Land Use and Land Cover Change in Vientiane Area, Lao PDR Using Object-Oriented Classification on Multi-Temporal Landsat Data

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Land Use and Land Cover Change in Vientiane Area, Lao PDR using Object-Oriented Classification on Multitemporal Landsat Data

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Monitoring of land use and land cover change using remote sensing is important to evaluate the impacts of anthropogenic activities on the environment. Digital change detection using post-classification can help to elucidate dynamics of landscape change. This study illustrates the effectiveness of object-oriented classification compared to pixel-oriented classification in generating land cover information and its temporal changes. Spatio-temporal dynamics of land cover types in Vientiane area, Lao PDR were analyzed using Landsat images in two-time series (1990 and 2015). We used the top-down approach to classify the Landsat images in iterative steps with three hierarchical scale levels. Scale levels of 25, 10 and 5 with different weighting parameters were used to map the land cover type of Vientiane in 1990 and 2015. With object-oriented classification, overall accuracy and Kappa statistic were improved by 13.44% and 0.16 for land cover classification (LCC) 1990. For LCC 2015, the improvements in overall accuracy and Kappa statistic were 28.71% and 0.25. Based on the LCC 1990 and 2015, we observed an significant growth of plantation areas over the 25 years in the study area . Instead of traditional agricultural activity, the plantation seemed to be the new driver in the rural areas of Lao PDR. The object-oriented classification approach can be applied in other areas of Lao PDR to generate accurate information on land cover changes for better land resource management.

Keywords: Object-oriented classification, Landsat, land use and land cover change

1. INTRODUCTION

Land use and land cover changes are major driving forces of the environmental changes such as deforestation, biodiversity loss and global warming [15]. Pressured by expanding human population, forested lands are increasingly converted to agriculture and urban land use in order to satisfy the increasing demands of natural resources. Rapid changes in land cover can potentially lead to deterioration of environmental conditions by removing the forests. Assessment of land use and land cover change using satellite remote sensing data is vital for monitoring the rates of deforestation. The extensive coverage of satellite images in time series such as Landsat dataset can be used to generate multitemporal land cover information to improve land use planning over a large region or country.

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Since Landsat satellites launched in the 1970s, traditional supervised and unsupervised pixel-oriented classification methods have been the main approaches to assess the land use and land cover changes. Pixel-oriented classification approach is based on the spectral signature

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of each pixel of the image by considering the spectral dissimilarities with the pre-defined land over classes[5]. However, over-dependent on the spectral signature of the training areas may result in misclassification as well as salt and pepper effect [3]. Such limitation strongly suggests that this method is unable to represent the spatial relationship between the landscape features that are continous to some extents.

In recent decades, the concept of object-oriented classification is introduced as an alternative to pixel-oriented classification[7]. In contrast to pixel-oriented classification, object-oriented classification utilizes the spatial and contexture information of an object such as object texture, shape, and relation to the adjacent region to differentiate land cover classes with similar spectral information. These additional information in object-oriented classification are able to differentiate land cover classes more effectively in order to produce land cover thematic maps with higher accuracies.

This study applied object-oriented classification on the multi-temporal Landsat images to examine the land cover changes at Vientiane area, Lao PDR between 1990 and 2015.

2. Study Area

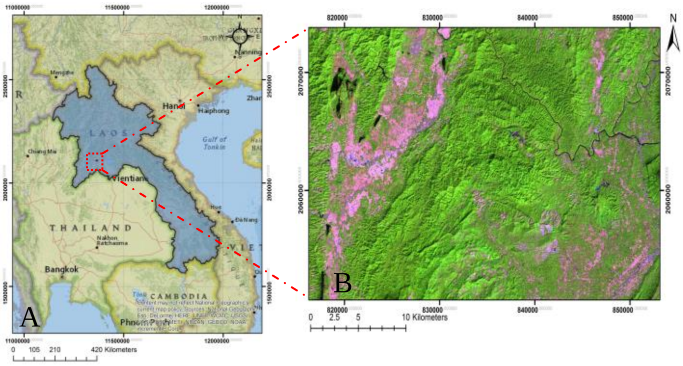


Figure 1: Location of study area in Laos (A) and Landsat 8 OLI 2015 RGB 5,4,3 (B)

Our study area is located at Vientiane Province Lao PDR, which is about 85km from the capital Vientiane city. The climate is dominated by tropical monsoon with pronounced wet and dry season. The rainy season is from May to September while the dry season is from October to April. The wet and dry seasons are vital for the agricultural activity in the study area as it is the main economic income source of the nation. Lowland areas of the study area are classified as tropical, whilst the higher elevations and mountainous areas in the north are considered sub-tropical.

3. Methodology

Data collection and pre-processing

The data collected for this study are satellite data and ancillary data. Ancillary data are the ground-truth data and also referrence data based on the Google Earth images. These data were used to train the land cover classifications. For satellite data, two clouds-free Landsat datasets (WGS 84, UTM zone 47N, path: 129, row: 047) with pixel size 30 × 30m were downloaded from the website of United State Geological Survey. The downloaded satellite data were Landsat 5 Thematic Mapper (31st January 1990) and Landsat 8 Operational Land Imager (12th May 2015). The images were pre-processed with atmospheric effect correction and topographic effect correction using Erdas Imagine 2014.

Atmospheric correction is needed to remove the scattering, absorption and atmospheric distortion [16,18] on the downloaded images. Dark Object Substraction (DOS) with the histogram method was used to reduce the atmospheric effect on the spectral reflectance of the objects[4]. In addition, topographic effect due to varying terrain slope angles and positions were also corrected. The non-Lambertian Minnaert correction method [17] was used to correct the different brightness values of the same land cover types due to the varying terrains.

Pixel-oriented Classification

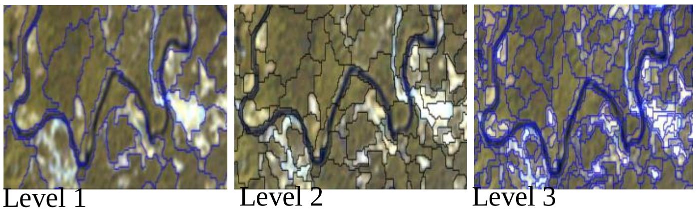
The pixel-oriented classification was conducted using supervised classification with maximum likelihood algorithm[12,14]. A number of training areas for each land cover class were selected to determine the spectral signature of each class. The image was then classified pixel by pixel based on the spectral signatures.

Object-oriented Classification

The eCognition software developed by Definiens Imaging was used in this study. The object-oriented classification process is divided into two main workflow steps. The first step involves image segmentation in order to generate a group of homogeneous pixels as an object. The Object is segmented based on the spectral and contextual information with the parameters scale, shape and compactness[19]. Multi-resolution segmentation approach was applied to control the size and spectral variation of each segmented object. The homogeneity criterion of object primitives was established from the weighting of these parameters. The result of the segmented objects of various weighting parameters was visually inspected to determine the overall values for the parameters weighting at each object scale level. The segmentation process was performed for three object scale levels in a hierarchical network.

The segmentation algorithm with top-down approach begins by generating large image object on the topmost image level with relatively large scale parameters. All the large image objects of mixed land cover type are subsequently split into smaller region (object primitives) in the lower level as a sub-object to simplify the complex data content [1]. Within each segmentation level, a segmented object is linked to the adjacent objects with the context information from the super-object and sub-object for classification analysis [9].

The second step of the analysis is supervised classification. Representative sample objects were assigned to the land cover classes to analyze the spectral and contextual separability of the land cover classes. The optimize space features with the nearest neighbor classifier was used in the classification. The features' spectral information and Haralick's texture using Grey Level Co-Occurance Matrix (GLCM) were added into the classifier to maximize the separability distance of the land cover types. The classification was conducted via iterative steps with three hierarchical scale levels as in Table 1



Level 1 Level 2 Level 3

Figure 1: Hierarchical network of image objects- level 1 (25 pixels), level 2 (10 pixels) and level 3 (5 pixels).

Table 1: Image segmentation using three different scale parameters for two Landsat datasets.

Year	Level	Scale	Shape	Compactness
1990	1	25	0.3	0.1
	2	10	0.5	0.5
	3	5	0.3	0.1
2015	1	25	0.3	0.1
	2	10	0.3	0.5
	3	5	0.1	0.1

4 RESULTS AND DISCUSSION

Classification accuracy

Ground truth data and reference data based on the Google Earth images were used to calculate the Kappa statistic to assess the accuracy of the land cover classifications. Producer and user accuracies for all classes were also calculated along with the overall accuracy[6].

Table 2: Result of accuracy assessment on pixel and object-oriented classified image in 1990.

Land cover class		Agriculture area	Bare land	Degraded forest	Highly degraded area	Intact forest	Plantation area	Water	Overall accuracy (%)	Overall Kappa
Pixel-oriented	Producer's accuracy (%)	40.00	77.78	81.82	100.00	88.89	12.50	62.50	68.65	0.63
	User's accuracy (%)	66.67	53.85	50.00	100.00	80.00	33.33	100.00		
Object-oriented	Producer's accuracy (%)	40.00	100.00	100.00	91.67	100.00	37.50	100.00	82.09	0.79
	User's accuracy (%)	100.00	56.25	73.33	100.00	90.00	100.00	100.00		

Land cover class		Agri-culture area	Bare land	Coal mine	Degrad-ed forest	Highly degraded area	Intact forest	Plant-ation area	Water	Overall accuracy (%)	Overall Kappa
Pixel-oriented	Producer's accuracy (%)	15.79	63.64	100.00	25.00	90.00	77.78	40.00	100.00	53.47	0.47
	User's accuracy (%)	37.50	53.85	100.00	50.00	26.47	87.5	58.82	100.00		
Object-oriented	Producer's accuracy (%)	89.47	100.00	100.00	75.00	20.00	100.00	80.00	100.00	82.18	0.72
	User's accuracy (%)	100.00	64.71	100.00	60.00	66.67	100.00	80.00	100.00		

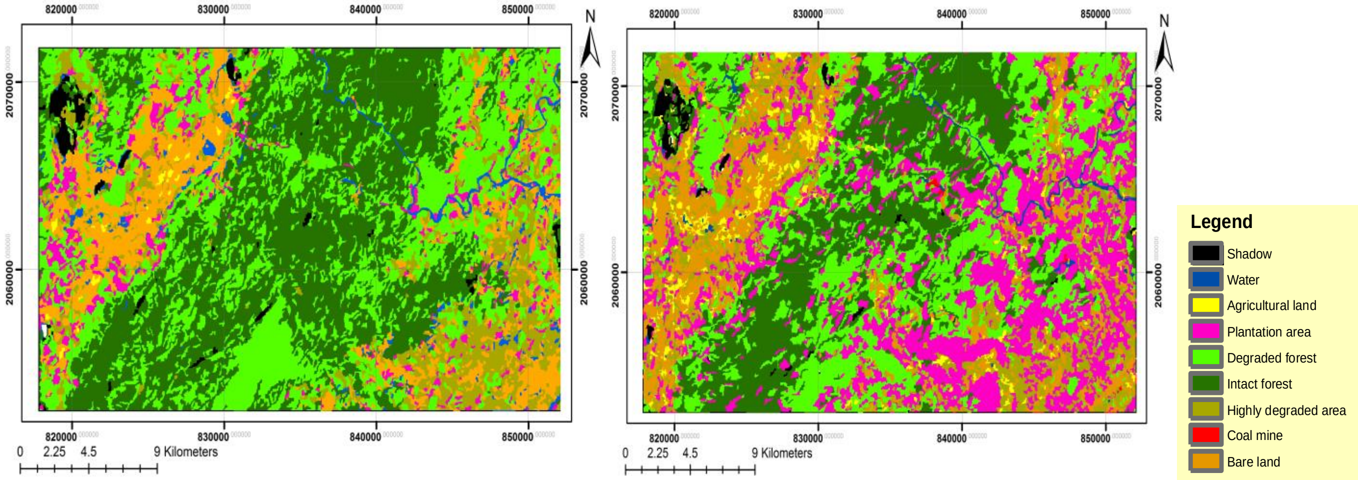
Table3: Result of accuracy assessment on pixel and object-oriented classified image in 2015.

Accuracies of land cover classification (LCC) of Landsat 1990 and 2015 are shown in Tables 2 and 3. The overall accuracies of LCC 1990 and 2015 were 82.09% and 82.18% versus 68.65% and 53.47%, in for object-oriented and pixel-oriented classification approaches, respectively. For LCC 1990, the Kappa statistic has improved from 0.63 to 0.79 with the object-oriented classification approach. Similarly, the Kappa statistic for LCC 2015 has improved from 0.47 to 0.72 with the object-oriented classification. The much-better results from the object-oriented classification suggests that the object-oriented classification was much superior to the pixel-oriented classification in extracting accurate land cover information from the satellite images. Object-oriented classification groups the homogeneous pixels based on spectral signature and contexture information to improve the accuracies of the LCC 1990 and 2015.

When we compared the user's accuracies for each land cover class, significant improvements were recorded for both LCC 1990 and 2015 when object-oriented approach was used. The object-oriented classification that utilizes the texture and spectral information with relation to the neighboring object was able to minimize the misclassification.

Land Cover Change detection

Land cover changes between 1990 and 2015 were analyzed using the LCC produced from object-oriented classification. The total area of each land cover class of the LCC 1990 and 2015 was compared. Referring to Table 4, there is a strong evidence of landscape changing patterns during the last two and half decades.



A B

Figure 2: Object-oriented classified images of 1990 (A) and 2015 (B).

Table 4: Summary of Landsat classification area statistics for 1990 and 2015.

Class		Agriculture area	Bare land	Coal mine	Degraded forest	Highly degraded area	Intact forest	Plantation area	Water
1990	Area (Ha)	186.3	8499.33	0	21761.1	6854.31	23180.49	3328.56	1390.86
	%	0.29	13.04	0	33.38	10.51	35.55	5.11	2.13
2015	Area (Ha)	1674.99	8647.11	84.06	17740.08	6232.5	14153.13	16140.42	528.66
	%	2.57	13.26	0.13	27.21	9.56	21.71	24.75	0.81
Relative Change	Area (Ha)	1488.69	147.78	84.06	-4021.02	-621.81	-9027.36	12811.86	-862.2
	%	2.28	0.23	0.13	-6.17	-0.95	-13.85	19.65	-1.32

In 1990, LCC shows that the largest land cover class was intact forest, which occupied 35.55% of the total area. This is followed by degraded forest (33.38%), and highly degraded area (10.51%). Other land cover classes covered a relatively small proportion of the study site. They included bare land (13.04%), plantation area (5.11%), water (2.13%) and agriculture area (0.29%). The bare land area was the third largest land cover class after intact forest and degraded forest.

As the acquisition date of the satellite data did not fall within the cropping season, most of the agriculture area were still appeared as bare area. Since 1990, agricultural activity is the main economic income source in the study area by generating 56% of Gross Domestic Product (GDP) [2]. Agriculture sector absorbs more than 80% of the work force [2] to fullfil the increasing demands on food resources. A study that analyzed more than 13,500 rice samples in 1990 concluded that Lao PDR is the center of biodiversity for glutinous rice[2]. These information combined with the LCC are evidents of assuming that most of the bare land areas were agricultural area that will be planted with paddy.

Between the 25 years, there was 5 times increment of plantation area (5.11% to 24.75%), attributable to rapid rate of economic development. Large-scale investment in rubber plantation in Lao PDR has triggered the 'rubber boom' with wide spread monoculture planting of rubber[13]. The sharp increment of plantation area has brought to the clearing of intact and degraded forest area. Consequently, intact forest in land cover 2015 had decreased by 13.85%, followed by degraded forest (6.17%) and highly degraded forest (0.95%). Land cover classes of agriculture area and bare land increased by 2.28% and 0.23%, respectively. This may indicate the rates of population increase and urbanization. In 2015, coal mine was also established in the study area. Although it only occupied 0.13% of the total land area, it is a new industry that provides job opportunity to local people.

5. CONCLUSIONS

Rapid land cover changes need to be quantified and monitored for land resource management. We confirmed that the object-oriented classification is able to produce accurate land cover classifications at Vientiane area, Lao PDR. The Vientiane area is predominantly a rural region that depends on agriculture activity. The land cover change analysis concluded that there is a shift in land cover change driver from traditional agriculture to plantation in the study site. With rapid economic development and population growth in recent years, we proposed that the object-oriented classification approach is to be applied in other regions to to support better land use planning in Lao PDR.

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