Village forms classification by object-based image analysis

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Abstract: This paper presents and discusses an application of object-based image analysis for rural land use/land cover classification based on village forms and shapes in Northeastern, Thailand. Increasing availability of VHRS data and object-based classification techniques can be extremely effective to delineate the complexity of land cover in the study area. Quick Bird pan-sharpened imagery with spatial resolution of 0.6 meters is being used in this study. First, a multi-resolution segmentation algorithm was used for creating image objects from heterogeneous pixel values. Transportation network and topographic information were also incorporated as ancillary data into the segmentation procedure. It allows a creation of different levels of segments supporting a hierarchical structure, including spatial relations between objects and sub-objects. Second, in order to use the best criterion and threshold selection, the NN classifier had been used for features analysis. The class hierarchy was divided into 3 levels, i.e. AOI/Non-AOI (L1), analysis level (L2) and top-most level (L3). Land use was classified into 8 classes based on the classification system, developed by Land Development Department, Thailand (e.g. urban/built-up land, agricultural area, range land, forest land and water). The classification was integrating not only spectral information, but also contextual and spatial relationships among image objects. A rule-based classifier has been used for the classification. The criterion of membership functions and the class descriptions were carried out from spectral information and spatial relation derived from image objects. Last, the classification result consists of 2 classes, non-village vs. residential. This study demonstrates that OBIA with topographic variables produces better classification results than OBIA with spectral information only. In the accuracy assessment, the result has been compared with reference ground truth points, including digital land use map, visual interpretation and TTA masks obtained from the pre-classification process. The overall accuracy achieved has reached approximately 70%, and Kappa index of agreement 0.64. OBIA technique is an effective tool for land use/land cover classification from VHRS data in rural areas aimed at land use planning, land use monitoring and ultimately for increasing the quality of life in rural societies.

INTRODUCTION

It is obvious that Thailand is an agricultural country; rice is the main food staple, for domestic consumption and export to several countries. The administrative boundaries are divided into 4 parts, the North, the Northeast, the Central and the South. The Northeast is the largest area, having an area of 170,266 square kilometers, comprising 20 provinces and 22 million population (Entwisle, Walsh, Rindfuss, & VanWey, 2005). The area is a large saucer-shaped plateau (the 'Khorat Plateau') bordered to the north and east by the Mekong river, and to the south and west by the Phnom Damrek and Phetchabun mountains respectively (Rigg & Ritchie, 2002). The majority of people are living in rural areas (Jonathan, 2006). The economy of the plateau is agriculturally based with 80 % of the population employed in the agricultural sector. Since livestock have increasingly demanded in European countries; forest areas have been cleared in order to extend cassava plantation areas (Vanwambeke, Somboon, & Lambin, 2007). The land use pattern in the rural area is related to several aspects, such as environmental ecology, social ecology and human ecology. The villages typically appear as forest patches due to the cultural practice of leaving trees in the village settlement areas (Kelley A, 2004). In order to understand rural settlement and land use, spatial relations, settlement forms and its distributions need to be analyzed for political planning and management of land use policy. When a new village is established, a village cluster is created composed of houses, vegetable gardens and public areas (Entwisle, et al., 2005). Presently, several technologies can incorporate the essential data for rural study through satellite products. It is obvious that there are two techniques to analyze remotely sensed data; pixel based and object based image analysis. The traditional pixel based classification approach is treating each image pixel individually without regard to its location in the image. Therefore, it is not a satisfactory approach for at least two reasons: (1) the context information of a pixel (its neighborhood) is ignored; (2) the pixel is not considered to be a “natural” element, or a true geographical object of an image scene (Marcal, Rodrigues, & Cunha, 2010). Pixel based classification includes two methods, namely supervised and unsupervised classification both depending on spectral statistics of pixels such as Maximum Likelihood Classifier (MLC). MLC was limited by utilizing spectral information only without considering contextual information (Li, Gu, Han, & Yang, 2010). Conversely, OBIA employs several classification methods allowing users to define a rule set for classification, including knowledge based criteria, image thresholds and spatial relations among the image objects (Blaschke, Lang & Hay, 2008). Image objects are created by image segmentation algorithms at the initial step prior to classification, which is the subdivision of an image into separated regions (Benz, Hofmann, Willhauck, Lingenfelder, & Heynen, 2004). The cells of a raster are grouped into objects through image segmentation in such a way that the incorporated heterogeneity is minimized and homogeneity is maximized. Heterogeneity refers to value and shape, the primary object features (Dragut, Eisank, & Strasser, 2011). Image objects will have been merging into larger objects based upon a rule-set not only at the same level but also between different image object levels (Benz, et al., 2004). In conclusion, the main objective of this paper is that is to extract rural land use and land cover relative to its form (shape) by applying object oriented image analysis. The demonstration area is at Srabua cultural settlement village in Mahasarakham province. The settlement shapes are also mainly objective of next stage of analysis covered whole area of Nadoon district. There are approximately 85 villages to be analyzed with transferability of the rule-set from this paper to the future work.

METHODS

The study area focuses on the cultural settlement called Srabua village, Nadoon district, Mahasarakham Province (Figure 1). It is located at 16°11′ to 16 18′N and 103°17′ to 103 29′ E (Fig 1). The Chi River flows northeast to southwest through the site. The climate of the area is that of a tropical savanna. The rainy season is from May to October, and the dry season is usually from November to April. The mean annual rainfall is about 1,200 mm (Wester & Yongvanit, 2005). Most agricultural areas in the region are typically rain-based. Some drought-resistant crops are cultivated especially cassava which is considered to be low maintenance since it requires neither irrigation nor frequent tending (Kelley A, 2004). The study area is known as the cultural settlement with the province being the former site of the ancient Dvaravati city of Nakhon Champa Si, Nadoon district. The Northeast has been occupied by the Khamer Angkorian empire during the King Jayaworaman VII since 17 B.C. (Welch, 1998). Based on excavation evidences and existing literatures indicated that the majority of people were usually immigrant from the surrounding areas such as Surin, Roi-et, Kalasin and another part of Mahasarakham province. Welch (1998) notes that the area has been explored by archeologists since 1971. From archaeological excavation, they found that there were the precious antiques such as pagodas, Buddha churches and Buddha images, which linked to the highest admiration for Buddhism in this region. Based upon the Khamer Angkorian empire, there are ancient temples were built in the period. In Nadoon district, there are at least 6 places have known as the ancient sites, a few places have been registered as the historical preservation. Remotely sensed data have indicated that there are more abundant forest areas than other districts, mixed with paddy rice and drought resistant crops such as cassava and sugarcane (Pendleton, 1943). The settlement patterns of the Northeast villages are the clustered settlement. They often built their houses on the upper terraces; thus, sizes of villages are depending on sizes and shapes of empty space areas. In addition Pendleton (1943) argue that the settlement pattern in the Northeast is clustered with dense houses. Robinson (1965) and Vanwambeke (2007) note that there are 5 factors for settlement site selection, such as water supply, farming land, defense possibility, dry land and shelter.

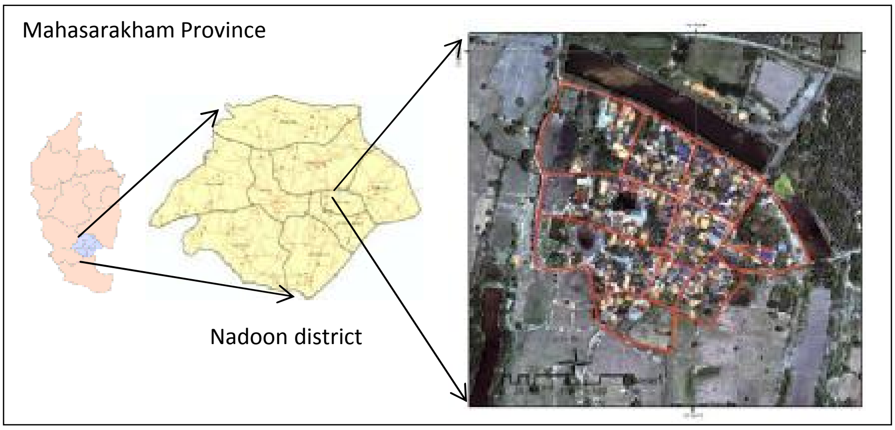


Figure 1: The study area

Remotely sensed imagery

Quick Bird multi-spectral images were used in this research, partially covering Nadoon district, Maha sarakham province, with spatial resolution of 2.44 meters consisting of Blue, Green, Red and NIR bands, acquired on March 8, 2008 (Table 1). The data are supported by Geo-Informatics and Space Technology Development Agency (Public Organization), Thailand. 14 vector layers with scale of 1:50,000 were used as reference information at local scale, especially the transportation network linkage among villages in the area. Moreover, the sub-scene of GDEM 30, which available downloads for free of cost via the Internet, was also used in this study as ancillary data aiming at differentiating the land use based on its elevation.

Table 1: The details of data collection

Sensor/Ancillary	Mode/Feature Type	Bands	Spectral Range	Scene Size (Pixels)	Pixel Resolution/Scale
		1 = Blue	450-520 nm		2.44x2.44 m.
Quick Bird 2	Multi-spectral	2 = Green	520-600 nm	2280x2429	2.44x2.44 m.
		3 = Red	630-690 nm		2.44x2.44 m.
		4 = NIR	760-900 nm		2.44x2.44 m.
	Panchromatic		445-900 nm	2280x2429	0.60 m.
GDEM 30	Raster			2280x2429	30 m.
Road network	Vector				1:50,000
Land use map	Vector				1:50,000

Classification

As mentioned above, the object-based approach was used in this study. The heterogeneous pixel values of the sub-scene of pan-sharpened image was segmented into image objects using Chessboard and Multi-resolution segmentation algorithms, implemented in eCognition (Trimble Geospatial) for creating the mask area (Laliberte, Fredrickson, & Rango, 2007). The pan–sharpened color bands with spatial resolution of 0.6 m. do not involve additional information but have proved to be advantageous in the subsequent segmentation step compared to multispectral and panchromatic bands in their original spatial resolution (Niemeyer, Marpu, & Nussbaum, 2008). The image hierarchies are divided into 3 levels representing homogeneous objects related to Land-use/Land-cover classes derived from the rule-set of the classification. In order to create an Area of interest (AOI) and Non-AOI, the mask of residential area was delineated by including the village road into the segmentation process as thematic layer. The image was then segmented into image objects under AOI by using the chessboard segmentation algorithm with larger object size. In addition, the topographic layer (GDEM30) was also involved in this process aimed at discriminating Land use/Land cover classes by the difference in their elevation. Image objects are characterized with mean NIR, NDVI and ratio Green. Thus, similar features in the image objects might be classified as backyards or herb gardens if those objects are included in residential area, whereas in Non-AOI would be recognized as other land uses, for example, orchards or plantation areas when NDVI feature was utilized with the same fuzzy range. On Level 2 (Analysis level) was segmented by using multi-resolution segmentation algorithm by its relation to super objects (Mori, Hirose, Akamatsu, & Li, 2004). This level refers to land use and land cover in both residential and non-residential area. It was separated into two processes with two scale parameters directly related to sub-objects (i.e., AOI/Non-AOI). The AOI area was segmented by using multiresolution segmentation with scale parameter = 20 and shape = 0.8 compactness = 0.8. At Non-AOI, the multiresolution segmentation was used with scale parameter = 80 and shape = 0.1 and compactness = 0.5 with classes related to sub-object with Non-AOI mask area at the lower level. The AOI mask are using for the classification of land-use/land-cover only in the residential area and village forms representation. The object features have been incorporated into the classification schema including spectral information, contextual information and spatial relations. An image band arithmetic, for instance, image bands ratio derived from spectral information (Lackner & Conway, 2008) is used for vegetation classification by applying the NIR and Red bands to generate the threshold. The NIR band is used for generating NDVI thresholds aiming at increasing the accuracy of vegetation vs. water area classification. Vegetation class consists of 2 classes, dense and sparse trees, which can be discriminated by the threshold ranging. The membership function of the vegetation class is greater than 0.3. The NDVI was not only used for vegetation classification but also applied for water bodies classification. All classes on this level have been classified using class description and membership function obtained directly from the image objects. Since Wester and Yongvanit (2005) illustrated the big picture of land use/ land cover cross section in the Northeast; therefore, this technique could easily be interpreted land use surrounding the village, this method was also implemented in Takahashi and Hara (2011). They described the land use relative to topographical and geomorphological variation. Due to the fact that some land use classes are located at a different elevation compared to neighboring objects, for example, a residential area should be at higher area than other land use such as paddy fields. It is clear that paddy fields in NE-Thailand are wet-paddy rice cultivation. It needs more water at the early state of growing season. It is usually rain-based agriculture dominated by earthen ridges designed for water logging in the growing season. Although in a harvest period, earthen rides are more likely permanently used for retaining water for the next growing season. In this case, the sub-scene of GDEM 30 was used as ancillary data at initial step of the analysis, i.e. incorporated to image segmentation process. It was classified as topographic layer in order to employ the classes relevant to sub-objects and neighboring objects at differ elevation. There were 3 classes of elevation layer derived from GDEM 30; high land moderate land and low land with elevation ranging from 127-175 m.a.s.l (Dehvari & Heck, 2009). Vegetation is comprised of 2 sub-hierarchical classes (dense tree and sparse tree); while some grassland is classified as miscellaneous land use. Most of the sub-classes have inherited of NDVI [1] threshold from its parent level with the fuzzy function are between 0.25-0.7 (Pu, Landry, & Yu, 2011). Dense tree inherited the NDVI value was that greater than 0.4. Then, band ratios of NDWI (Normalize difference water index) was calculated for water bodies classification (Karydas & Gitas, 2011). Roof areas were also classified by contextual information, such as size, shape, area, etc. Internal and border roads are obtained from applying thematic layer into segmentation process. The border roads were used for classification the settlement area based on existing transportation network in the village. Chessboard algorithm used for creating the polygon in order to represent the village area and settlement form. Most of houses/buildings in the village are always located along the road. Therefore, internal roads are the crucial feature for building classification by particular distances from its objects to the border of roads. Because of road is the single line; therefore, overlay with the high-resolution remote sensing imagery does not perfectly fit to road width. In order to solve the problem, vector layer was extended to the same size of the reality feature by applying pixel-base object resizing algorithm (growing mode). Water bodies were also classified by NDWI threshold [2] (Dupuy, Herbreteau, Feyfant, Morand, & Tran, 2012; Yu, Cheng, Ge, & Lu, 2011). By visual interpretation, water areas indicated in dark objects. Thus, brightness values could be helpful to calibrate classified objects.

$$NDVI = \frac{\rho\text{NIR}-\rho\text{RED}}{\rho\text{NIR}+\rho\text{RED}} \qquad (1)$$

$$NDWI = \frac{\rho\text{Green}-\rho\text{NIR}}{\rho\text{Green}+\rho\text{NIR}} \qquad (2)$$

Bare land is identified from brightness threshold condition, which correspondent to bright objects and SAVI threshold [3]. This land use class is generally adjacent to houses or backyards. It is used for specific purposes, including private and public activities of villagers. The Soil-Adjusted Vegetation Index (SAVI) is a vegetation index that attempts to minimize soil brightness influences using a soil-brightness correction factor (Aguilar, Vicente, Aguilar, Fernández, & Saldaña, 2012). This is often used in arid regions where vegetative cover is low, which should suitable for bare land classification. NIR and Red are the bands associated with those wavelengths. The L value varies depending on the amount of green vegetative cover. Generally, in areas with no green vegetation cover, L=1; in areas of moderate green vegetative cover, L=0.5; and in areas with very high vegetation cover, L=0 (which is equivalent to the NDVI method). This index outputs values between -1.0 and 1.0. In order to get good results, SAVI threshold are being used for bare land refinement.

$$SAVI = \frac{\rho\text{NIR}-\rho\text{RED}}{\rho\text{NIR}+\rho\text{RED}+\text{L}} x\ (1+L) \quad (3)$$

Furthermore, on Non-AOI area comprised 4 classes; field crop, paddy rice, vegetation and water body. Field corps and paddy rice are the sub-group of agricultural area or arable land. Both classes were classified by mean of GDEM

30. Paddy fields were classified by mean of GDEM30 by value less than 149 m.a.s.l whereas field crops were classified with the same of those value, but mean of GDEM 30 are greater than 149. In addition, texture-based features (GLCM Homogeneity NIR all dir.) were applied for paddy field refinement. The idea behind this is that the texture of paddy fields often is smoother than field crops, even if it is at a similar elevation. Nevertheless, the cultivation season should be taken into account because of vegetation availability of those areas resulted in texture-base feature reliability. Water bodies and vegetation areas were classified by the criterion as same as used on AOI level. The 3rd level refers to the residential area (topmost level), which knows its lower level neighborhood related to the lower image objects level. All of classified classes in this level were merged together into one object; therefore, the village shape can be illustrated in irregular shape. The village shapes can automatically be interpreted into particular settlement types from a developing rule-set depending on shape learning features, such as roundness, compactness, rectangular fit and so on. These threshold conditions are often related to physically shape of a village, namely, nuclear, clustered, round and dispersed village. This method will be discussed in the next paper.

Table 2: Feature used for the classification

Classes	Feature used	Sources
AOI, Non-AOI		
Area of Interest (AOI)		
Water	NDWI, Area, Brightness	(Dupuy, et al., 2012; Yu, et al., 2011)
Vegetation	NDVI, Mean NIR, Standard deviation NIR	
Road	Thematic layer	
Brightness object	Brightness, SAVI, Existence of super objects	(Aguilar, et al., 2012)
Bare land	Brightness, Existence of super objects, Relations to neighbor objects	
Other	Unclassified, NDVI, Existence of super objects	
Roofs	Unclassified, Existence of super objects, Mean NIR, Rectangular fit	(Aldred & Wang, 2011; Hu & Weng, 2010)
Non-AOI		
Water	Unclassified, Brightness, NDVI	
Vegetation	Unclassified, NDVI	
Agricultural area		
- Paddy field	Unclassified, Grass, Mean GDEM 30, GLCM Homogeneity NIR (all dir.)	(Aguilar, et al., 2012; Dehvari & Heck, 2009; Pu, et al., 2011)
- Field crop	Unclassified, Grass, Mean GDEM 30	(Hofmann, 2001)
Residential Area	Existence of sub objects	

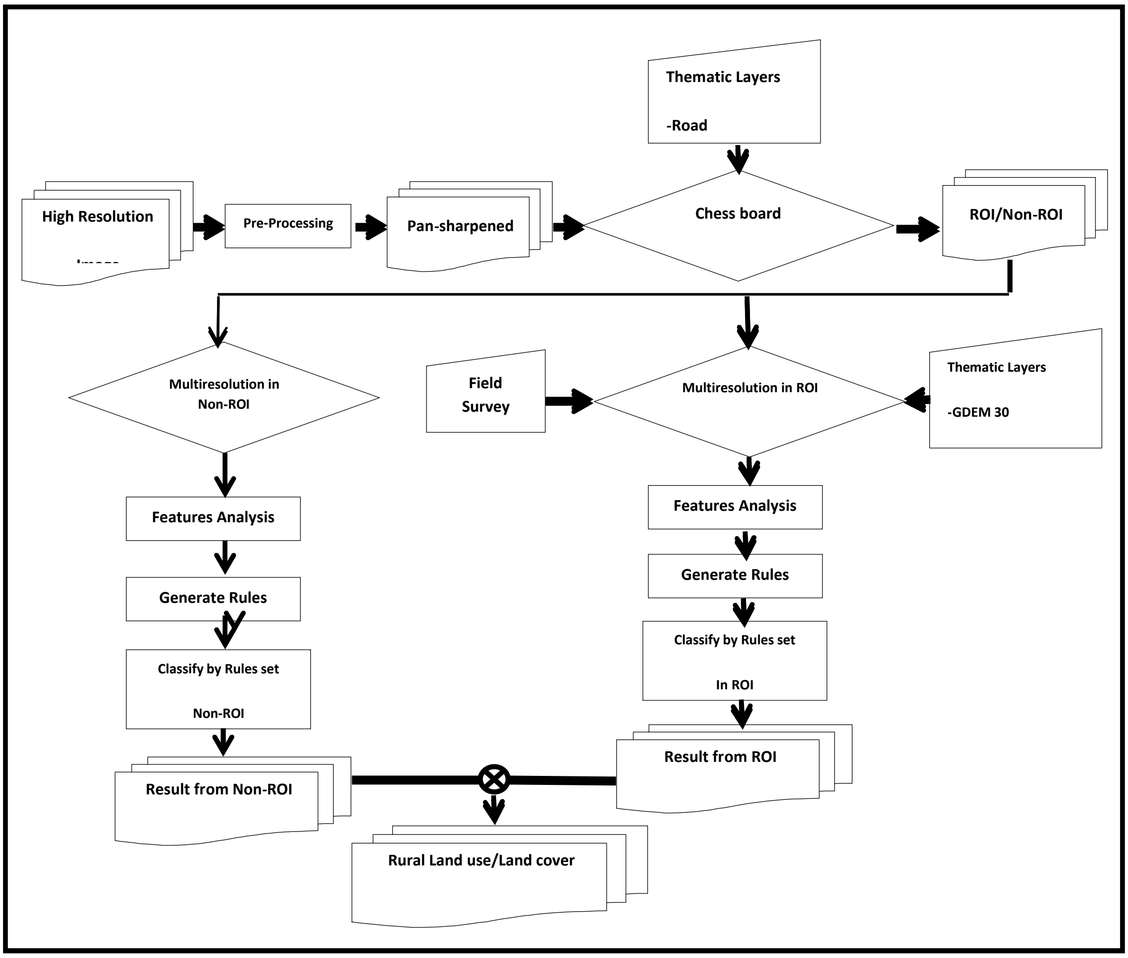
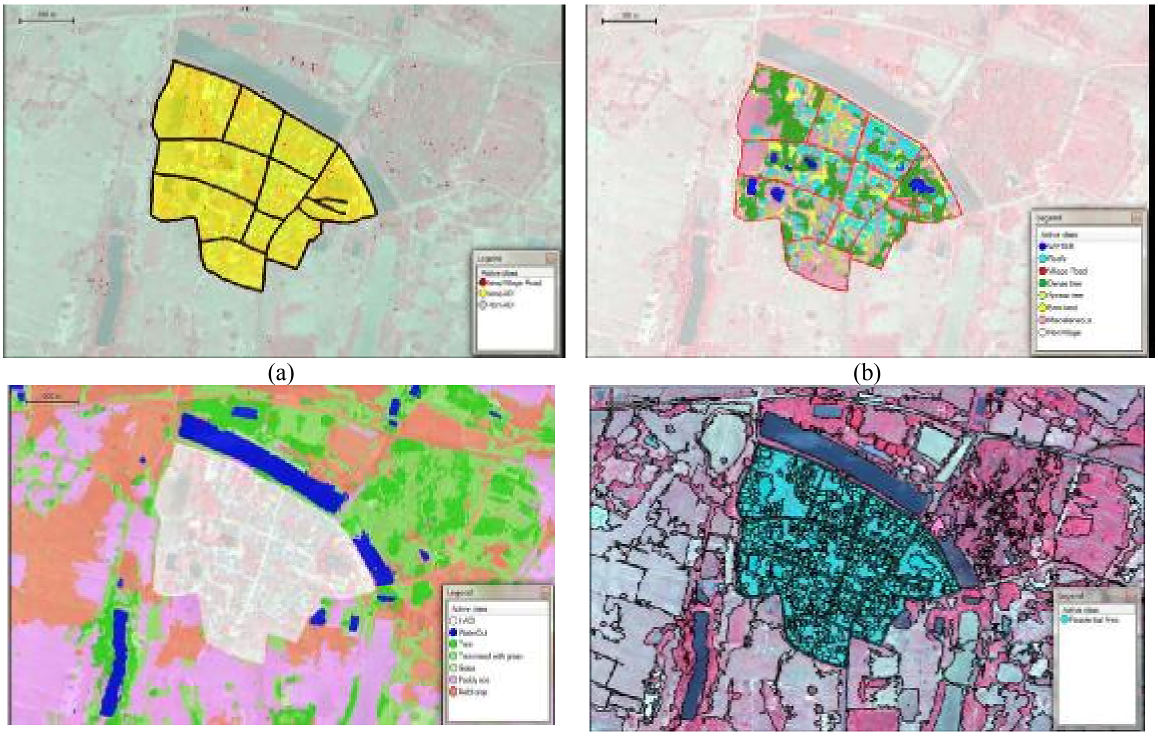


Figure 4: Schematic diagram of the analysis

RESULTS

From all processes mentioned above, the residential area components were extracted by using an object-based approach based on its shape. Fig. 6(a) shows village shape object as a polygon feature. The polygon areas are individual segments. These segments are being used for each block analysis. Land use under the AOI is classified into 7 classes, such as water body, roof, road, dense tree, sparse tree, bare land and mixed area. Village components are consist of at least 3 surrounding factors such as houses, vegetation garden and road network. On the 2nd level was aimed at land use classification (Fig 6b) under the AOI area. There are 900 objects classified as roofs; 1,461 objects as water bodies, 15,435 objects as dense tree, 3757 objects as sparse tree, 464 objects as bare land and 1,012 objects as mixed area. Only dense tree is classified with 89% of producer ´s accuracy. Fig. 6c shows that agricultural areas surrounded the village. The lower areas have been used for rice cultivation and upper land used for field crops. The results indicated that the agricultural areas mixed by vegetation areas and water bodies. The 3th level aims at representing village form (Fig 6d). All objects on this level are grouped into one object for village forms analysis.



(a) (b)

(c) (d)

Figure 6: Classification results; (a) AOI and Non-AOI, (b) LU/LCC at AOI level, (c) LU/LCC at Non-AOI Level and (d) Residential area at the Top most level

ACCURACY ASSESSMENT

To improve the classification results, the ground truth of reference points crated from ArcGIS by visual interpretation have been used as TTA (Test and Training Area) mask for creating error matrix. It was approximately 30 points/class, 221 point in total. In order to perform accuracy assessment in eCognition; the reference points have been exported from vector into raster format. It was then imported into eCognition as TTA mask. The evaluation has been done in only the residential area with the 6 out of 7 classes of land use. The road class was not evaluated because of it was directly classified from the thematic layer. The error matrix indicated that the classification result was statistically significant at the 70% of overall accuracy, and with 0.64 of Kappa Index of Agreement (Table 3).

Table 3: Error matrix derived from the TTA

	Water Ref.	**Roofs Ref.**	**Dense tree Ref.**	**Sparse tree Ref.**	**Bare land Ref.**	**Miscellaneous Ref.**	**Total**	**%**
Water	20	2	0	0	0	0	22	95.2
Roofs	0	44	1	0	3	0	48	66.6
Dense tree	0	1	25	4	3	8	41	89.2
Sprase tree	0	2	2	14	3	5	26	66.6
Bare land	0	11	0	0	30	1	42	62.5
Miscellaneous	1	6	0	3	5	23	38	62.1
Total	21	66	28	21	48	37	**221**	
%	90.9	91.6	60.9	53.8	71.4	60.5		
Overall Accuracy	0.70							
KIA	0.64							

DISCUSSION

It is clear that an object-based image analysis approach is suitable for VHRS imagery classification. It allows creating image objects from those similar pixels by using appropriate algorithms. By using traditional classification methods, the result might not be satisfactory due to several reasons. In this paper, the algorithms are being used for particular purposes that depend on spatial characteristics of the study area. Prior to classification, field survey has been done in order to data gather both for geo-referencing and ground truth. It is known that land use/land cover in NE-Thailand has its own characteristics based on water availability and utilization. Agricultural areas such as paddy fields, field crops, etc., are typically surrounding a residential area in rural communities. In order to conserve water in paddy fields; farmers usually construct earthen ridges. These can be seen on some remotely sensed data as a rectangular form. On the other hand, some field crops such as sugar cane or cassava do not need to retain water in their fields. These crops always are allocated at up-land. With these patterns, the image can be classified by shape-based analysis, including geographical properties and shape objects related to land use. On level 1, the classification procedure is based upon spectral information from vegetation and water bodies classes are based on NDVI thresholds. In addition, spatial relations are also considered in the classification procedures. These precisely make sense of real world related to each other such as when a village needs to be constructed, including the transportation network not only in the village itself but also connecting villages and the market places for trading agricultural products. The spatial information has been used in the classification process for the description of relations for each land use class to its neighbors, rather than using only spectral information. A village usually consists of vegetation area, internal road, house or area of houses, bare land; while non-village area is representing the surrounding land use used for villagers' subsistence.

CONCLUSIONS AND RECOMMENDATIONS

This study proposed an object-based land use/land cover classification based on shapes, forms and geographical data by demonstration in Srabua cultural settlement village, Northeast, Thailand. First of all, the image objects have been created by using multiresolution segmentation algorithm based on homogeneity criteria of similar pixels integrated in eCognition version 8.7 (Trimble Geospatial). The image object levels were divided into 3 levels, AOI/Non-AOI level (L1), Analysis level (L2) and Residential level (L3). The 1st level aims at creating a mask area, whereas the 2nd level represents village land use/land cover classification. The 3th level was prepared for village form classification, which each image objects known its neighboring objects at image object levels, for instance relations to neighbor objects can be evaluated by class relates to sub-objects. By applying object-based techniques; it is no doubt that this method clearly shows classification results, which are highly satisfactory. The workflow allows the integration of some advance features related to reality of the analytical area such as contextual, textural and spatial information, which cannot be performed in any other software. In addition, the thematic data such as the road network was also used in the segmentation process in order to discriminate the spectral variances of internal and border roads of the village. In order to exceed the optimum results; the process was improved by utilizing of GDEM30 to be the thematic layer. By using this data, however, its resolution is too coarse with 30x30 meters compared with 0.6x0.6 meters of image resolution. The classification of any further steps relevant to its elevation should be based on fine-scale near to image pixel size. Moreover, the exactly polygon boundaries of villages might be crucial for discriminating the connected areas between villages. Unfortunately, these are no longer available from any local government organization in the region. Therefore, the border of the village used this study, was derived from road network, not from administrative boundary. By visual interpretation, the village form is clustered or nuclear with dense dwelling. It simply expresses that village forms are based on the shapes and sizes of the existing upper land. Hence, pattern of settlements in Northeast are differ from other areas. For the future work plan, all of 85 villages in Nadoon district will analyze with the same techniques and some complexities will be identified, classified and, if possible, explained. Village shapes and forms will be figured out by shape-based classification and landscape matrix analysis throughout the region.

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