COMPARING PIXEL BASED AND OBJECT BASED APPROACHES IN LAND USE CLASSIFICATION IN MOUNTAINOUS AREAS

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ABSTRACT:

Remote sensing imagery needs to be converted into tangible information which can be utilized in conjunction with other data sets, often within widely used Geospatial Information Systems (GIS). Remote sensing data help in mapping land resources, especially in mountainous areas where accessibility is limited. Classification of remote sensing data in mountainous terrain is problematic because of variations in the sun illumination angle. Traditional approaches have many problems in these conditions. In object based approach can utilized GIS tools for improvement of classification results. In the present work we used pixel based and object based approaches that in both we imported GIS concepts and ancillary data for refining of classification results. The results showed that object based approach have higher accuracy than pixel based approach.

1. INTRODUCTION

Land use and land cover mapping is very important for resource evaluation. RS data help in mapping land cover and land use through conventional classification. The object-oriented approach can contribute to powerful automatic and semiautomatic analysis for most remote sensing applications. This is especially useful in areas where accessibility is a major issue. Combination of mountain area and land cover or land use classification is complex issue and must be utilized data fusion algorithms and ancillary data about study area for solving problem. Various algorithms are available for land cover classification, each having its own limitations and advantages in different environments. Apart from conventional classification algorithms, fractals, neural networks and linear immixing techniques and object based approaches have been applied (De Jong, 1994; Kressler and Steinnocher, 1991; Antonarakis A.S et al 2008).

Integration of remote sensing and Geospatial Information System (GIS) is a good and powerful idea in image analysis. This structure can be used in both conventional image analysis (pixel based algorithm) and object based image analysis. But in object based image analysis GIS tools can be used well than conventional image processing because in this approaches objects are basic units.

In areas with strong topographic variations, results obtained by running a conventional 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. In this paper we want to increase accuracy of conventional image processing by ancillary data and GIS tools after the initial classification. Then in next step, an object based classification must be done in this area and in final step we compare results of two methods.

In extent of remote sensing, there are a large diversity of space borne and airborne sensors. These systems provide a huge amount of data about all landscape for any applications. Many image processing methods are introduced and developed to explore the raw data of sensors.

However, all these image analysis algorithms are applied on pixels and do not take into account contextual information and relationship between real worlds and image (Ursula C. Benz et al. 2003).

The basic processing units of object-oriented image analysis are segments, so-called image objects, and not single pixels. Advantages of object-oriented analysis are meaningful statistic and using semantic ideas in information extraction, and topological features (neighbour, super-object, etc.), shape features (area, length/width, etc) and the contiguous relation between real-world objects and image objects. In object oriented analysis in remote sensing, many GIS tools can be used easily in processing (Ruvimbo Gamanya et al.2006).

2. METHODOLOGY

2.1 Pixel based method

The content of reflected solar radiation received by detectors depends not only on the type of earth surface features but also on sun elevation angle and topography and aspect (Qian Yu et al. 2006). Relief lines perpendicular to the light direction are emphasized, and the ridges or valleys may be over- or under-emphasized depending on their orientation (Tayyebi et al.2009). Thus, slope gradient and aspect influence received reflectance.

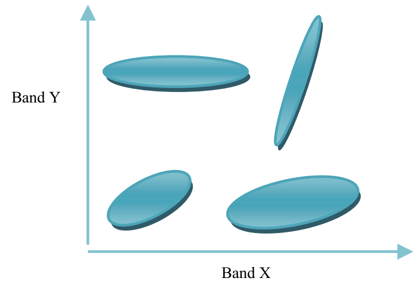

Figure 1. Lengthened clusters of training samples because of topographic impression

Considering the very short time required scanning a full satellite scene, the sun angle must be considered constant. If the

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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. This results in lengthened clusters of the training samples (Figure .1) 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 (Law K.H. et al 2004).

Qian Yu et al (2006) evaluated the ability of the high spatial resolution airborne Digital Airborne Imaging System (DAIS) imagery for detailed vegetation classification at the alliance level with the aid of ancillary topographic data and object based analysis by fractal network approach. Gao .Y and Zhang(2006) utilized DEM based topographic correction upon LanSat ETM+. In traditional classification of multispectral data, the maximum likelihood classifier is considered to provide the best results since it take into consideration 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. 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. The distribution of the training samples may be biased towards either fully illuminated or shaded slopes. Conese et al (1993) proposed principal component analysis to overcome the topographic effect. Lees and Ritman (1991) used decision-tree rules to map vegetation in hilly areas.

Besides, the spatial complexity and internal heterogeneity of natural and semi-natural nature tend to cause non normal distribution of their spectral response in medium resolution images. Taking into consideration just the statistic assumptions of classification algorithms, the non-normality of the individual spectral bands would advise the use of normalizing the spectral bands by the total intensity. In the present paper normalization of the individual spectral bands is implemented for removing the variations in the solar illumination angle. Mulder (1981) demonstrated that decomposition into intensity variation and spectral color 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 RS, GIS and expert knowledge of the area is needed to improve spectral classification, as demonstrated below using an example from Iran.

2.2 Object based method

The basic elements of an object-oriented approach are image objects. Image objects are contiguous regions in an image. Image objects can be linked to a hierarchical network, where they are attributed with a high-dimensional feature space. Objects are created by image segmentation, which is the subdivision of an image into separate regions. This segmentation can be realized as an optimization process. Regions of minimum heterogeneity given certain constraints have to be found. Segmentation in eCognition (Baatz and Scha¨pe, 1999; Baatz and Mimler, 2002) allows both segmentations based on primary features (gray tone and shape) and (after an initial classification) the more advanced classification-based segmentation. The method is applicable for many data types with different dynamic and distribution. ECogniion's multi-resolution segmentation is a bottom up region-merging technique starting with one-pixel objects. In numerous subsequent steps, smaller image objects are merged into bigger ones. In eCognition considers as primary object features color and shape. Segmentation parameters for multi resolution segmentation are: scale, color, shape, compactness, smoothness.

Scale determines the occurrence or absence of a certain object class. Scale determines size of image object in a level. Color parameter defines importance of spectral information of image object. The shape is a value that describes the improvement of the shape with regard to smoothness and compactness of an object's shape. Thus, the smoothness heterogeneity equals the ratio of the de facto border length and the border length given by the bounding box of an image object parallel to the raster. The compactness heterogeneity equals the ratio of the de facto border length l and the square root of the number of pixels forming this image object. Blaskchke et al (2006) utilized object based image analysis and GIS for model and visualize landscape upon DTM and ortho photo.

3. DATA AND STUDY AREA

California is a state on the West Coast of the United States, along the Pacific Ocean. It is bordered by Oregon to the north, Nevada to the east, Arizona to the southeast, and, to the south, the Mexican state of Baja California. California is the most populous U.S. state. Its four largest cities are Los Angeles, San Diego, San Jose, and San Francisco. The state is home to eight of the nation's fifth largest cities. It is known for its varied climate and geography as well as its diverse population. The area known as Alta California was colonized by the Spanish Empire beginning in the late 18th century. California is the most populous U.S state, and the third-largest U.S. state by land area after Alaska and Texas. Its geography ranges from the Pacific coast to the Sierra Nevada mountain range in the east, to Mojave desert areas in the southeast and the Redwood-Douglas fir forests of the northwest. The center of the state is dominated by the Central Valley, one of the most productive agricultural areas in the world. The California Gold Rush dramatically changed California with a large influx of people and an economic boom that caused San Francisco to grow from a tiny hamlet of tents to a world-renowned boomtown in the 19th century. The early 20th century was marked by the establishment of Los Angeles as the center of the American entertainment industry, in addition to the growth of a large tourism sector in the state as a whole. Along with California's prosperous agricultural industry, other industries include aerospace, petroleum, and computer and information technology (Tayyebi et al.2009).

4. PIXEL BASED APPROACH

4.1 Initial classification

Normalization: Landsat ETM+ Image was georeferenced using 1:25,000 scale digital maps and the previously generated orthophotos mosaic as references. Geometric correction was fitted to an RMSE of less than half the pixel size. The nearest neighbor resampling method was applied in order to keep the integrity of original imagery information (Lillesand and Kiefer 1994). Output resolution was 20m for all the bands. Although in general terms, the study site corresponds with a mountain area, no topographic correction was done in the image.

Land Sat ETM+	R,G,B,NIR

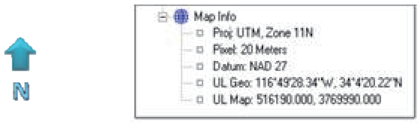


Figure 2. Study area (Land Sat ETM+)

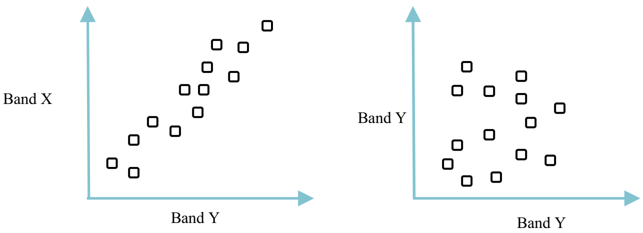
The relatively smooth relief of the area with 98% of the surface with slopes less than 30° and the value of the cosine of solar zenith angle lower than 0,8 suggested potentially a low effect of topography in the final results (Song and Woodcock 2003).

$$E = E_0 Cos\theta \tag{1}$$

To minimize the effect of illumination differences on the surface reflectance, spectral bands were normalized by the total intensity as follows:

$$NB_i = 255\left(OB_i \Big/ \sum OB_i\right) \quad i = 1 \quad to \quad n \tag{2}$$

Where NBi is the band normalized by total intensity and OBi is the original spectral bandi. 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 normalization. Training samples from the original ETM bands result in elongated clusters due to topographic effect (Fig. 3a). After normalization of the bands, the elongation effect disappears and the training samples can be assumed to be approximately normally distributed (Fig. 3b).



a. Uncorrected training samples b. Corrected training samples
Figure 3. Distribution of our training samples

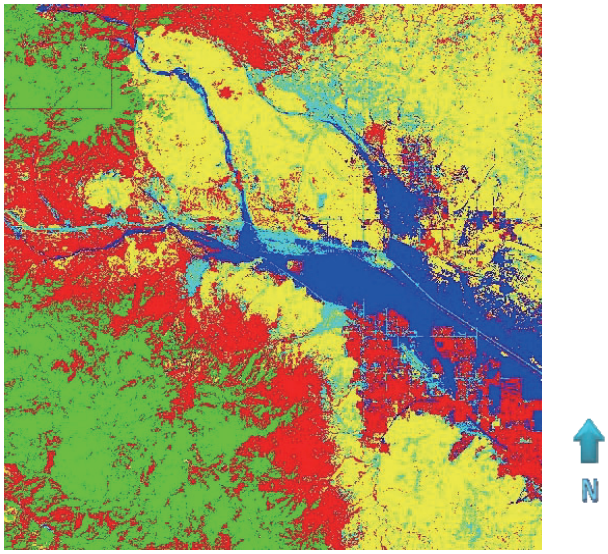
4.1.1 Classification procedure: The maximum likelihood algorithm is applied, which calculates the distance from each feature vector to the class means. The within-class variability is taken care of by adding a factor, which is a function of the variance-covariance matrix of that class.

4.1.2 Classification results: Classification of agriculture was found only 27.10 percent correct since 21.67 percent of the test pixels were mis-classified as road. Similarly, mountain was confused with forest: only 56 percent of the test samples were correctly classified; the rest (44 percent) were classified as forests and road. Mean classification accuracy was 55 percent and the overall classification accuracy was 41 percent. The results clearly demonstrate the difficulty in classifying mountain, road and agriculture (Fig. 4).

The classification results were checked against a set of test pixels, showing 65 percent accuracy for forests, 56.43 percent accuracy for bare soil, 65.21 percent accuracy for water, 18 percent accuracy for road and only 20.10 percent accuracy for built-up and urban area (Table 1). The overall classification accuracy was 50.12% and the value of Kappa index is 0.4838.

4.2 Refining initial classification

Except for the protected forests and the forests located far from the villages and the foot-trails, the forests in general in the area



Legend

Vegetation(forest)	Green
Road	Cyan
Water	blue
Bare soil	Yellow
Built up	Red

Figure 4. Result of initial classification

Table 1: Contingency table of classification results

Accuracy result	
Vegetation(forest)	65%
Road	18%
Water	51%
Bare soil	56%
Built up	18%

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. 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 Normalized Difference Vegetation Index (NDVI) was generated from the spectral bands in the near infrared and red portions of the spectrum, using the following calculation:

$$NDVI = 127\left\{ {(NIR - R)}/{(NIR + R)} \right\} + 127 \tag{3}$$

The normalized 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 (Table 2).

Table 2: Classification improvement of the forest cover

	NDVI class 1 (up to 40% canopy)	**NDVI class 2 (up to 40 – 70 % canopy)**	**NDVI class 3 (more than 70% canopy)**
Low altitude forest	Degraded low altitude forest	Moderately dense low altitude forest	Dense low altitude forest
High altitude forest	Degraded high altitude forest	Moderately dense high altitude forest	Dense high altitude forest

4.2.1 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 practiced in Iran since ancient times to make cultivation possible on very steep slopes.

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 120m 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. But agriculture class merged to vegetation class because low resolution of image and small patch of rice terrains.

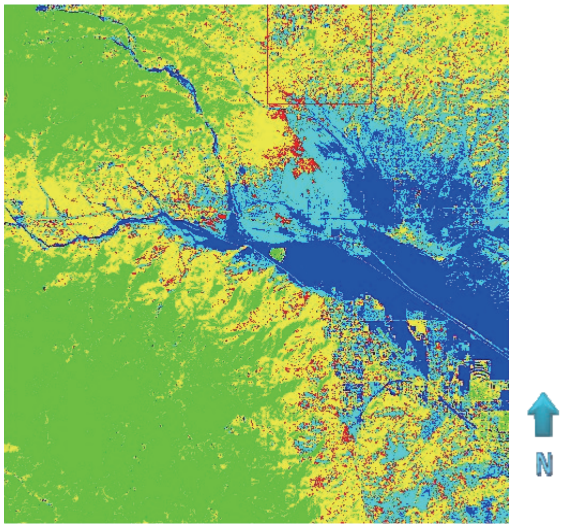
Use of elevation data: Digital elevation data at 10 m resolution, based on SPOT panchromatic images and the topographic map of Iran at a scale of 1:25,000, were used to improve the classification by means of conditional statements as follows:

$$\begin{aligned} &\textit{If Land cover} = \textit{"high\_altitude\_forest"} \quad \textit{And} \quad \textit{Elevation} < 1100 \\ &\quad \textit{Then} \quad \textit{Land cover} = \textit{"low\_altitude\_forest"} \\ &\quad \textit{Else} \quad \textit{Land cover} = \textit{"high\_altitude\_forest"} \end{aligned}$$

This made it possible to further improve forest classification. Field knowledge was mobilized to improve the classification. Firstly, rained 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 rained agriculture or not.

4.2.2 Final classification results: The final map shows the integration of remote sensing data processing and spatial analysis, making use of digital elevation data and distance analysis from the streams and the main rivers in the valley (Figure 5).

Accuracy assessment was carried out using test samples and leading to the results of Table 3. Data synergy considerably improved the land use classification. The overall classification accuracy was 74.38% and the value of Kappa index is 0.7023.



Legend

Forest	Green
Mountain	Purple
Water	Blue
Road	Yellow
Agriculture	Red

Figure 5. Result of final classification

Table 3: Contingency table of final pixel based classification results

Accuracy result	
Vegetation(forest)	88%
Road	50%
Water	76%
Bare soil	70%
Built up	52%

5. OBJECT BASED CLASSIFICATION

5.1 Segmentation

Firstly, image was segmented by multi resolution approach in four scales (150, 75, 50, and 25). Based on smallest object in the classes such as built up area and agriculture patch, scale of 25 was accepted (Fig. 6). Segmentation parameters in this level contain: 0.9 for color coefficient, 0.1 for shape coefficient and equal coefficients for smoothness and compactness in shape parameters (Table 4).

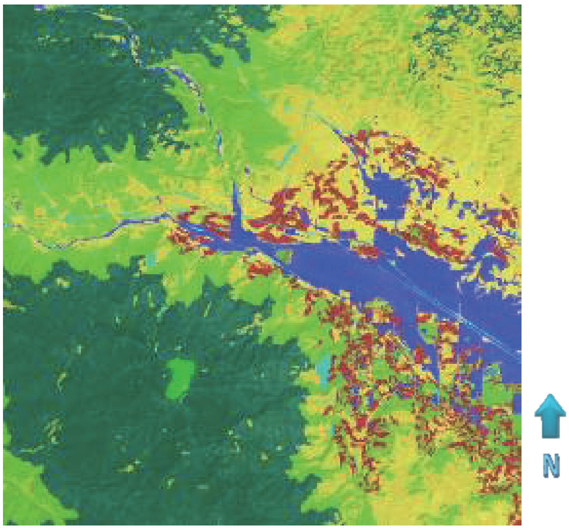
Table 4: Used features for object based classification

ROAD	Contrast to neighbor pixels	StdDev. to neighbor pixels	Mean diff. to neighbors	Length	Length/width
WATER	Spectral features	StdDev. to neighbor pixels	Elevation threshold	Class related features, classified as	Aspect(based on DEM layer)
BUILT UP	Spectral features	Class related features, border to	Elevation threshold		
BARE SOIL	Spectral features	Elevation threshold			

5.2 Classification

In object based classification, we try to model pixel based approach and improvements in previous section. For vegetation extraction we used NDVI layer. We utilized fuzzy c-means algorithm to find cluster centers of vegetation and non vegetation class. Then a vegetation mask was built. For forest recognition we used both spectral and elevation thresholds. As forest region is in elevated land in this area.

Figure 6. Segmented image



Legend

Forest	Green
Agricultur e	Light Green
Road	Cyan
Water	blue
Bare soil	Yellow
Built up	Red

Figure 7. Result of final object based classification

Accuracy assessment was carried out using test samples and leading to the results of Table 5. The overall classification accuracy was 87.38% and the value of Kappa index is 0.8234.

Table 5: Contingency table of object based classification results

forest	91%
agriculture	85%
Road	78%
Water	92%
Bare soil	89%
Built up	79%

6. CONCLUSIONS

Variations of the solar illumination angle can be easily corrected by normalization of the individual bands by the total intensity. This is indispensable, if the classification algorithm assumes normal distribution of the training samples. Traditional image classification methods tend to suffer shortcomings due to non-normality of 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. Results show that integration of RS and spatial analysis functions in GIS improves the overall classification result from 50.12 to 74.38 percent (24 percent increase).

But in object based classification, we try to model same knowledge that was used in pixel based approach. Besides in object based analysis there is more potential that lead us to higher accuracy. However with these limited features, object based approach obtained 13 percent accuracy more than pixel based approach. Also result of object based approach is without any noisy outcome. Whereas in traditional approach, scene is noisy. Object based strategy can use GIS tools in analysis of remote sensing image very well.

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