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REMOTE SENSING APPLICATION IN FOREST MONITORING: AN OBJECT BASED APPROACH

Tran Quang Bao[1] and Nguyen Thi Hoa[2]

[1] Department of Environment Management, Vietnam Forestry University, Ha Noi, Vietnam
[2] Institute of Forest Ecology and Environment, Vietnam Forestry University, Ha Noi, Vietnam

ABSTRACT: *Object-based methods for image analysis have the advantage of incorporating spatial context and mutual relationships between objects. Few studies have explored the application of object-based approaches to forest classification. This paper introduced an object based method to SPOT5 image to map the land cover in Yen Nhan commune in 2015. This approach applied multi-resolution segmentation algorithm of eCognition Developer and an object based classification framework. In addition, forest maps from 2000 to 2015 were used to analyze the change in forest cover in each 5 years period. The object based method clearly discriminated the different land cover classes in Yen Nhan. The overall kappa value was 0.73 was achieved. The estimation of forest area was 89.05 % of forest cover in 2015. By overlaying achieve forest maps of 2000, 2005, 2010 and the classified map of 2015 shows vegetation changed during 2000-2015 remarkably.*

KEYWORDS: Remote Sensing, GIS, SPOT 5 Image, Forest Classification, Change Detection

INTRODUCTION

Forest ecosystem is responsible for much of our climate physiology, plays important roles for human and animals. According to the U.N. FAO, 44.5% or about 13,797,000 ha of Viet Nam is forested. Hence general information about change is necessary for updating forest cover maps and the management or natural resources. From 1990 to 2010, Vietnam has done four forest inventory surveys. In these surveys, Landsat and SPOT imageries were used [4].

In the previous years, to investigate forest resources are mainly based on survey and mapping by manual methods. It requires a lot of time, money, effort and low accuracy, information is not often updated because forest cover change over time. In recent years, geographical information systems (GIS) and remote sensing are well-established information technologies, the value of which for applications in land and natural resources management are now widely recognized [4]. Recent improvements in satellite image quality and availability have made it possible to perform image analysis at much larger scale than in past.

Recently, object based approaches have been applied successfully in many ecology-related remote sensing studies, such as landslide inventories [12], mapping burned areas using different sensors [13,14], monitoring land conversion [15], or assessing forest structural complexity [16]. Object based approaches applied multi-resolution segmentation which is the partition of an image into spatially continuous, mutually disconnected and homogeneous regions at various segmentation levels [17]. Multi-scale segmentation starts considering each pixel as an object and merges them to create larger objects based on homogeneity thresholds defined by the analyst [18]. Multi-scale segmentation has the advantage of considering homogeneity criteria such as color, shape compactness and smoothness, during the creation of

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image objects. The scale parameter set by the operator is influenced by the heterogeneity of the pixels. The color parameter balances the homogeneity of a segment's color with the homogeneity of its shape. The form parameter is a balance between the smoothness of a segment's border and its compactness. The weighting of these parameters establishes the homogeneity criterion for the object primitives. The technique offers the possibility of varying the size of output segments and creates object hierarchy levels that facilitate their accurate extraction.

Forest has long been regarded as a nation treasure in Thanh Hoa. Farming activities and illegal logging are posing a serious threat to quality and quantity of forest. Mapping forest cover changes is the standard way to monitor changes; a change detection analysis was performed to determine the nature; extent and rate of forest cover change over time and space. The results will quantify the forest cover change patterns in the area and demonstrate the potential of multi-temporal satellite data to map and analyze changes in forest spatial temporal framework. This can be used as inputs to land management and policy decisions with regard to varied themes have link with space such as urbanization, water management, deforestation and forest degradation. This research investigated the spatial temporal change detection of forest cover of Yen Nhan – Thuong Xuan in period 2000-2015.

METHODOLOGY

*** Study Sites and Data Sources**

- Study Sites: Yen Nhan Comune, Thuong Xuan disstrict, Thanh Hoa province.

- Softwares: ecognition Developer V8.9, ArcGIS Desktop 10.1, Mapinfo 10.5.

- Secondary data: provincial forest maps for 2000, 2005 and 2010.

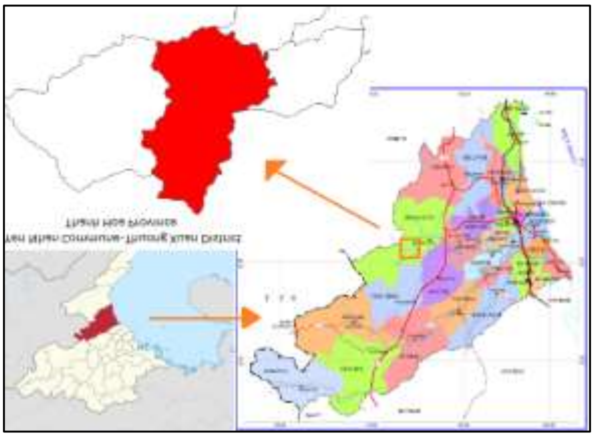

Figure 1: Location of the Yen Nhan Commune in Thanh Hoa Province

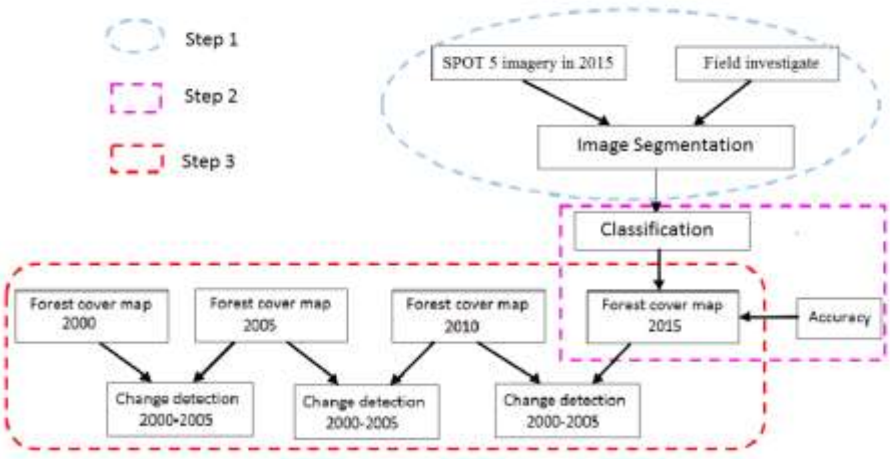

Figure 1: Flowchart of research's methodology

The proposed methodology is illustrated in Figure 2. This study used an object-based approach to map forest cover at Yen Nhan in 2015 based on SOPT 5 data (Step 1 and Step 2). After that, we performed a change-detection analysis based on object-based mapping results and map from period time (2000-2010) (Step 3).

*** Image segmentation (step 1)**

The segmentation algorithm applied in this study is the so-called "multi-resolution segmentation". The algorithm was applied to all four SPOT bands (green, red, NIR and SWIR) with the same weight for each band. After trying to use different parameters for the segmentation, we found that scale parameter = 70, shape = 0.5, and compactness = 0.8 were satisfied (shown figure 3). Because the SPOT 5 image was divided into 11135 objects, smallest object is 0.11 ha and the largest object is 112.11 ha. This shows that the image is very detailed segmentation and helps reduce errors in automated sorting process.

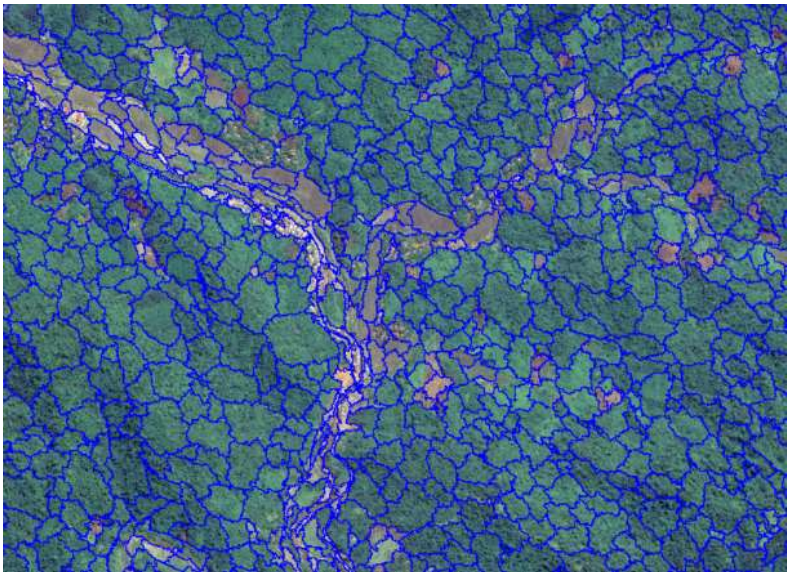

Figure 3: Objects with multi-resolution segmentation (Scale parameter = 70, shape = 0.5, and compactness = 0.8)

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*** Classification and accuracy (Step 2)**

Classification

Initially, to define land covers in study area, an object-based classifier was developed to assign each object to a land cover class. The classes were derived utilizing object-based classification framework in combination with interactive visual interpretation, expert knowledge, training data, and existing maps of the area.

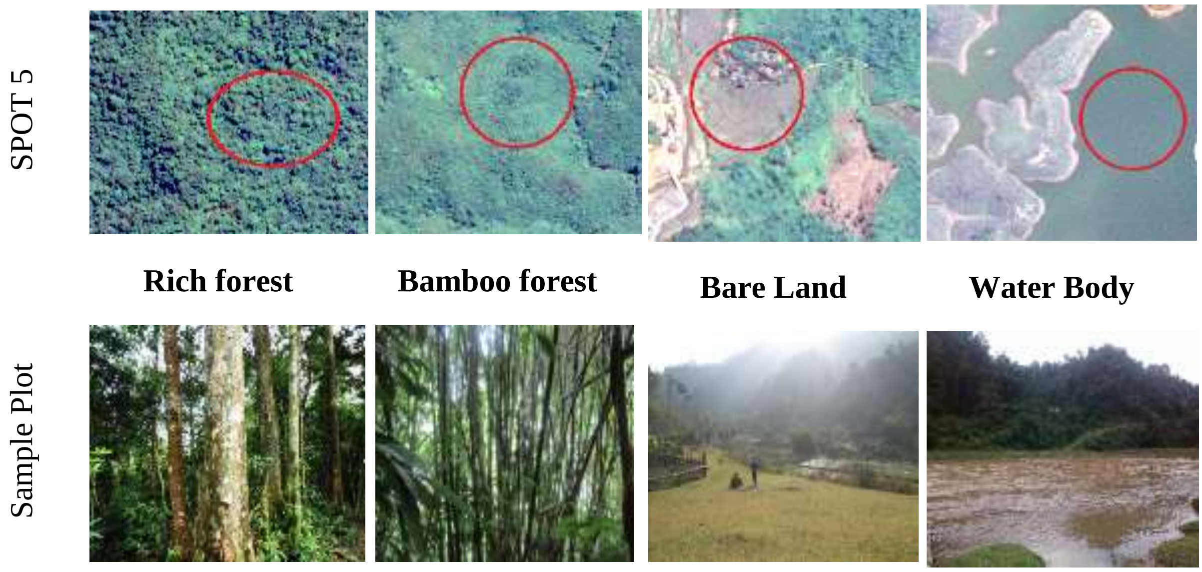

Figure 3: Example of some objects in object based classification framework

Accuracy assessment

Accuracy assessment is an important part of the image classification procedure and can be computed by assessing either positional or thematic accuracies. This paper reviews a total of 80 reference points were surveyed in the field to serve as validation samples for the classification. And then 50 sample points were selected randomly (figure 4). The author used Kappa coefficient that was computed using equation:

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

Where N is the total number of sites in the matrix, r is the number of rows in the matrix, $x_{ii}$is the number in row i and column i, $x + i$ is the total for row i, and x_{i+} is the total for column.

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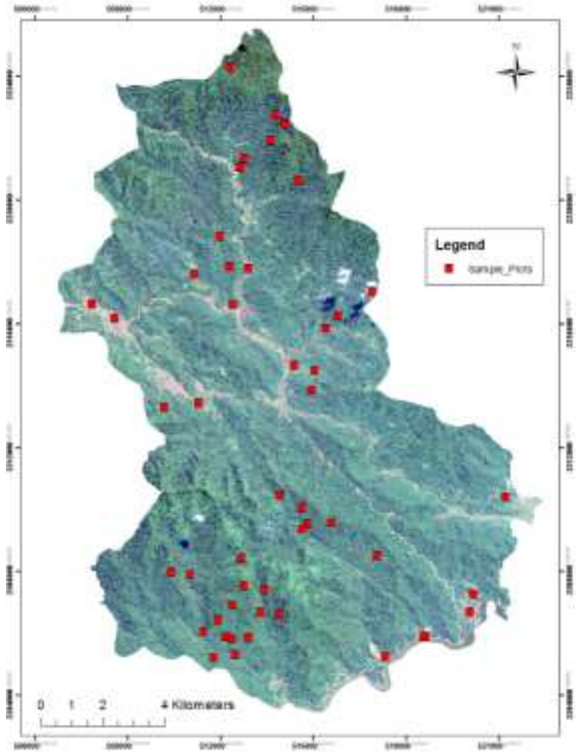

Figure 2: The distribution of sample points in the study area

*** Change detection (Step 3)**

The area of each land cover class was calculated and the forest cover changes were analyzed. Forest cover change map covering a period of 15 years (2000-2015), was first derived in order to see the overall change in the region. The commune scale (Yen Nhan) was then chosen to characterize the forest cover changes in 3 short-term periods (2000-2005, 2005-2010, and 2010-2015). Detection of land cover changes was achieved by overlay (in ArcGIS 10.1) and post-classification comparison of the forest cover maps of the different time periods. The resulting change maps were accompanied by the respective cross tabulation matrix showing the change pathways, in order to determine the quantity of the conversions. Change dynamics are presented in maps using grouping of changes for more clarity in the results.

RESULTS AND DISCUSSION

*** Object-Based Classification**

The SPOT 5 imagery was classified in eCoginition software (2015) including 10 classes: rich evergreen, medium evergreen, poor evergreen, rehabilitation evergreen, bamboo, mixed wood and bamboo, plantation forest, bare land, shrub and grass, and water body.

The structural features of each forest state were different and complex. Natural forest is often more complex than plantation forest; rich forest is more complex than medium forest, poor forest or rehabilitation forest; bare land and water body are always the most recognizable.

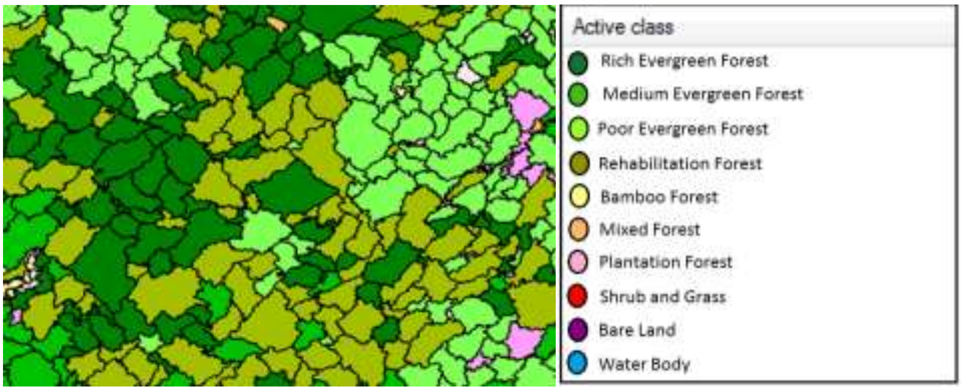

Figure 5: Object-based classification result (2015)

*** Classification**

Forest Classification

Yen Nhan exhibits diverse forest types, predominantly seen types that are specific to the region: rich evergreen, medium evergreen, poor evergreen, rehabilitation evergreen, bamboo, mixed wood and bamboo, plantation forest (Figure 6). Forest area covers 16077.9 hectares, representing 89.05% of the total hectare. This is basically found in the Northern and Western part of the map. And non-forest area covered 1977.7 hectares representing 10.95% which is scattered around the rivers such as Khao, Chu, Dat and Dan river.

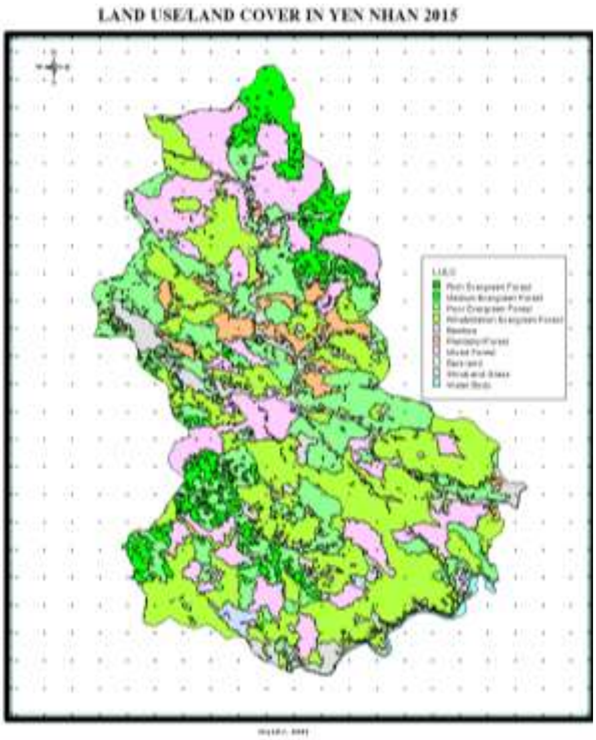

Figure 6: Land use/land cover in Yen Nhan 2015

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Accuracy assessment

A Kappa coefficient of 0.733 was achieved (95% confidence interval from 0.603 to 0.864). The strength of agreement is considered to be good.

Limitations of the methodology

The classification errors were sometimes due to spectral mixture between rich forest and medium forest, poor forest and rehabilitation forest, mixed forest and plantation forest, shrub, grass and bared land. The resolution of SPOT 5 imagery of the study is low and some areas were covered by cloud, it affected to the results. Moreover, classifying the spatial temporal forest cover changes patterns using object-based classification method need who is expertise. Therefore, careful selection of training sites and majority filters after supervised classification were applied in order to reduce these issues.

*** Land Cover Change**

Forest cover

Land cover/ Land use classification maps of Yen Nhan Commune from the four time periods were analyzed and are illustrated in Figure 7.

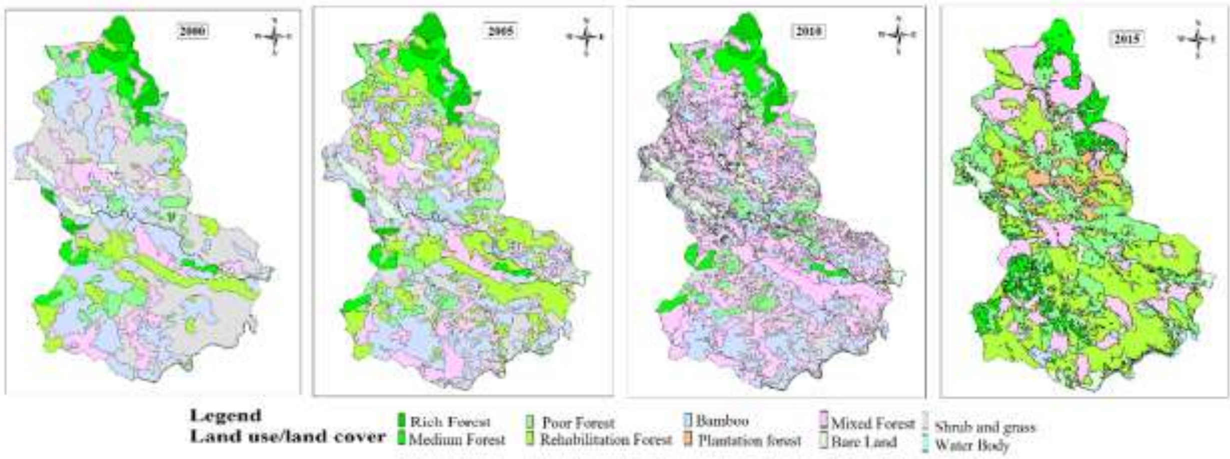

Figure 7: Land cover/land use classification maps of Yen Nhan commune in year 2000, 2005, 2010 and 2015

Rich evergreen forest was located mainly in the Northern part of the commune in period 2000-2010. Since 2015, it decreased area and just covered land area of only 11.33 hectares (representing 0.1%) and around is medium evergreen forest. Medium evergreen forest is observed in in the northern part and some small patches in the western part of commune from 2000 to 2010. The change in the spatial extent is noticed in 2015 and this forest is located in areas which converted from rich evergreen forest. Poor evergreen forest was scattered areas in the eastern, northwest and southwest parts of commune. In 2015, this type of forest can be found in the central of commune. In 2000, rehabilitation evergreen forest was found in small patches from western and southwestern to southeastern regions of commune. From 2005, it expanded to eastern and northern parts. Plantation forests were almost totally absent from the commune until 2005. It started to develop in the central and southeast parts with very small scattered areas from 2010 and it was expanded in 2015.

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Change detection

Figure 8 illustrates the spatial distribution of changes over different time interval. From 2000-2005, the changes occurred in large patches and scattered throughout the commune. From 2005 to 2010, the changes were more fragmented. In the end of study time period 2010-2015, the changes occurred in large scale.

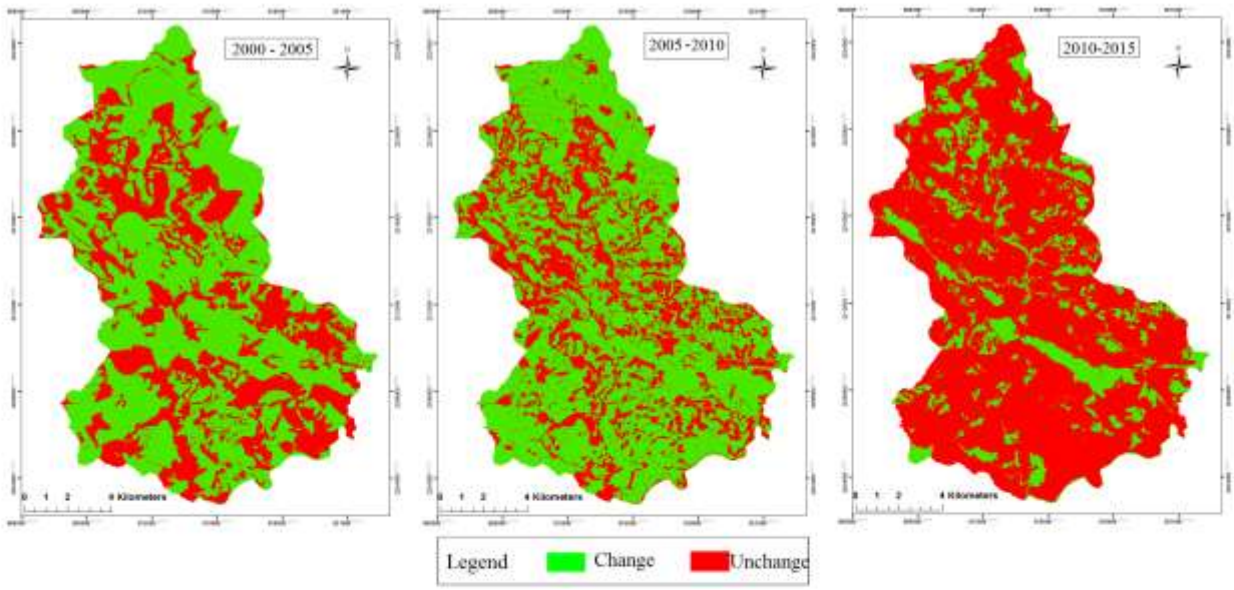

Figure 8: Spatial distribution of land cover/land use changes in Yen Nhan commune from 2000-2015

The details of change in forest cover at Yen Nhan from 2000-2015 were illustrated in figure 9. The magnitudes of changes in hectares per year, standardizing the absolute change by the duration of each year analyzed interval for the 9 main land cover/land use categories. Only the plantation areas class shows a continuous increasingly trend. The other land cover/land use types fluctuated over the different time periods. Rich forest, poor forest, rehabilitation forest, bamboo forest, shrub and grass, and bare land had higher magnitudes of change than the limited changes for medium forest, mixed forest and the negligible variation of water bodies.

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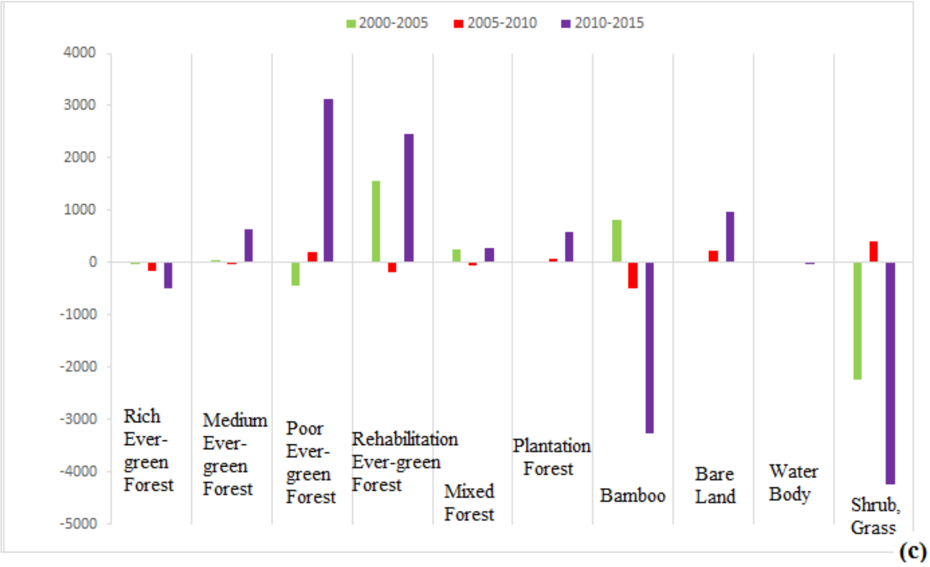

Figure 3: The magnitude of the land cover/land use changes in ha/year for each time interval.

CONCLUSION

The object-based change detection method proposed in this paper proved to be very efficient to identify forest land cover changes with high accuracy assessment (Kappa coefficient was 0.73). In the case of the classification of the SPOT images, this could provide the base for a very efficient monitoring system.

This paper indicates Yen Nhan commune is diverse land cover/land use pattern. The results demonstrate that (i) the main land cover/land use categories of Yen Nhan commune, for the last 15 years from 2000 to 2015, include rich evergreen, medium evergreen, poor evergreen, rehabilitation evergreen, bamboo, mixed wood and bamboo, plantation forest, bare land, shrub and grass, and water body; (ii) almost all land cover/land use types display variations in magnitude over the different time periods, with rich evergreen, poor evergreen, rehabilitation evergreen, bamboo and shrub, grass changing more drastically compared to the other types.

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