APPLICATION OF OBJECT BASED IMAGE ANALYSIS FOR FOREST COVER ASSESSMENT OF MOIST TEMPERATE HIMALAYAN FOREST IN PAKISTAN

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ABSTRACT:

The study aims at developing forest cover inventory from high resolution satellite imagery (0.6m) of Ayubia National Park, NWFP, Pakistan. The 3372 ha study area is one of the best examples of existing moist temperate Himalayan forest in Pakistan. Landscapes composed of large number of heterogeneous and complex elements, exhibit multi-scale hierarchical dependencies. A multi-scale object based image analysis has been carried out for the forest cover assessment of the park. Image objects representing homogenous landscape components were delineated using image segmentation routine. This approach allows efficient inclusion of spatial concepts by segmenting the digital image according to image resolution and scale of expected objects. Following the multi-resolution segmentation a classification tree was developed that used a fuzzy nearest neighbor classifier to assign respective class to image segments at their respective scale. After manual classification of unclassified or misclassified objects, overall accuracy of the final out put was around 90%. Keeping in view the operational advantages and limitation of object based technique of Definiens, the proposed methodology can be easily replicated to other parts of moist temperate Himalayan forests in Pakistan. In order to meet growing needs of harmonized land cover system, class definition of FAO's Land Cover Classification System (LCCS) has been adopted.

1. INTRODUCTION

The Western Himalayan mountain ranges are known for its verdant forests, snow-crested lofty peaks, cascading streams and sun-bathed valleys. Ayubia is one of the best remaining examples of moist temperate Himalayan forest in the Galliat Forest landscape.

Landscape is a heterogeneous area composed of a cluster of interacting eco-systems. It is a mosaic of habitat patches that are repeated throughout the landscape in various shapes, sizes, and spatial relationships (Thomas, 2000). In addition, landscape exhibit, characteristics of multi-scale hierarchical interactions, unexpected behavior and self organization. All of these patterns characteristics that can be changed depending upon their scale of observation. Thus, the roles of observer and of scale are of fundamental importance in the process of 'pattern recognition' or 'object delineation'; which in turn, makes it necessary to understand the processes that generate such patterns or objects (Hay et al., 2003).

Remotely sensed data is one of the primary data sources for landscape patterns recognition. Therefore, it requires interpretation theories and methods to identify and abilities to link these pattern components or objects at their respective scales, within the appropriate hierarchical structures (Hay et al., 2003). Classical pixel-based approaches of pattern recognition have shown some difficulties to adequately or conveniently exploit such kind of expert knowledge or contextual information from satellite imagery (Flanders et al., 2003). Particularly, with the launch of Ikonos in 1999 (Goetz et al., 2003), intra-class spectral variations and inter-class spectral confusion have been increased in high resolution satellite imagery (Kozak et al., 2008; Mathieu et al., 2007). Due to higher pixel to pixel variability and information contained in patch based landscape structures, classical methods of image analysis are becoming out of date.

Recently emerged image processing techniques of pattern recognition, object based image analysis, overcomes these difficulties by first segmenting the image into multi-pixel image object primitives according to both spatial and spectral features of group of pixels. The defined objects maximize between-objects and minimize within-object variability according to image resolution and spatial scale of landscape components (Mathieu et al., 2007; Flanders et al., 2003). Unlike conventional "pixel-based methods", which classify each pixel according to statistical values, object based techniques can also use shape, textural and contextual information of the image objects being assessed.

In the present analysis; the object-based approach of 'Definiens' is presented to derive the forest cover information for 'Ayubia National Park' using Quickbird imagery.

2. METHODS

2.1 Study Area

Ayubia National Park (ANP), covering an area of 3,372 hectares area, is geographically located between 34° 0′ 43″ to 34° 6′ 18.9″ North and 73° 22′ 53″ to 73° 27′ 34″ East (Figure

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1). The area was declared as National Park by the government of NWFP (North West Frontier Province) in 1984.

The topography of Ayubia National Park is rugged with precipitous slopes. The main axis of the mountainous range is north-north-east extending to the south and south-east forming two major mountainous ridges extending to the peaks of ‘Miranjani’ in the north-east and ‘Mukshpuri’ in the central area of the park. The altitude ranges from approximately 1800m to 2980m.The highest peak in the park is ‘Miranjani’ and second highest peak is ‘Mukshpuri’ with altitudes of 2980m and 2820m, respectively.

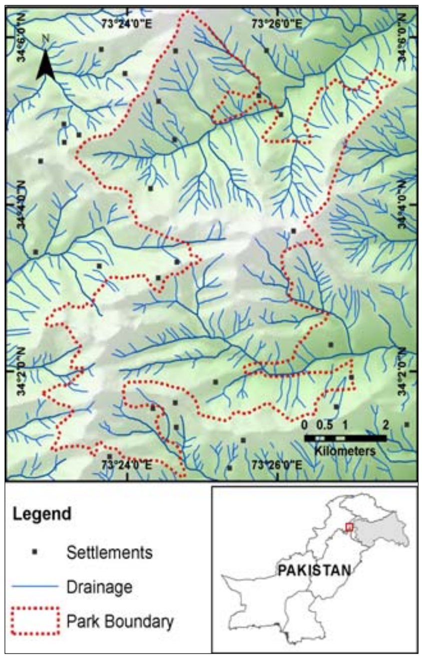

Figure 1: Map of study area

The common forest cover of the national park is dominated by coniferous species. Primarily, *Pinus wallichiana* (blue pine) and *Abies pindrow* (fir) is mixed with scattered broadleaved tree species such as *Quercus dilatata, Aesculus indica, Ulmus wallichiana* and *Prunuspadus*. Due to human impact in the park, populations of broadleaved trees have declined; on the other hand coniferous being very resilient, large areas now have been colonized by these two species (*Pinus wallichiana* and *Abies pindrow*) leaving seemingly little space for broadleaved species to grow and relatively poor vegetation in the understory. Outside the National Park, forested areas are almost entirely composed of Abies pindrow in the northern aspects, and Pinus wallichiana elsewhere (Thomas et al., 2004). There are about 64 tree species, 200 species of herbs and shrubs and about 10 species of Gymnosperm trees found in park area (Rizwana & Aneel, 2005).

2.2 Data acquisition and pre-processing

Digital image data were acquired over the study area by the Quickbird satellite in May 2005. The Quickbird dataset consisted of single band panchromatic imagery (450 – 900 nm) with the spatial resolution of 0.61 x 0.61 m and four band multispactral imagery with spatial resolution of 2.4 x 2.4 m divided in to the spectral bands: blue (450 – 520 nm), green (520 – 600 nm), red (630 – 690 nm) and NIR (760 – 900 nm).

The preliminary processing of the image data included ortho-rectification, as well as sub-setting of the imagery to the geographic extent of Ayubia National Park (Figure 1). Conventional image enhancement techniques were performed to improve the visual quality and interpretability of the images.

2.3 Object based Image Analysis

The approach of object based image analysis (OBIA) has been adopted for the land cover classification. For this purpose commercially available software, ‘Definiens Developer (formerly known as eCognition)’ (Zhou et al., 2008), was used to carry out the object based image analysis. ‘eCognition’ was developed and released by a German company ‘Definiens Imaging’ in 2000 (Hay et al., 2005; Mather, 2004; Flanders et al., 2003).

The first and foremost step of object based image analysis is segmentation of the image into image object primitives. In ‘eCognition’ technology; segmentation is an operation in which a new image object level is created or morphology of already existing object is altered (Definiens, 2007).

Outcome of segmentation phase is controlled by user-defined parameters (scale, shape, compactness) that must be assigned accurately according to the feature being extracted (Mathieu et al., 2007). These parameters are defined by trial and error approach in order to acquire image objects of interest (Definiens, 2007; Mathieu et al., 2007: Flanders et al., 2003). Although Moller et al., (2007) proposed a comparison index to support the selection of an optimal segmentation scale; however, Baatz et al. (2004) suggested that beyond quantitative evaluation of segmentation procedures, no segmentation result is fully convincing if it does not satisfy the human eye (Mathieu et al., 2007). For the current image analysis parameters applied for segmentation hierarchy (Table 1).

Table 1 Segmentation parameter applied

Hierarchy	Scale	Shape	Compactness
Level 1	60	0.3	0.5
Level 2	40	0.3	0.5
Level 3	20	0.3	0.5

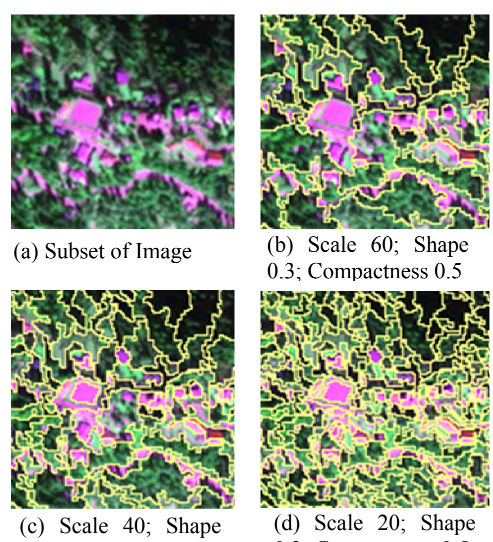
(a) Subset of Image
(b) Scale 60; Shape 0.3; Compactness 0.5
(c) Scale 40; Shape 0.3; Compactness 0.5
(d) Scale 20; Shape 0.3; Compactness 0.5

Figure 2: Image segmentation hierarchy

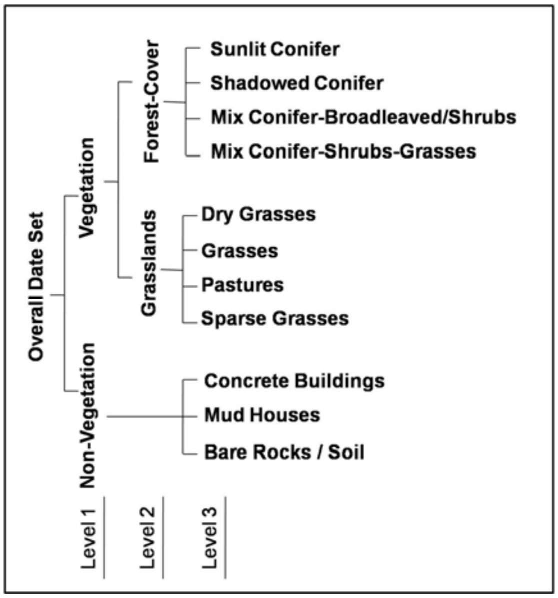

Figure 3: Optimal tree for the discrimination of classification categories

Classification is the procedure to associate image objects with an appropriate class (Mather, 2004). Procedurally, classification method in eCognition is supervised which starts with taking typical representative samples for reach class and it uses *'NN Fuzzy classifier'* for objects categorization (Mathieu et al., 2007, 2007; Santos et al. 2006).

In the present study, throughout the process of image analysis, subsequent steps of classification and segmentation algorithms were applied to perform hierarchical classification. The first level of classification hierarchy was constructed by stratifying the 60-scale segmentation layer (first level of segmentation) into two broad categories 'vegetation' and 'non-vegetation' (Figure 3). In numerous iterative steps of 'Classification Based Segmentation', smaller neighbouring image objects of similar classes were fused together into bigger objects. In the next level of classification, vegetated areas were locally processed at second level of segmentation (40-scale segmentation layer) and categorized into two broad sub-classes; 'forest-cover', and 'grasslands' (Figure 3). Contiguous regions of similar classes were merged together to form continuous patches of each class. Later on, 20-scale segmentation was used to analyze further variations in 'forest-cover', and 'grasslands' as well as 'non-vegetation' classes. In first phase of third level classification, 'forest logic' was prepared to categorize 'forest cover' into four sub-classes; 'sunlit-conifer', 'shadowed conifer', 'mix Conifer-broadleaved/shrubs', and 'mix conifer-shrubs-grasses' (Figure 3). In second phase localized classification of 'grasslands' results in four major variations constructing sub-classes; 'dry grasses', 'pastures', 'grasses', and 'sparse grasses' (Figure 3). Likewise, in the final phase of third level classification, 'non-vegetation' was further categorize into three sub-classes; 'mud houses', 'concrete buildings' and 'bare rocks / soil' (Figure 3). At the end, misclassified and unclassified image object objects were manually classified. In each step of classification, MOV (Mean Object Value) along with DEN, slope and aspect were considered to build the *Nearest Neighbor* feature space and hierarchical dependencies of image objects.

For better analysis and visualization of significant vegetation classes, eleven land cover classes were merged into six general classes i.e., 'Conifer forest', 'Conifer forest (shadowed)', 'Mix forest', 'Grasses/Shrubs', 'Bare soil/Rocks' and 'Built-up area'. To determine the degree of error in the end product (classification results), a 'K x K' confusion matrix' was generated using 'Definiens'. Due to limitations of sufficient ground survey data it was rather difficult to select reference samples randomly. However, availability of high resolution imagery and ancillary information (digital photographs) of the study area, made it possible to manually select the test samples for accuracy assessment. The minimum recommendation of 50 reference samples per class (Lillesand et al., 2004) was comfortably achieved for most of the classes.

The Land Cover Classification System (LCCS) is being used to define classification legend scientifically. It has been developed by FAO and UNEP to cope with the need for improved access to reliable and standardized information on land cover and land cover change. It is a comprehensive, standardized and a priori classification system designed to meet specific user requirements, and has been created for mapping exercises, regardless of the scale or means used to map. It enables a comparison of land cover classes independent of mapping scale, land cover type, data acquisition method, or geographical location. The LCCS system enhances the standardization process and minimizes the problem of dealing with a very large amount of pre-defined classes (Gregorio & Janson 2005). Keeping in view all the benefits of a standardized legend, LCCS technique of legend definition was adopted to standardize the classification legend of land cover map for Ayubia National Park.

3. RESULTS AND DISCUSSIONS

The layers chosen for the segmentation (Figure 2) were empirically based on visual inspection of results.

During the classification process, it was observed that some objects that were characterized by 'sparse grasses', at level three of classification, were wrongly classified as objects of 'conifer'. Similarly, some of segments comprising 'mud houses' were classified as 'sparse grasses' (due to presence at mud roofs of such houses). However, incorporation of DEM, slope and aspect made it possible for linked super objects of these objects to be correctly classified as 'grasslands' and 'non-vegetation' respectively. Therefore, results of third level were improved by incorporating rules that were linked to classification of super objects (i.e. second level objects for 'grasslands' and first for 'non-vegetation'). In the improved classification, due to *fuzzy* realization of *Nearest Neighbor* feature space distance, these objects were assigned to the class with the second highest membership grade.

The area of all land cover classes were computed for the whole park (Table 2). The most dominant forest over type of the park consists of conifer forest; covers an area of 2100 ha (62..2 %) (Figure 4).

Table 2. Statistical distribution of land covers classes

Land cover	**Area Covered (ha)**	**(%)**
Conifer Forest	2100	62.2
Conifer forest (Shadowed)	497	14.7
Mix Forest	359	10.6
Grasses/Shrubs	349	10.3
Bare soil/Rocks	66	1.9
Built-up area	8	0.2

A simplified classification scheme was created by regrouping eleven land cover classes into six land cover classes. The new classification scheme consisted of four vegetation cover classes (conifer forest, conifer forest (shadowed), mix forest and grasses), two non-vegetated cover classes (build up area and bare rocks/soil).

The overall accuracy of the initial land cover was 89.99 percent. After post classification processing (re-coding), due to decrease in number of classes, over all accuracy was increased to 91.66 percent. Confusions between the classes, 'dry grasses', 'pastures' and 'grasses' were eradicated after merging these classes into a single class (grasses). Likewise, confusions between the other classes were reduced after being merged into a single class.

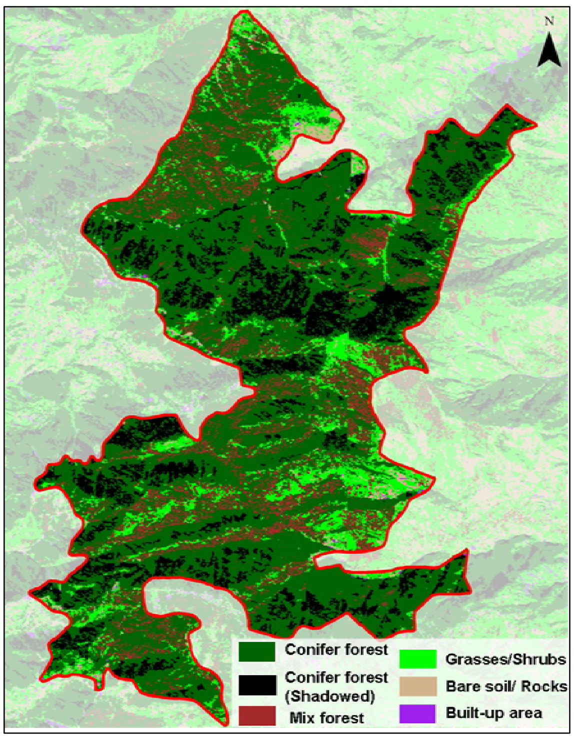

Figure 4: Land cover map of Ayubia National Park

Conclusions

Object-based Image Analysis approach, used in this study, proved to be very effective for deriving forest cover information based on high spatial resolution multi-spectral imagery in the heterogeneous forest environment. The results suggest that image objects delineated through multi-scale segmentation are carriers of important forest related information in the form of image object hierarchy. Overall accuracies seems to be superior (90.61 percent and 91.99% percent) in relation to other studies of ANP by applying classical pixel-based methods.

Although similar things may also be accomplished by incorporating a series of masks and expert rules with conventional pixel-based approach, yet, object-based approach is efficient and easy to use. The adoption of objects instead of pixels as the primary unit of classification provides much more information for the assignment of information to classes, but also posed the challenge of how to use this information efficiently.

Flip side of such image analysis is that the analyst has to have a high level of knowledge about the objects of interest to define the best parameters to identify and classify the objects. He must also know the spectral and spatial behavior of the objects, understand the underlying processing and have a good grasp of information to select decision key. However, any kind of effective image analysis procedures would depend on user knowledge at some point of analysis.

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