vegetation types may differ markedly in terms of floristic species composition and therefore vary in terms of ecological and economic value (Cohen *et al.* 1996). Therefore, information on vegetation types is required for vegetation conservation and planning (Toumisto *et al.,* 1995). Remotely sensed spectral data have been used to identify broad categories of forest cover, for example, coniferous versus deciduous stands. Studies which have focused on different forest vegetation types have generally separated forests of different structural and biochemical attributes (Malik *et al.,* 2005).

One of the most difficult challenges in remote sensing of vegetation classification has been species identification (Key *et al.,* 2001). There are a multitude of factors influencing the spectral response of digital imagery and species is only a minor influence relative to vegetation structure and topography (Cohen *et al.,* 1996). Number of studies has used broad band sensor data such as Landsat TM and ETM, SPOT SX, MSS, and AVHRR to classify vegetation types at detailed species resolution with varying degree of success (Franklin, 1994; Schriever & Congalton 1995; Clark *et al*., 2001). In the last 10 years, a number of satellite sensors with higher spatial and spectral resolution have been developed, providing spectral resolution necessary to improve upon existing vegetation classification based on species identification and ecological types (Martin *et al*., 1998; Thomas *et al.,* 2003). Additionally, a temporal data set was also found advantageous in capturing the phenological events associated with different tree species and also for vegetation type mapping (Cohen *et al.,* 2001; Key *et al*., 2001).

Satellite remote sensing data have not been fully exploited in Pakistan for mapping vegetation types in general and particularly in the Foothills of the Himalayas, which is one of the species rich zones (Anon., 1999), few attempts have been made using SPOT XS data (Malik & Husain, 2006a). Himalayan Foothill forests of Pakistan are present in the north of the country and wide range of climatic and topographic variations have resulted in different vegetation types within few kilometers (Ellis *et al.,* 1994). Many vegetation types can be recognized, each varying in terms of floristic species composition, structure, physiognomy and habitat. In this region, the potential of remote sensing has yet to be explored in terms of providing information on ecological communities. The study was designed to focus on the use of multivariate methods such as clustering and ordination analyses to establish relationship between vegetation communities that are of ecological importance and remote sensing data. The information will be used for mapping of vegetation communities in the study area.

Materials and Methods

The location of the study area and its detail description is given in Fig. 1 (Malik & Husain, 2006b). Sampling strategy represents the skeleton of a study design, and when a remote sensing data is incorporated into the vegetation analysis, then ground data should be collected at the same time as data acquisition by the remote sensing satellite, or at least within a period in which the environmental conditions do not change (Wolter *et al.,* 1995). Considering this, the floristic data (floristic species composition) were collected between March-June 2000 to correlate with the remote sensing data which were obtained in the first week of June, 1998. Before collection of the floristic data, field visits were made to obtain an overview of the region to gain familiarity with the local flora, topography and land-use/cover patterns. This proved invaluable for vegetation sampling and later during the computer processing of the imagery. These visits showed well-marked differences in vegetation in relation to different vegetation types. A hand held Global Positioning System (Gamin GPS 12) and colour paper prints of the SPOT XS data were used in the field to determine the location of the sites to be sampled where sufficiently large areas of homogenous vegetation occurred on the imagery (based on colouration) and also identified in the ground, it was selected as a site for floristic data collection. After the selection of the site, three randomly placed plots measuring 20mx20m were recorded. A total of 90 randomly selected plots were recorded from 30 field sites for floristic data collection. Floristic species composition of each species from each plot were measured using percentage cover 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 (Kent & Coker 1992). The geographic locations (latitude and longitude) of each field plot from where floristic species composition was collected were taken using a Global Position System (GPS). Other parameters such as deforestation, urban encroachment, grazing pressure, land-use/cover patterns, topography of the area and cultivation which could be helpful in describing the vegetation types and other land-cover types were also recorded during sampling. All plants collected during the field work are deposited in the Quaid-i-Azam University Islamabad Herbarium (ISL) as voucher specimen.

Four non-vegetation types were also identified during field surveys. These types include urban land, cultivated area, degraded land (land excavated for soil extraction for making bricks) and water bodies (i.e. rivers, streams, seasonal nullahs and small ponds). The latitude and longitude of representative sites of these non-vegetation types were also recorded with the help of GPS.

SPOT HRV2 multi-spectral (XS) sensor data (Scenes No. 195 282 and 196 282) was acquired on 8th June 1998. A subset covering the study area was extracted from the whole image of SPOT XS sensor data and was geometrically corrected with an Root Mean Square Error (RMSE) i.e. the average of the errors in the reference points or sigma of ±10m using Ground Control Points (GCPs). GCPs were either obtained using GPS in the field or identified on a topographic map at the scale of 1:50,000.

Field data from all plots (vegetation and non-vegetation types) were imported in ERDAS Imagine software (Anon., 1996) and were overlaid on the subset of the study area as a point map. Field plots boundaries were drawn using ‘Area of Interest (AOI)’ tools (Anon., 1996). For each filed plot, an area of 120mx120m was delimited on the satellite image. This area was selected in order to reduce the effect of hilliness on the results and the error in GPS coordinate at the time of sampling may have exceeded. DN values were extracted in three SPOT XS bands which include near infrared (NIR) and visible green and red for each field plot of vegetation types and non- vegetation sites.

Floristic data were converted into Domin scale (Kent & Coker 1992) and used in the classification and ordination analyses for identification of vegetation types based on floristic species composition. Floristic species composition data were analyzed using Windows version (ver.4.34) of PC-ORD (McCune & Mefford 1999). For vegetation classification *Two Way Indicator Species Analysis* (TWINSPAN) was used (Jongman *et al.*, 1995).

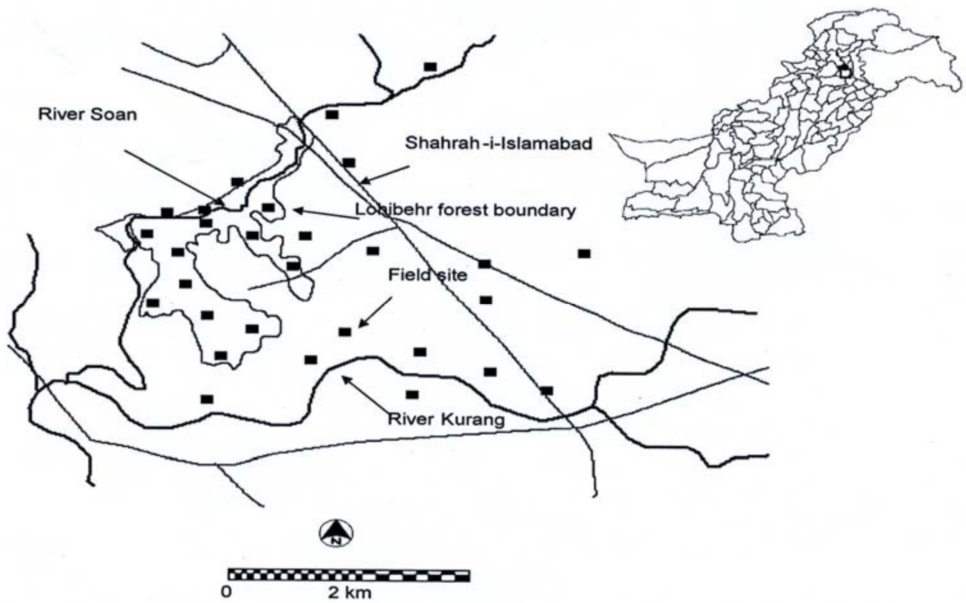

Fig. 1. Location of the study area and field sites from where floristic species composition and geographical coordinated were collected.

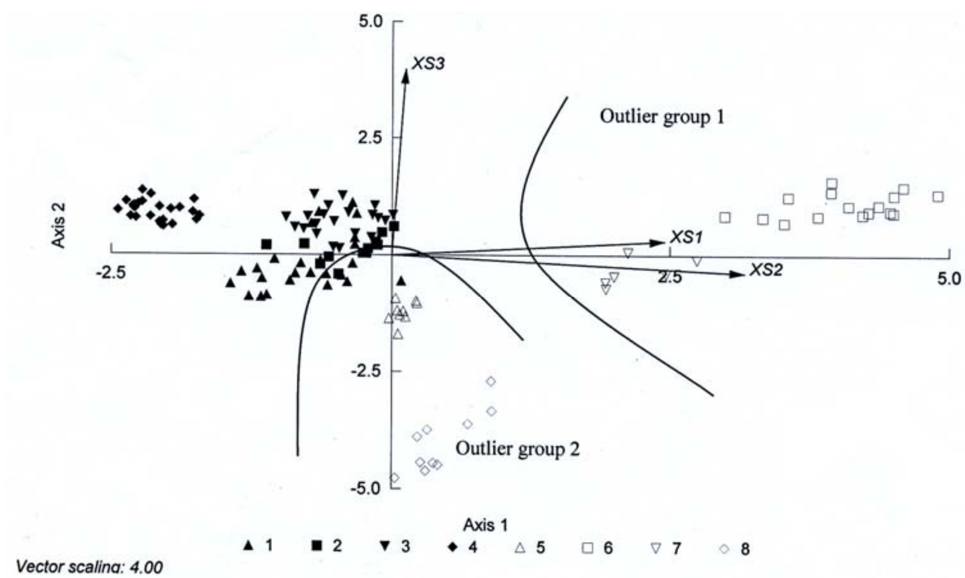

Fig. 2. PCA of spectral variables, each point representing data for a single field plot where field data and corresponding digital numbers of SPOT XS bands were collected.

Data analysis

All plant species recorded during the field visits as well as in the field plots were subjected to TWINSPAN for an ecological classification into vegetation communities. Classification by TWINSPAN was stopped at the 3rd level of the division so that the size of plots would demonstrate ecological meaning through their floristic structure. This resulted in four ecologically distinct groups (Fig. 2 in Malik & Husain, 2006a), together with the indicator species used by the software for every level of division.

The spectral data which include DN values of all plots of vegetation and non-vegetation types in three SPOT XS bands were analyzed using Principal Component Analysis (PCA) which is a multivariate indirect ordination technique that considers intercorrelations of the spectral data to produce an optimized and simplified representation of the underlying data structure (Legendre & Legendre, 1998) PCA based on the correlation matrix was used (Fig. 2). Spectral data in three SPOT XS bands (green, red and NIR) from vegetation and non-vegetation groups were used. The main use of PCA was to reduce the dimensionality of a data set while retaining as much information as is possible.

PCA is well suited to the identification of outlier groups in multidimensional spectral band space (Brook & Kenkel, 2002). Land-cover types appearing as prominent outliers in the two-dimensional ordination space were identified and removed. Land-cover types were considered outliers when the cluster defining the land-cover type was clearly separated from the remaining land-cover types. After one or more outliers identified in the data set were removed, PCA was run again on the reduced data set. This process was repeated until no strong outlier groups remained (Kenkel *et al.*, 2002). Once the main outlier groups were removed from the spectral data set, Canonical Correspondence Analysis (CCA) was performed on the floristic data and three spectral bands of SPOT XS sensor data (Fig. 3).

CCA in which a set of species is related directly to a set of measured environmental variables and the axes of a vegetative ordination are restricted to linear groupings of environmental variables (Jongman *et al*., 1995) was used to explore the relationships between natural species distribution shown in the classification and the image DN values to see how well DN values (spectral response) using three SPOT XS bands described the natural species clusters which describe the ecological importance in defining vegetation communities for vegetation classification of the whole study area using remotely sensed data (Malik & Husain, 2006c).

CCA was performed on species abundance data using the ‘Domin scale’. Rare species were down-weighted to reduce distortion of the analysis. CCA was accomplished using ‘Hill’s Scaling’ and site scores scaled by ‘species’. A Monte Carlo test (P=0.05) was then used to evaluate whether the Spectral variables (environmental variables) were significantly related to the floristic species composition of plots. A finding of no significant difference among the correlations of the real data set and the randomized data sets will suggest that the relationship between the matrices (floristic species composition matrix and SPOT XS spectral bands matrix) is not stronger than that expected by random chance and supports the hypothesis of no linear relationship between the two matrices (McCune & Mefford, 1999; Qadir *et al.*, 2007). The main data matrix consisted of the floristic species composition of field plots and the second matrix contained the mean reflectance values of three SPOT XS spectral bands of field plots. The Monte Carlo test was set at 1000 randomized runs and the result was compared with that of the nonrandomized data.

PCA were performed using *MVSP* software *(version 3.13f)* of Kovach (2003) and CCA was performed using Windows version (ver.4.34) of PC-ORD (McCune & Mefford, 1999).

DN values extracted from all land-cover types (vegetation and non- vegetation) in three spectral bands of SPOT XS were statistically tested for their separability with transformed divergence using different band combinations (i.e. band 1, bands 2, 3 and bands 1, 2, 3). Transformed divergence takes into account the covariance matrix and mean vectors of the different land-cover types and gives exponentially decreasing weights to increasing distance between the land-cover types (Jensen, 2000). The scale of the divergence values ranged from 0 to 2,000. If greater than 1,900 then the land-cover types are highly separable. Between 1,700 and 1,900, the separation is fairly good and below 1,700 it is poor (Jensen, 2000). However, Foody & Hill (1996) working on the forest mapping of tropical rain forest considered divergence values of 1,500 acceptable. Transformed divergence was calculated using the following equations (Swain & Davis, 1978):

$$D_{ij} = \frac{1}{2} tr\left((C_i - C_j)(C_i^{-1} - C_j^{-1})\right) + \frac{1}{2} tr\left((C_i^{-1} - C_j^{-1})(\mu_i - \mu_j)(\mu_i - \mu_j)^T\right) \quad \textit{Equation 1}$$

$$TD_{ij} = 2000\left(1 - \exp\left(\frac{-D_{ij}}{8}\right)\right) \quad \textit{Equation 2}$$

where $_i$ and $_j$ = the two signatures (types) being compared, C_i = the covariance matrix of signature $_i$, μ = the mean vector of signature $_I$, Tr = the trace function (matrix algebra), and T = the transposition function.

An ‘analysis of variance’ (ANOVA) using a ‘Generalized Linear Model’ was employed for pair-wise comparisons at the 95% level of significance. The results will indicate whether the groups identified earlier using classification and ordination analysis can be significantly differentiated from each other based on DN values of SPOT XS data. This will further strengthen and give information to establish relationship between vegetation communities and remote sensing data. The results of these (statistical and spectral analyses) will be used for classification of remotely sensed data (Malik & Husain 2006a).

Results

The TWINSPAN analysis divided the field plots into four vegetation groups (Four plant community types were recognized from the TWINSPAN and their detailed description is given in Malik & Husain (2006b). Based on the PCA ordination results, non-vegetation types were spectrally separable from vegetation types and were identified as outlier groups (sites identified as outliers if all sites belonging to individual land-cover types are strongly separated from the other sites in the data set) in the ordination space (Fig. 2). PCA ordination of all land-cover types indicated two strong outliers. These outlier groups were characterized by their high DN values in visible bands compared to vegetation types which showed high DN values in NIR. These could easily be separated using SPOT XS1 and XS2 bands when compared with vegetation types. DN values of outlier groups are more influenced by the visible bands rather than the NIR band of the SPOT XS imagery. These outlier groups (land-cover categories) formed distinct groups on the right and lower side of the ordination diagram (Fig. 2). The outlier group identified on the lower site was represented by urban land (cluster 6) and degraded land (cluster 7) land-cover categories, while the other was represented by cultivated land (cluster 5) and water bodies (cluster 8) land-cover categories. PCA analysis also revealed that SPOT XS1 and SPOT XS2 are highly correlated, whereas SPOT XS3 is non-correlated with them and place a strong emphasis on distinguishing vegetation from non-vegetation types. SPOT XS1 and XS2 are important in the separation of non-vegetation types, whereas SPOT XS3 is important in the separation of vegetation types. The first PCA axis explains the greatest variance and the second PCA axis, perpendicular to the first, explained the remaining variance, and so forth. A cumulative variance of axis I was 63.18%, where as for axis II, it was 35.31%. *Ziziphus-Malcolmia* dominated by *Acacia modesta* was separated from other vegetation types using PCA whereas the other three vegetation types (i.e. *Capparis-Eleusine*, *Salix-Saccharum* and *Prosopis-Chrysopogon*) were not distinctly segregated using PCA ordination (Fig. 2). Although sites belonging to the *Salix-Saccharum* vegetation type formed a separate group, but showed some overlap with the *Capparis-Eleusine* and *Prosopis-Chrysopogon* community types. PCA ordination analysis did not separate the *Capparis-Eleusine* and *Prosopis-Chrysopogon* community types based on their DN values, because two vegetation types overlapped in the ordination space. This could be attributed to the fact that the boundaries between these two vegetation types could not be drawn based on their DN values. As these vegetation types are characterized by open shrubs and scanty vegetation and their spectral response depends upon the soil/bedrock as well as the vegetation.

CCA ordination results: The results revealed that four vegetation community types could be discriminated using CCA ordination analysis when floristic species composition data were incorporated along with the spectral variables (Fig. 3). Three vegetation types (*Salix-Saccharum* and *Ziziphus-Malcolmia*) were distinct from each other whereas *Capparis-Eleusine* and *Prosopis* showed some overlap. SPOT XS1 and XS2 were highly correlated (r=0.96) with each other. Similarly when correlations of these bands were calculated with SPOT XS3, they provided similar information. The floristic species composition - environment (DN values in three spectral bands) correlations for the first two CCA axes were high. The species-DN values correlations accounted for by the first three CCA axes were 0.85, 0.78 and 0.44 (Table 1). The first two CCA axes were highly correlated with the SPOT XS bands. SPOT XS3 showed high correlation with CCA axis 1 (r = -0.74) compared to the other bands (Table 2). A total of 35.57% cumulative variance (of three CCA axes) in the floristic species composition data was explained by three spectral variables extracted from satellite sensor data (Table 1). The Monte Carlo test statistic also indicated that the relationship between floristic species composition (axis 1) and the spectral variables (SPOT XS bands) was significantly greater than expected by chance (P = 0.01). CCA ordination biplot revealed that the plots of the *Ziziphus-Malcolmia* dominated by *Acacia modesta* scrub were associated with the high DN values in SPOT XS3 and low DN values in SPOT XS1 and XS2. *Salix-Saccharum*, *Capparis-Eleusine* and *Prosopis-Chrysopogon* community types are more differentiated by the SPOT XS1 and XS2 due to their high DN values in these bands (Figs. 3 and 4).

Table 1. Summary statistics for the CCA ordination

CCA	Axis 1	Axis 2	Axis 3
Eigenvalues	0.24	0.14	0.03
Cumulative variance explained (%)	8.36	13.11	14.1
Floristic species composition and DN values (extracted for three SPOT XS bands) correlation (Pearson)	0.85	0.78	0.44
Floristic Species composition and DN values (extracted for three SPOT XS bands) correlation (Kendall Rank)	0.65	0.59	0.33

Table 2. Interset and intraset correlation coefficients of the spectral variables of CCA ordination.

Bands	Interset correlation coefficients Axis 1	Interset correlation coefficients Axis 2	Intraset correlation coefficients Axis 1	Intraset correlation coefficients Axis 2
SPOT XS1	0.57	0.57	0.67	0.74
SPOT XS2	0.66	0.48	0.78	0.62
SPOT XS3	-0.74	0.31	-0.87	0.40

From the CCA biplot (Fig. 3), three species groups were evident. The first was highly associated with the high DN values in SPOT XS2 and XS1 and includes plots belonging to the *Capparis-Eleusine* and *Prosopis-Chrysopogon* community types. A second group is evident in the lower right of the CCA diagram associated with low DN values in SPOT XS3 and higher values in the visible bands (SPOT XS1). This group is characterized by plots belonging to the *Saccharum-Salix* vegetation type. A third group was evident through the lower left side of the biplot closely associated with SPOT XS3. This group is represented by the *Ziziphus-Malcolmia* vegetation type and was associated with high DN values in this band.

Spectral and statistical analyses results: The mean spectral values of land-cover types (vegetation and non-vegetation) identified along with their standard deviations as given in Fig. 4 show the spectral variability and mean pixel values of vegetation types and non-vegetation types in three SPOT XS bands. The results obtained from separability analysis using Transformed divergence of three different band combinations are given in Table 3 which showed that the vegetation types are clearly distinct from non-vegetation types. Water bodies, urban, degraded, and cultivated land categories were separable and distinct from each other and also from vegetation types in each band combinations and also showed high transformed divergence values. Similarly significant differences were found (P=0.05) between non-vegetation types and the vegetation types. The urban land category was more prominent in visible bands compared with the NIR band and transformed divergence analysis indicated the highest values of this category from other land-cover types. Similar trend was found for degraded land. The cultivated land showed lower DN values in all spectral bands from other non-vegetation types. Water bodies were separated and distinct in their spectral behavior from other land-cover types; showed high DN values in visible bands compared to the near infrared band, where low DN values due to absorption by water bodies making them dark black where it is characterized by high DN values in SPOT XS1 and XS2 bands and low DN values in SPOT XS3.

The results of transformed divergence analysis also revealed a very high transformed divergence value, greater than 1999, indicating its spectral separation from other land-cover types. CCA results demonstrated that near infrared band was particularly effective in differentiating *Ziziphus-Malcolmia* community type from other vegetation types.

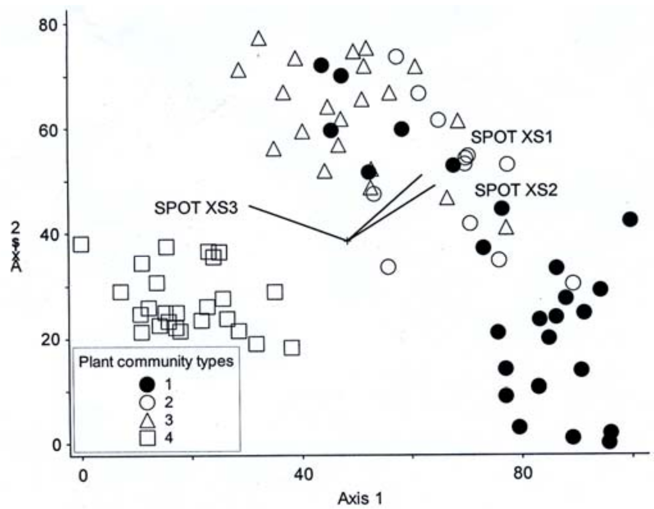

Fig. 3. CCA based on three SPOT XS spetctral bands. The numbers indicate vegetation community types (1) Salix-*Saccharum*, (2) *Capparis-Eleusine*, (3) *Prosopis-Chrysopogon* and (4) *Ziziphus-Malcolmia* plant communities.

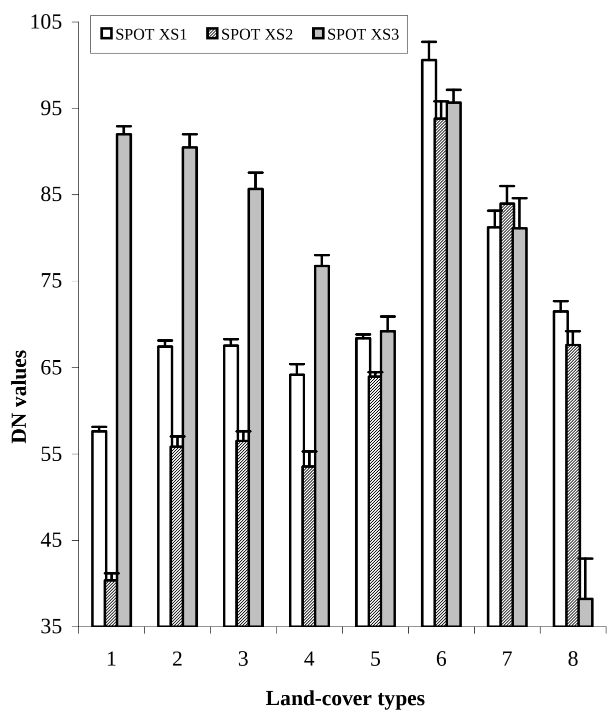

Fig. 4. Mean DN values values extracted from SPOT XS three bands for land-cover types showing level of significance where (1): *Ziziphus-Malcolmia*, (2): *Prosopis-Chrysopogon*, (3): *Capparis-Eleusine*, (4): *Salix-Saccharum* community types, (5): cultivated land, (6): urban land, (7): degraded land, and (8): water bodies. Y-bars represent LSD values.

Table 3. Transformed divergence of land-cover types.

	Class names	*Ziziphus-Malcolmia*	*Capparis-Eleusine*	*Prosopis-Chrysopogon*	Degraded land	Cultivated land	*Salix-Saccharum*	Water bodies	Urban land
(a)	*Ziziphus-Malcolmia*	0							
	Capparis-Eleusine	2000	0						
	Prosopis-Chrysopogon	2000	1263	0					
	Degraded land	2000	2000	2000	0				
	Cultivated land	2000	1639	1990	2000	0			
	Salix-Saccharum	2000	1999	1925	2000	2000	0		
	Water bodies	2000	1999	2000	2000	1583	2000	0	
	Urban land	2000	2000	2000	1937	2000	2000	2000	0
(b)	*Ziziphus-Malcolmia*	0							
	Capparis-Eleusine	2000	0						
	Prosopis-Chrysopogon	2000	1613	0					
	Degraded land	2000	2000	2000	0				
	Cultivated land	2000	1596	1993	1999	0			
	Salix-Saccharum	1990	1999	1993	2000	2000	0		
	Water bodies	2000	2000	2000	2000	1999	2000	0	
	Urban land	2000	2000	2000	2000	2000	2000	2000	0
(c)	*Ziziphus-Malcolmia*	0							
	Capparis-Eleusine	2000	0						
	Prosopis-Chrysopogon	1995	1174	0					
	Degraded land	2000	1999	1999	0				
	Cultivated land	2000	1649	1981	1999	0			
	Salix-Saccharum	1997	1932	1842	2000	1996	0		
	Water bodies	2000	2000	2000	2000	1999	2000	0	
	Urban land	2000	2000	1999	1999	2000	2000	2000	0

(a) Band 1; (b) Bands 2, 3; and (c) Bands 1, 2, 3. Best average statistical separability of different wavebands was Band 1=1940, Bands 2, 3 = 1971, and Bands 1, 2, 3 = 1948 respectively.

Spectral and statistical analyses of remotely sensed data indicated a high degree of interclass separability in some ecological communities (Table 3 and Fig. 4). *Ziziphus-Malcolmia,* and *Prosopis-Chrysopogon* plant community types were separable in the infrared and green band (XS3 and XS2) from each other and from non- vegetation types (urban land, cultivated land and water bodies). *Acacia modesta* scrub was significantly different from *Salix-Saccharum* and *Capparis-Eleusine* vegetation types, whereas it showed insignificant differences in spectral reflectance from *Prosopis-Chrysopogon* in SPOT XS3. Insignificant differences were observed in their spectral reflectance in SPOT XS1 and XS2 (P=0.05) but could be differentiated in SPOT XS3. Similarly these vegetation types remained inseparable based on transformed divergence values (Table 3). The *Salix-Saccharum* community type remained distinct and significantly different (P=0.05) from vegetation and non-vegetation types. Transformed divergence also confirmed these results.

Discussion

The results illustrated that the SPOT XS bands did not relate well with the distribution of species abundance data, suggesting that classification at the species level would be difficult. The CCA results indicated that 26% of the variance in the ordination space could be explained by variations in DN values extracted from SPOT XS1, 2 and 3. This suggested a weak relationship between floristic species composition and SPOT XS DN values, but not surprisingly a large amount of the variation in floristic species composition remained unaccounted for. This occurs because spectral reflectance is largely a function of structural, rather than floristic properties of vegetation (Brook & Kenkel, 2002). Beside the structural attributes, the reflectance information is affected by a number of other factors, including soil moisture, substrate, topography and atmospheric effects as well as amount, vigour and productivity of the vegetation (Vogelmann & Moss 1993). Multivariate techniques such as ordination analyses to some extent proved very useful in relating the species floristic characteristics to the spectral reflectance data (Kent *et al.,* 1997). The ancillary and field data along with satellite imagery also proved very useful in the present study which is the first such detailed investigation in the study area. The use of satellite imagery during field data collection was found helpful in the selection of sampling areas and avoiding routes with steep slopes. *Ziziphus-Malcolmia* plant community type was spectrally separable in the NIR band from other vegetation types. This is possibly because the NIR region of light experiences very little absorption by a leaf and most near infrared energy impinging upon the leaf is either transmitted or reflected (Jensen, 2000). Reflection of the leaf is not controlled by the plant pigments in this region but by the structure of the mesophyll tissue (Jensen, 2000; Schmidt & Skidmore 2003). Differences in reflectance of plant species are more pronounced in this region than in the visible regions making the discrimination of vegetation types possible. The results also indicated the usefulness of near infrared and visible red bands for the separability of different land-cover types. The NIR 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 types and these bands were also found useful for detecting the presence or absence of the understorey vegetation for various degrees of canopy closure. 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).

The classification of ecological groups using floristic species composition produced by TWINSPAN at each level were not tested using spectral types, because the vegetation group identified using TWINSPAN division cannot be spectrally separable or ecologically similar groups can be spectrally distinct (Thomas *et al.*, 2003). For instance in the present study, some of the vegetation types obtained at the third level of TWINSPAN could be spectrally as well as ecologically distinct, but sites classified by TWINSPAN classification on the left side of the third division which comprise of vegetation types such *Ziziphus-Malcolmia*, *Capparis-Eleusine* and *Prosopis-Chrysopogon* are not separable ecologically but could be separated spectrally. Similarly, if classification is tested at the fourth level of division, more ecological types 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).

As to some extent vegetation types identified, were spectrally separable and corresponded to ecological groups. It may be possible, therefore to map such ecological types over large areas with remote sensing data, but the results need to be tested in different areas particularly with different vegetation types in climatic and topographic condition. This could lead to the conclusion that remote sensing may be an effective method for producing a vegetation map showing the spatial distribution of the plant communities.

References

Anonymous. 1996. *ERDAS IMAGINE (ver. 8.2) Field Guide.* ERDAS inc., Atlanta, Georgia, USA.

Anonymous. 1999. *Government of Pakistan, Biodiversity Action Plan, Pakistan.* IUCH/WWF.

Brook, R.K and N.C. Kenkel. 2002. A multivariate approach to vegetation mapping of Manitoba's Hudson Bay Lowlands. *International Journal of Remote Sensing,* 23: 4761-4776.

Chavez, P.S. and D.J. MacKinnon. 1994. Automatic detection of vegetation changes in the southwestern United States using remotely sensed images. *Photogrammatic Engineering and Remote Sensing,* 60: 571-583.

Clark, P.E., M.S. Seyfried and B. Harris. 2001. Intermountain plant community classification using Landsat TM and SPOT HRV data. *Jounal of Range Management,* 54: 152-160.

Cohen, W.B, J.D. Kushla, W.J. Ripple and S.L. Garman. 1996. An introduction to digital methods in remote sensing of forested ecosystems: focus on the Pacific Northwest, USA. *Environmental Management,* 20: 421-435.

Cohen, W.B., T.K. Maiersperger and T.A. Spies. 2001. Modeling forest cover attributes as continuous variables in a regional context with Thematic Mapper data. *International Journal of Remote Sensing,* 12: 2279-2310.

De-Fries, R.S. and R.G. Townsend. 1994. Global land cover: comparison of ground-based data sets to classification with AVHRR data. In: *Environmental Remote Sensing from Regional to Global Scales.* Chichester: (Eds.): GM. and Foody, PJ. Curran Wiley. pp. 84-104.

Ellis, S., D.M. Taylor and K.R. Masood. 1994. Soil formation and erosion in the Murree Hills, northeast of Pakistan. *Catena* 22: 69-78.

Foody, G.M. and R.H. Hill. 1996. Classification of tropical forest types from Landsat TM data. *International Journal of Remote Sensing,* 17: 2353-2367.

Franklin, S.E. 1994. Discrimination of sub-alpine species and canopy density using CASI, SPOT, PLA and Landsat TM data. *Photogrammatic Engineering and Remote Sensing,* 60: 1233-1244.

Hill, M.O. 1979. TWINSPAN*: FORTRAN Program for Arranging Multivariate Data in an Ordered Two-way Table by Classification of Individuals and Attributes.* Cornell University, Ithaca, NY.

Jensen, J.R. 2000. *Remote Sensing of Environment: An Earth Resource.* 1st ed. Saddle River: Prentice-Hall, Inc, New Jersey.

Jongman, R.H.G., C.J.F. ter Braak and O.F.R. Van Tongeren. 1995. *Data analysis in community and landscape ecology*. Cambridge University Press, Cambridge, MA.

Kenkel, N.C., D.A. Derksen, A.G. Thomas and P.R. Watson. 2002. Multi-variate analysis in weed science research. *Weed Sci*., 50: 281-292.
Kent, M. and P. Coker. 1992. V*egetation Description and Analysis, A Practical Approach*. Belhaven Press, London.
Kent, M., W.J. Gill, R.E. Weaver and R.P. Armitage. 1997. Landscape and plant community boundaries in biogeography. *Progress in Physical Geography,* 21: 315-353.
Key, T., T.A. Warner, J.B. McGraw and M.A. Fajvan. 2001. A comparison of Multispectral and Multi-temporal Information in High Spatial Resolution Imagery for Classification of Individual Tree Species in a Temperate Hardwood Forest. *Remote Sensing of Environment,* 75: 100-112
Kovach, W. 2003. *MVSP (Ver 3.13f): Multivariate Statistical Package, Kovach* Computing Services, Wales, UK.
Legendre, P. and R. Legendre. 1998. *Numerical Ecology,* 2nd ed. Elsevier Science, New York, USA.
Malik, R.N. and S.Z. Husain. 2005. Assessment of image value gradient problem in the Amazon Landsat TM data. *Pakistan Journal of Botany,* 37: 843-852.
Malik, R.N. and S.Z. Husain. 2006. Land-cover mapping: A remote sensing approach. *Pakistan Journal of Botany*, 38: 559-570.
Malik, R.N. and S.Z. Husain. 2006. Classification and ordination of vegetation communities of the Lohibehr reserve forest and its surrounding areas, Rawalpindi, Pakistan. *Pakistan Journal of Botany*, 38: 543-558.
Malik, R.N. and S.Z. Husain. 2006. Spatial distribution of ecological communities using remotely sensed data. *Pakistan Journal of Botany*, 38: 571-582.
Martin, M.E., S.D. Newman, J.D. Aber and R.G. Congalton. 1998. Determining forest species composition using high spectral resolution remote sensing data. *Remote Sensing of Environment,* 65: 227-375.
McCune, B. and M.J. Mefford. 1999. *Multivariate Analysis of Ecological Data*, Ver. 3.0. MJM Software, Glenden Beach, Oregon.
Muller-Dombois, D. and N. Ellenberg. 1974*. Aims and Methods of Vegetation Ecology*. John Wiley & Sons, NY.
Palmer, M.W. 1993. Putting things in even better order: the advantages of canonical correspondence analysis. *Ecology,* 74: 2215-2230.
Qadir, A., R.N. Malik and S. Z. Husain. 2007. Spatio-temporal variations in water quality of Nullah Aik-tributary of the river Chenab, Pakistan. *Environmental Monitoring and Assessment,* DOI 10.1007/s10661-007-9846-4.
Salovaara, K., J. Thesseler, R.N. Malik and H. Tuomisto. 2005. Clasification of Amazonia primary rain forest vegetation using Landsat ETM+ satellite imagery, *Remote Sensing of Environment, 97:* 39-51.
Schmidh, K.S. and A.K. Skidmore. 2003. Spectral discrimination of vegetation types in a coastal wetland. *Remote Sensing of Environment,* 85: 92-108.
Swan, P.H. and S.M. Davis. 1978. *Remote sensing; The Quantative Approach,* McGraw-Hill Inc.
Thomas, V., P. Treitz and D. Jelinski. 2003. Image classification of a northern peat land complex using spectral and plant community data. *Remote Sensing of Environment,* 84: 83-99.
Toivonen, T., K. Kalliola, K. Ruokolainen and R.N. Malik. 2006. Across-path DN gradient challenge the Landsat TM interpretations in the Amazonian lowlands. *Remote sensing of Environment*, 100: 550-562.
Trisurat, Y., A. Eiumnoh, S. Murai, M.Z. Husain and R.P. Shrestha. 2000. Improvements of tropical vegetation mapping using a remote sensing technique: a case study of Khao National Park, Thailand. *International Journal of Remote Sensing*, 21: 2031-2042.
Vogelmann J.E. and D.M. Moss. 1993. Spectral reflectance measurements in the genus *Sphagnum. Remote Sensing of Environment,* 45: 273-279.
Wolter, P.T., D.J. Mladenoff, G.E. Host and T.R. Craw. 1995. Improved forest classification in the northern lake states using multi-temporal Landsat TM imagery. *Photogrammatic Engineering and Remote Sensing*, 61: 1128-1143.

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