Land use classification in mountainous areas: integration of image processing, digital elevation data and field knowledge (application to Nepal)

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ABSTRACT
Remote sensing data help in mapping land resources, especially in mountainous areas where accessibility is limited. In such areas, land degradation is a main concern. Land is degraded not only by natural processes but also by human activities through inappropriate land use practices. Land cover and land use mapping is thus very important for evaluating natural resources. Classification of remote sensing data in mountainous terrain is problematic because of variations in the sun illumination angle. This results in biased reflectance data, the distribution of which does not fulfill normality as required by the maximum likelihood classifier. In the present work the topographic effect is corrected by normalising the spectral bands by the total intensity. Classification results are further refined by using ancillary data and expert knowledge of the area. The integration of image processing and spatial analysis functions in GIS improves the overall classification result from 67 to 94 percent (a 27 percent increase).

INTRODUCTION
Land degradation is a common phenomenon in mountainous regions. Although causal factors are mainly natural, inappropriate land uses enhance the degradation processes. Land use practices have a direct effect on soil losses and mass movements [Kienholz et al, 1983; Kienholz et al, 1984; Hurni, 1990; Shah et al, 1991]. Land use and land cover mapping is thus very important for resource evaluation. Remote sensing data help in mapping land cover and land use through multispectral classification. This is especially useful in areas where accessibility is a major issue.

CONSTRAINTS TO LAND USE CLASSIFICATION IN MOUNTAINOUS REGIONS
Various algorithms are available for land cover classification, each having its own limitations and applicability in different environments. Apart from conventional classification algorithms, fractals, neural networks and linear unmixing techniques have been applied [Mulder & Spreeuwers, 1991; De Jong, 1994; Kressler & Steinnocher, 1999]. But in areas with strong topographic variations, results obtained by running a classification are not satisfactory for mapping land cover and land use. The main reasons are elevation differences, illumination variations, effect of topographic shadow and parcel size. Variations in topography have an effect on microclimates, which may influence land cover and land use patterns. Spectral classification alone is not sufficient for extracting land cover/use data. Even in areas without topographic distortions, the accuracy of land cover mapping can be increased by integrated processing of remote sensing and ancillary data in a GIS environment [Molenaar & Janssen, 1991].

The amount of reflected solar radiation received by sensors aboard satellites depends not only on the type of earth surface features but also on sun elevation and topography (Figure 1). Sun-facing slopes receive more illumination. Relief lines perpendicular to the light direction are emphasised, and the ridges or valleys may be over- or under-emphasised depending on their orientation [Hobbs, 1999]. Thus, slope gradient and aspect influence surface reflectance. Full topographic shadow results in the absence of data.

FIGURE 1: Effect of topography on the amount of sun illumination
Considering the very short time required to scan a full satellite scene (e.g., 28.7 seconds for a Landsat scene of 185 km × 185 km), the sun angle can be considered constant. If the surface cover type is the same, any variation in reflected energy received by the sensor can be attributed to variations in topography, resulting in illumination differences due to slope gradient and aspect. Assuming all other factors are constant, the amount of energy received by the sensor depends on slope gradient and exposition with respect to sun elevation. This results in elongated clusters of the training samples (Figure 2) with degree of elongation depending on the locations where samples are taken. This causes bias and results in non-normal distribution of the training samples, which is not ideal for classification.

In conventional classification of multispectral data, the maximum likelihood classifier is considered to provide the best results since it takes into account the shape, size and orientation of a cluster. Based on the class mean and the variance-covariance matrix, an unknown pixel is assigned to the most likely class. To down grade the effect of any outlying training sample, which may influence the class mean and variance-covariance matrix, the Mahalanobis distance function can be implemented [Campbell, 1980]. The technique of principal component analysis can be applied to reduce the number of spectral bands [Mulder & Hempenius, 1974; Donker & Mulder, 1977]. This may be important since the maximum likelihood algorithm takes considerable processing time if several spectral bands are used. The classification method assumes that the training samples are normally distributed. This ideal situation, however, may not occur in mountainous areas. Within a given cover type, variations in reflected energy might be considerable due to variations in illumination, resulting in non-normal distribution of the training samples (Figure 3). The distribution of the training samples may be biased towards either fully illuminated or shaded slopes. Thus, the procedure of conventional classification cannot be directly applied in mountainous regions. Conese et al. [1993] proposed principal component analysis to overcome the topographic effect. Lees & Ritman [1991] used decision-tree rules to map vegetation in hilly areas.

In the present paper intensity normalisation of the individual spectral bands is implemented for removing the variations in the solar illumination angle. The intensity normalisation technique is also used for natural colour coding of multispectral data. Mulder [1981] demonstrated that decomposition into intensity variation and spectral colour variation can be used meaningfully for feature extraction.

Elevation differences between ridges and valley bottoms cause climatic variations, which influence the land cover and land use types. In studying such areas, a combination of ancillary data and expert knowledge of the area is needed to improve spectral classification, as demonstrated below using an example from Nepal.

**STUDY AREA**

The study area belongs to the watershed of the Likhu Khola river, in the Middle Mountain region of Nepal (Figures 4 & 5). The watershed occupies about 160 km² and lies between the co-ordinates 27°48’15” and 27°53’55” north and between 85°13’01” and 85°27’51” east. The river Likhu Khola flows from east to west and is joined by many tributaries from both sides. Mountain ridges are mainly east-west oriented. The valley is narrow and elongated, but widens downstream. Elevation varies from 780 m above mean sea level at the valley floor to 2600 m above mean sea level at the highest mountain.
ridge. Due to the east-west orientation of the ridges and the elevation differences between valley bottom and mountain summits, the variations in sun illumination between north- and south-facing slopes are considerable.

The climate varies from subtropical at lower elevations (main valley and foothills) through warm temperate at mid-elevations to cold temperate in the high mountains. In the lowlands, the average summer temperature is 26º C (May) and the average winter temperature is 15º C (December). At higher elevations, the average summer temperature is 19º C and average winter temperature is 11º C. Annual precipitation also varies according to elevation from 1000 mm in the lowlands (Chhahare, 780 m above mean sea level) to 2800 mm at higher elevations (Kakani, 2064 m above mean sea level). The average annual rainfall increases by 104 mm for every 100 m increase of elevation [Shrestha, 1997]. Most of the rain falls from May to September.

Vegetation changes according to elevation, due to its effect on climate. At higher elevations, land cover is mainly forest with chir pine (Pinus roxburghii) and broad leaf trees (Schima wallichii). Rainfed maize and millet are the cultivated crops. At lower elevations, the forest is dominated by sal trees (Shorea robusta). Cultivation normally takes place on contour terraces. Irrigated rice and rainfed maize and millet are the main crops. For the cultivation of rice, level terraces are made for retaining the water, while sloping terraces (10 to 15 percent) are built for rainfed cultivation. The slope and width of the terraces are determined by the topography: the steeper the topography, the higher the slope gradient of the terrace and the narrower the width. The width of the sloping terraces varies from 2 to 3 m, making the parcel size quite small. Rice is cultivated on level terraces, if irrigation water is available and the temperature is suitable. Elevation, which controls climate, determines the variations in land cover and land use types.

Maximum soil losses occur on steep slopes under rainfed conditions, followed by bare land and degraded forest [Kunwar, 1995; Shrestha, 1997]. Mass movement processes are related to land use types. For example, slumping is common in rice fields, while debris slides seem to occur more in degraded forests and on rangeland than in cultivated areas [Shrestha & Zinck, 1999]. Thus, land use mapping helps in assessing erosion susceptibility and land-use-induced mass movement hazards.

**REMOTE SENSING DATA PROCESSING**

**PRE-PROCESSING**
Landsat TM data, acquired on 12 October 1988, were geo-referenced using control points from the 1:25,000 topographic map of the area (sheets 2785 01B, 2785 02C and 2785 02D, edition 1994). Nearest neighbour
interpolation was followed during resampling. All the spectral bands, excluding TM band 6, were used. To minimise the effect of illumination differences on the surface reflectance, spectral bands were normalised by the total intensity as follows:

\[ \text{NB}_i = 255 \left( \frac{\text{OB}_i}{\sum \text{OB}_i} \right) \quad i = 1 \text{ to } n \quad (1) \]

where \( \text{NB}_i \) is the band normalised by total intensity and \( \text{OB}_i \) is the original spectral band. The constant (255) is used to fit the data in a byte range of 0-255. The resulting bands have the property that the sum of any pixel values is 255 due to normalisation. In Figure 6, the hypothetical location of water, vegetation and soil is shown in a two-dimensional feature space. After normalisation, the location of these objects is projected onto a diagonal line of uniform intensity (Figure 7), indicating that the objects are free from intensity variation.

CLASSIFICATION PROCEDURE
Training samples from the original TM bands result in elongated clusters due to topographic effect (Figure 8). After normalisation of the bands, the elongation effect disappears and the training samples can be assumed to be approximately normally distributed (Figure 9). The maximum likelihood algorithm is applied, which calculates the distance from each feature vector (pixel to be classified) to the class means. The within-class variability is taken care of by adding a factor, which is a function of the variance-covariance matrix of that class. The formula used [Mather, 1987] reads:

\[ D_i(X) = \ln |V_i| + (X-M_i)^T V_i^{-1} (X-M_i) \quad (2) \]

in which: \( D_i(X) \) = distance between pixel vector \( X \) and a class mean based on probabilities; \( X = \) pixel vector \( X; M_i \) = mean vector of the class considered; \( V_i \) = the variance-
covariance matrix of the class considered; \( V^{-1} \) = the inverse of \( V \); \(|V_i|\) = determinant of the variance-covariance matrix \( V_i \); \((X - M_i)\) = the distance towards a class mean; and \((X - M_i)^T\) = the transposition of \((X - M_i)\).

During classification, the shortest distance to a class mean is found and the pixel is class-labelled if the distance is smaller than the threshold value.

**CLASSIFICATION RESULTS**

The classification results were checked against a set of test pixels, showing 97 percent accuracy for low altitude forests, 98 percent accuracy for bare surfaces and 93 percent accuracy for rice fields (Table 1). Classification of rainfed agriculture was found only 76 percent correct since 21 percent of the test pixels were mis-classified as bare land. Similarly, high altitude forests were confused with low altitude forests: only 65 percent of the test samples were correctly classified; the rest (35 percent) were classified as low altitude forests. Mean classification accuracy was 87 percent and the overall classification accuracy was 67 percent. The results clearly demonstrate the difficulty in classifying high altitude forests and rainfed agriculture.

**IMPROVING FOREST CLASSIFICATION**

Except for the protected forests and the forests located far from the villages and the foot-trails, the forests in general in the study area are degraded because of the collection of firewood and the collection of tree branches and leaves for cattle fodder and household use. Under degraded forest, soil erosion takes place because of reduced canopy and litter cover. Annual soil loss from the degraded forests can be up to 9 t/ha, while it is less than 1 t/ha under dense forest [Shrestha, 1997]. It was thus important to separate the forest types into dense forest and degraded forest, using the canopy density as an indicator of forest degradation. For this purpose, the intensity normalised difference vegetation index (NDVI) was generated from the spectral bands in the near-infrared and red portions of the spectrum (Landsat TM bands 4 and 3), using the following calculation:

\[
NDVI = 127 \left( \frac{TM4 - TM3}{TM4 + TM3} \right) + 127 \quad (3)
\]

The normalised difference of near-infrared and red bands was multiplied by 127 to convert the fractional values into integer numbers, and the constant 127 was added to the result to avoid a possible negative value. From the resulting image three vegetation density classes, based on sample pixels, were generated: low density (less than 40 percent canopy), moderate density (40 - 70 percent canopy) and high density (more than 70 percent canopy). Using the vegetation indices, it was possible to divide the forest types into various subclasses, by means of conditional ("IF, THEN, ELSE") and logical ("AND") statements. The resulting classes are degraded sal forest, moderately dense sal forest and dense sal forest. Similarly, the high altitude forest type was also further divided into degraded high altitude forest, moderately dense high altitude forest and dense high altitude forest. Table 2 shows forest cover classification improvement.

<table>
<thead>
<tr>
<th>TABLE 1</th>
<th>Contingency table of classification results</th>
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<tbody>
<tr>
<td></td>
<td>Low altitude forest</td>
</tr>
<tr>
<td>Low altitude forest</td>
<td>971 (97%)</td>
</tr>
<tr>
<td>Bare land/ Landslide area</td>
<td>0</td>
</tr>
<tr>
<td>Rainfed agriculture</td>
<td>0</td>
</tr>
<tr>
<td>Rice fields</td>
<td>37 (6%)</td>
</tr>
<tr>
<td>Water body</td>
<td>0</td>
</tr>
<tr>
<td>High altitude forest</td>
<td>579 (31%)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>TABLE 2</th>
<th>Classification improvement for the forest cover</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDVI class 1 (up to 40% canopy)</td>
<td>NDVI class 2 (40 – 70% canopy)</td>
</tr>
<tr>
<td>Low altitude forest (sal forest)</td>
<td>Degraded low altitude forest</td>
</tr>
<tr>
<td>High altitude forest (association of pine, quercus and chilaune)</td>
<td>Degraded high altitude forest</td>
</tr>
</tbody>
</table>
MASKING OF CLOUD AND SHADOW AREAS
The Landsat TM image included cloud-covered and cloud shadowed areas, the latter enlarged because of the rugged topography. As no information could be extracted from these areas, they were masked and replaced by the classification result obtained from a Landsat MSS image acquired on 28 October 1976.

INTEGRATION OF SPATIAL ANALYSIS FUNCTIONS IN GIS
PROXIMITY ANALYSIS
Since rice is a staple as well as a cash crop, farmers prefer to grow rice more than other cereals. If the climate is suitable and water is available, up to two rice crops are harvested in a year. Rice is planted in level terraces along the contours. Terracing has been practised in Nepal since ancient times to make cultivation possible on very steep slopes. A small bund of about 10-15 cm high is made on the outer edge to store water. Irrigation water is diverted from the streams and allowed to pass from one terrace to another. As the average effective distance for irrigation is approximately 200 m from a stream, areas close to streams are readily converted into rice fields if the temperature is favourable. Rice fields are susceptible to slumping because of continued soil saturation and the extra weight caused by standing water. The classification and mapping of the areas cultivated with rice were improved using a distance function from the streams.

USE OF ELEVATION DATA
Sal forest does not develop at higher elevations, while the forests consisting of pine, quercus, chilaune and utish do not occur at elevations lower than 1100 m above mean sea level. Digital elevation data at 20 m resolution, based on SPOT panchromatic images (Right HRV2, 7 Nov 1986; Left HRV1, 12 December 1986) and the topographic map of Nepal at a scale of 1:50,000, were used to improve the classification by means of conditional statements as follows:

\[
\text{IF land cover } = \text{"high\_altitude\_forest" AND elevation } < 1100 \\
\text{THEN land cover } = \text{"low\_altitude\_forest"} \\
\text{ELSE land cover } = \text{"high\_altitude\_forest"}
\]

It was also found that, above elevation 2200 m above mean sea level, the forest type is dominated by quercus species (essentially Quercus semicarpifolia). This made it possible to further improve forest classification.

Because of spectral confusion, riverbeds were originally misclassified as rainfed agriculture. Field knowledge was mobilised to improve the classification. Firstly, rainfed agriculture normally does not develop along rivers. Secondly, riverbed width and configuration change with elevation. At higher elevations, riverbeds are restricted to entrenched and narrow incisions, while at lower elevations, approximately below 700 m above mean sea level, riverbeds widen into an intricate network of braided channels; the latter allows better spectral discrimination and facilitates mapping. Consequently, proximity to main rivers and elevation data were used to decide whether to classify a given area as rainfed agriculture or not. At elevations lower than 700 m, the land cover class was riverbed; at elevations above 700 m it was considered to be rainfed agriculture.

FINAL CLASSIFICATION RESULTS
The final map reflects the integration of remote sensing data processing and spatial analysis, making use of digital elevation data and calculation of distances from the streams and the main rivers in the valley (Figure 10). The areas of the various land cover types are shown in Table 3. Accuracy assessment was carried out using test samples and leading to the confusion matrix of Table 4. Data synergy considerably improved the land use classification. The mean accuracy of the final classification is 97 percent and the overall classification accuracy increased to 94 percent.

<table>
<thead>
<tr>
<th>Land cover/use</th>
<th>Area (Ha)</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dense high altitude quercus forest</td>
<td>358</td>
<td>2</td>
</tr>
<tr>
<td>Dense high altitude mixed forest</td>
<td>1235</td>
<td>8</td>
</tr>
<tr>
<td>Dense low altitude sal forest</td>
<td>131</td>
<td>&lt;1</td>
</tr>
<tr>
<td>Moderately dense high altitude mixed forest</td>
<td>2568</td>
<td>16</td>
</tr>
<tr>
<td>Moderately dense low altitude sal forest</td>
<td>1402</td>
<td>9</td>
</tr>
<tr>
<td>Degraded high altitude quercus forest</td>
<td>248</td>
<td>2</td>
</tr>
<tr>
<td>Degraded high altitude mixed forest</td>
<td>1598</td>
<td>10</td>
</tr>
<tr>
<td>Degraded low altitude sal forest</td>
<td>801</td>
<td>5</td>
</tr>
<tr>
<td>Rainfed agriculture</td>
<td>4950</td>
<td>31</td>
</tr>
<tr>
<td>Rice fields</td>
<td>2349</td>
<td>15</td>
</tr>
<tr>
<td>Bare land/landslide area</td>
<td>106</td>
<td>&lt;1</td>
</tr>
<tr>
<td>River/streams</td>
<td>415</td>
<td>2</td>
</tr>
</tbody>
</table>

One-third (31 percent) of the watershed area is used for rainfed agriculture. The area under degraded forest is 17 percent. Thus nearly half of the watershed area is exposed to topsoil removal by sheet erosion. The area covered by rice fields is 15 percent, with only 1 percent located in the floodplain of the Likhu Khola river. The rest (14 percent) corresponds to terraces that are built on steep slopes and are therefore highly susceptible to slumping.
CONCLUSIONS

Variations of the solar illumination angle can be easily corrected by normalisation of the individual bands by the total intensity. This is indispensable, if the classification algorithm assumes normal distribution of the training samples. Land use classification can be further refined by using digital elevation data in areas with high topographic variation. Expert knowledge of the area considerably improves classification accuracy.

ACKNOWLEDGEMENTS

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REFERENCES


RESUME

Des données télédétection se révèlent une aide précieuse dans la cartographie des ressources naturelles, particulièrement dans les zones montagneuses où l’accès est limité. Dans de telles zones, la dégradation des terres est un souci principal. Les terres sont dégradées non seulement par des processus naturels mais aussi par des activités humaines à travers des pratiques impropre d’utilisation des terres. La cartographie de l’occupation et de l’utilisation des terres est donc très importante pour l’évaluation des ressources naturelles. La classification des données de télédétection est problématique dans les terrains montagneux, à cause de l’angle d’éclairement du soleil. Ceci se traduit par des données de réfléctance biaisées, dont la distribution ne satisfait pas à la normalité requise par une classification selon le maximum de vraisemblance. Dans le présent travail l’effet topographique est corrigé en normalisant les bandes spectrales par l’intensité totale. Des résultats de classification sont encore améliorés en utilisant des données auxiliaires et des connaissances expertes de la zone. L’intégration du traitement d’image et les fonctions d’analyse spatiale dans un SIG améliore le résultat de la classification totale de 67 à 94 pour-cent (une augmentation de 27 pour-cent).