URBAN LAND USE MAPPING BASED ON OBJECT-BASED IMAGE ANALYSIS USING WORLDVIEW-3 SATELLITE IMAGERY

Kanoksuk Chankon, Sanwit Iabchoon, Sangdao Wongsai
Andaman Environmental Research and Innovation Center, Faculty of Technology and Environment, Prince of Songkla University, Phuket Campus, Kathu, Phuket 83120 Thailand
Email: sming.gt@gmail.com

KEYWORDS: OBIA, LULC, WorldView-3, Rules set, Image segmentation

ABSTRACT: Land Use and Land Cover (LULC) data are important to monitor and assess environmental change. LULC classification using satellite images is a method widely used on a global and local scale especially, in urban areas that have various land cover types that are important components of the urban landscape and ecosystem. The objectives of this study aim to classify urban land use using WorldView-3 very high spatial resolution satellite imagery and the Object-Based Image Analysis (OBIA) method. A decision rule set was applied to classify the WorldView-3 images in Kathu sub-district, Phuket province, Thailand. The main steps were as follows: (1) the image was orthorectified with ground control points and using the Digital Elevation Model (DEM), (2) multi-scale image segmentation was applied to divide the pixel image to image object level, (3) development of the rules set for LULC classification using spectral bands, spectral indices, spatial and contextual information and (4) accuracy assessment was made using testing data which sampled using statistical random sampling. The results show that six classes (vegetation, grass, water, road, open space, built-up area) were been successfully classified with overall classification accuracy of 87.61% and a Kappa coefficient of 0.84. In terms of producer's accuracy, we achieved more than 85% accuracy for water, vegetation, grass and built-up area. Open space and road is still fairly difficult to identify.

1. INTRODUCTION

The need for studies of urban areas is important to guide more efficient city planning policies. This need has increased in the context of recent massive urban sprawl, adverse effects on natural and human systems at global and local scales. Worsening conditions of crowding, insufficient public utility, and increasing urban climatological and ecological problems require consistent monitoring of urban regions (Thapa and Murayama, 2009). One of the most basic data for urban planning is based on the Land Use and Land Cover (LULC) map of an urban area. For example, in a study of urbanization effects on rainfall-runoff and urban expansion, the LULC map is generally accepted as a basic need for assessing this problem (Dams et al., 2013; Verbeiren et al., 2013). An up-to-date LULC map can be obtained most efficiently with support of remote sensing data.

Recent advances in remote sensing technologies and the increasing availability of high-resolution earth observation satellite data provide great potential for acquiring detailed spatial information. Despite advances in satellite imaging technology, computer-assisted image classification is still unable to produce land use and land cover maps and statistics with high enough accuracy (Lo and Choi, 2004). Nevertheless, automated classification procedures of satellite imagery have been based mainly on multi-spectral classification techniques (pixel-based classifiers). These procedures assign a pixel to a class by considering its statistical similarities, in terms of reflectance, with respect to a set of classes (Gong et al., 1992). The pixel-based classification approach provides an automated platform for image analysis, mainly based on surface reflectance and generally ignoring basic land cover characteristics (i.e., shape and size) of landforms (Chust et al., 2004) and but still faces some limitations. Satellite images of urban areas form complex mosaic pixels of trees, grass, roofs, bare land, concrete, and asphalt: such a complex urban features generate mixed pixel problems.

Recently, the WorldView-3 satellite was successfully launched in 2014. It is a high spatial resolution remote sensing platform with eight spectral bands covering a wavelength range from 400 nm to 1,040 nm. According to its designers, the new additional Coastal, Yellow, Red-Edge and Near-IR2 bands can provide an increase in classification accuracy (Carvalho et al., 2012; Zhou et al., 2012; Shahi et al., 2015). With the WorldView-3, imagery provides an effective combination of spectral resolution of eight bands and a very high spatial resolution of 0.5 m. This combination of fine spatial and spectral resolutions has presented new opportunities for detailed classifications of urban land use. The high-resolution satellite images and object-oriented image classification has been successfully used for urban mapping in China and Canada (Kong et al., 2006; Lackner and Conway, 2008). The object-based image analysis approach, based on very high spatial resolution data, is advantageous for most urban remote sensing applications. Widely used classification methods for urban region such as Object-Based Image Analysis (OBIA) should be selected for such studies to allow for comparisons with similar studies elsewhere. The purpose of this study was to classify land use in a mixed urban/rural area of Thailand using Object-Based Image Analysis (OBIA) techniques.

2. STUDY AREA AND DATA

This study was carried out on a WorldView-3 (WV-3) image within the Khatu sub-district, Phuket province,Thailand. Khatu sub-district is located between 98°18′ E- 98° 22′ E and 7° 52′ N - 7° 57′ N and it was chosen as the study area because it was a small easily defined watershed with a mixed urban and rural environment and representative of the type of development on Phuket (Figure 1). This region, covering an area of approximately 36.04 square kilometers with a basin-like landform with surrounding hills. Khatu sub-district is a small sized city in Phuket with over 10 thousand inhabitants. The main visible land cover in this area is composed of green area as natural vegetation, some rubber plantation areas, golf courses, a university campus, water bodies (reservoirs and water-filled former open cut tin mines), built-up areas, streets and open space (or bare land), where roofs, streets and built-up surfaces are made of different construction materials such as asbestos roofing, asphalt and concrete. These urban objects are frequently spatially arranged in a dense and complex pattern. Moreover, despite having similar colorations, these objects have very different physical properties. Table 1 lists the specification of the WorldView-3 satellite image.

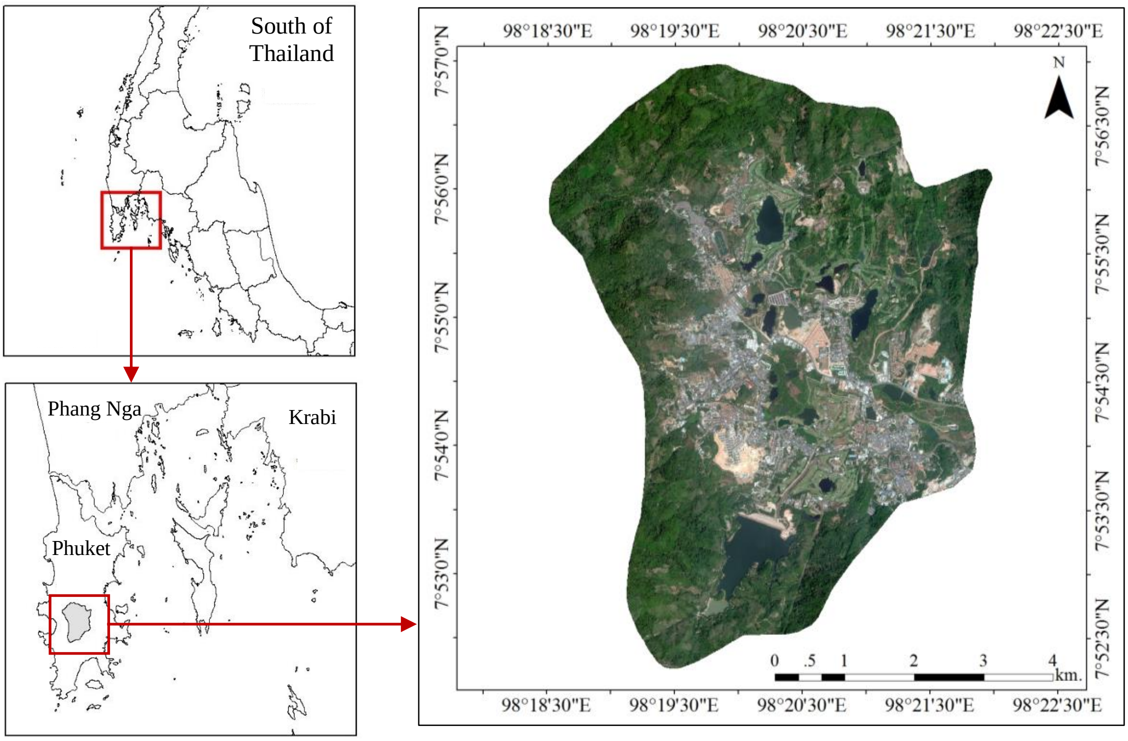

Figure 1. Location of study area and WorldView-3 image with true color composite.

Table 1. Specification of WorldView-3 satellite image (DigitalGlobe, 2014).

Satellite	WorldView-3
Data Acquisition	11 February 2015
Spectral Resolution	Panchromatic: 450 - 800 nm
	8 Multispectral: -Coastal: 400 - 450 nm , -Red: 630 - 690 nm -Blue: 450 - 510 nm, -Red Edge: 705 - 745 nm -Green: 510 - 580 nm, -Near-IR1: 770 - 895 nm -Yellow: 585 - 625 nm, -Near-IR2: 860 - 1040 nm
Spatial Resolution	Panchromatic: 0.5 m
	Multispectral: 2.0 m
Radiometric Resolution	11-bits per pixel

3. METHODOLOGY

In this study, a multi-scale object based hierarchical classification was performed, which models the image region at different scales of objects starting from vegetation and water cover at the first non-complicated scale to individual built-up area as the most complicated scale. In our study, we were interested in six land use classes including vegetation, grass, water, road, open space and built-up areas. To classify land use there were four main steps; data preprocessing, customized features, object based hierarchical classification and accuracy assessment as described below.

3.1 Data Preprocessing

The WV-3 multispectral (MS) image with eight bands was orthorectified based on reference data including ground control points acquired by survey using a global positioning system receiver distributed by the Geo-Informatics and Space Technology Development Agency (Thai Public Organization), ortho-image map with a scale of 1:4000 and a 5-meter Digital Elevation Model distributed by the Ministry of Agriculture and Cooperation. The geo-referencing was determined based on the Universal Transverse Mercator and World Geodetic System 1984 Zone 47 North. Acceptable root mean square error (RMSE) is less than one pixel or less than 2 meters.

3.2 Customized Features

In this study, four spectral indices were used to develop a rule set in conjunction with spatial and contextual information composed of homogeneity, contrast, shape, geometry, and class-related features. The definitions of the spectral parameters and their calculation formulae are presented below;

Normalized difference vegetation index (NDVI) created based on band 7 and band 5 of WV-3 MS data (Zhou et al., 2012):

$$NDVI = (B7_{near\text{-}IR1} - B5_{red}) / (B7_{near\text{-}IR1} + B5_{red}) \qquad \text{(Equations 1)}$$

Normalized difference water index (NDWI) created based on band 3 and band 8 of WV-3 MS data (Belgiu et al., 2014):

$$NDWI = (B3_{green} - B8_{near\text{-}IR2}) / (B3_{green} + B8_{near\text{-}IR2}) \qquad \text{(Equations 2)}$$

Normalized difference bare soil index (NDBSI) was created based on band 1 and band 2 of WV-3 MS data. This is a new criterion based on the new spectral bands now available based upon previous work by Zhou et al. (2012) before bands 1 was available on the WorldView-3 satellite (2014):

$$NDBSI = (B2_{blue} - B1_{coastal}) / (B2_{blue} + B1_{coastal}) \qquad \text{(Equations 3)}$$

And Built-up Area Index (BAI) created based on band 2 and band 7 of WV-3 MS data (Shahi et al., 2015). The formula is as follows:

$$BAI = (B2_{blue} - B7_{near\text{-}IR1}) / (B2_{blue} + B7_{near\text{-}IR1}) \qquad \text{(Equations 4)}$$

3.3 Object Based Hierarchical Classification

To begin object-based image analysis, the first important step is image segmentation, in order to take complete advantage of both spatial and spectral information. This step is used to divide a pixel image or group of pixel images to image object level. An image object is defined as a group of contiguous pixels that share some similar characteristics (Definiens, 2007). The size of the segments is extremely dependent on the parameters of band weight, scale, shape/color and compactness/smoothness.

The WV-3 image was segmented with a multi-resolution segmentation algorithm. For segmenting the WV-3 imagery, all the eight bands were used. Based on a trial-and-error analysis, multi scale layers were created according to the patch size of the different land use classes. The parameters of the multi-resolution segmentation algorithm are defined in Table 2 below.

Band weight is the parameter used to define the boundary of an object, because some ground feature was clearly appearing in an image band. Consequently, band weight for each feature (coastal, blue, green etc) has consequences at each level of segmentation (1^{st}, 2^{nd}, 3^{rd}).

Table 2. Parameters of the multi-resolution segmentation

Segmentation order	Weight (coastal, blue, green, yellow, red, red edge, near-IR1, near-IR2)	Parameters		
		Scale	Shape	Compactness
1st	1, 1, 1, 2, 2, 1, 1, 1	30	0.1	0.5
2nd	1, 1, 1, 1, 1, 1, 1, 2	60	0.7	0.7
3rd	1, 0, 1, 2, 0, 1, 0, 0	40	0.7	0.9

At the first segmentation level of the hierarchical classification, there is a basic distinction between vegetation and non-vegetation, the normalized difference vegetation index (NDVI) was used as the basis for this basic distinction. After that, the feature threshold separated water and non-water (other land cover) by using the normalized difference water index (NDWI), developed by McFeeters (1996). Furthermore, we can distinguish grass from other vegetation by the threshold of the gray-level co-occurrence matrix (GLCM) of homogeneity. A road can be extracted by the threshold of thematic object attribute of road vector data and geometry features such as the length of the road object. Second and third segmentation focused on open space and built-up area on a different scale. Open space and built-up area can be distinguished using the normalized difference bare soil index (NDBSI), built-up area index (BAI), brightness, shape feature such as rectangular fit and class-related features such as distance and texture feature like GLCM of contrast.

This multi-scale object based hierarchical classification is useful to reduce the complexity of classification, which occurs in the subsequent classification levels. Nevertheless, the accuracy of classification at the final scale is also dependent on the accuracy of the previous scale because the errors may be propagated from the scale at one level down to the next scale level. Carefully selected scale and appropriate classifiers should be selected to reduce this impact. The decision rule set flowchart and all processes for classification of the urban land use in this study are given in Figure 2.

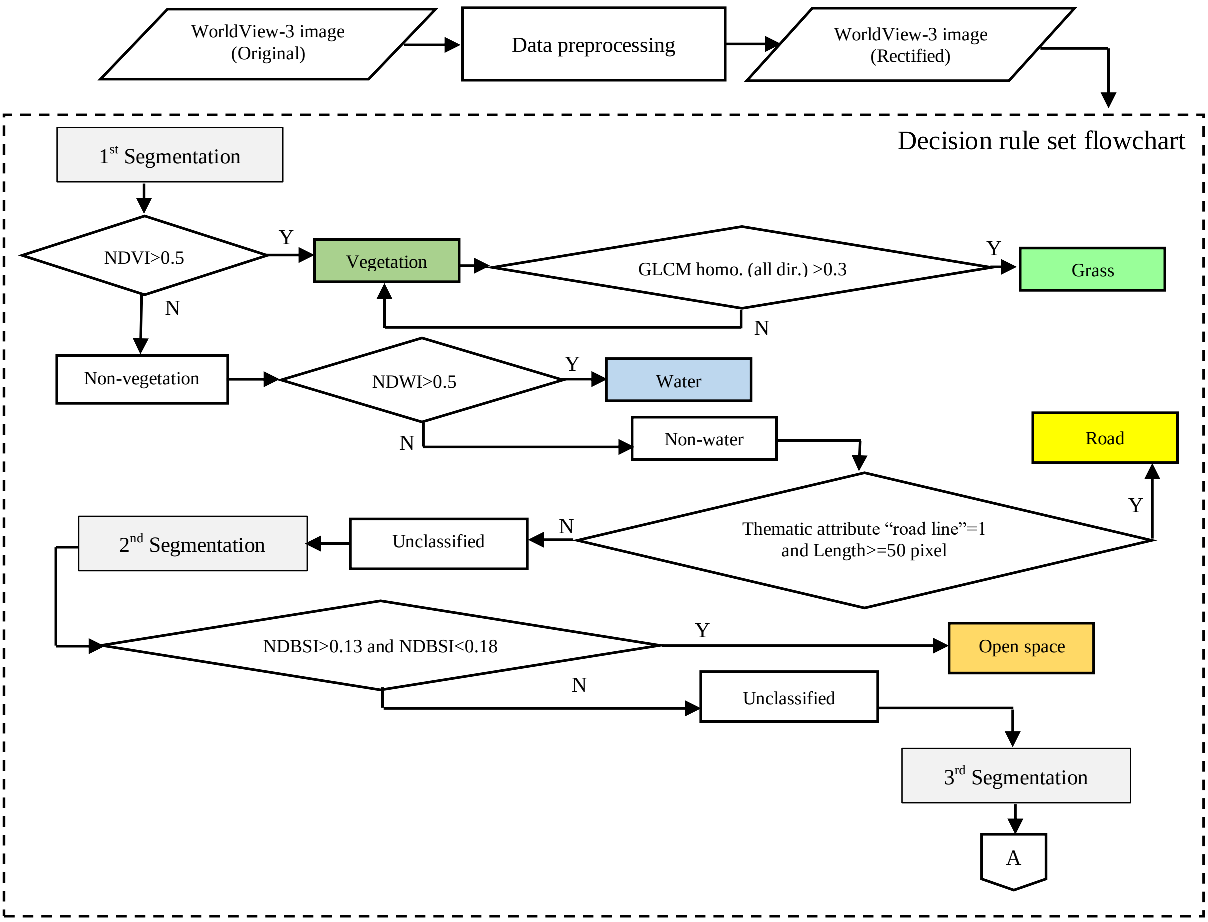

Figure 2. A flowchart of the decision rule set and all processes in this study.

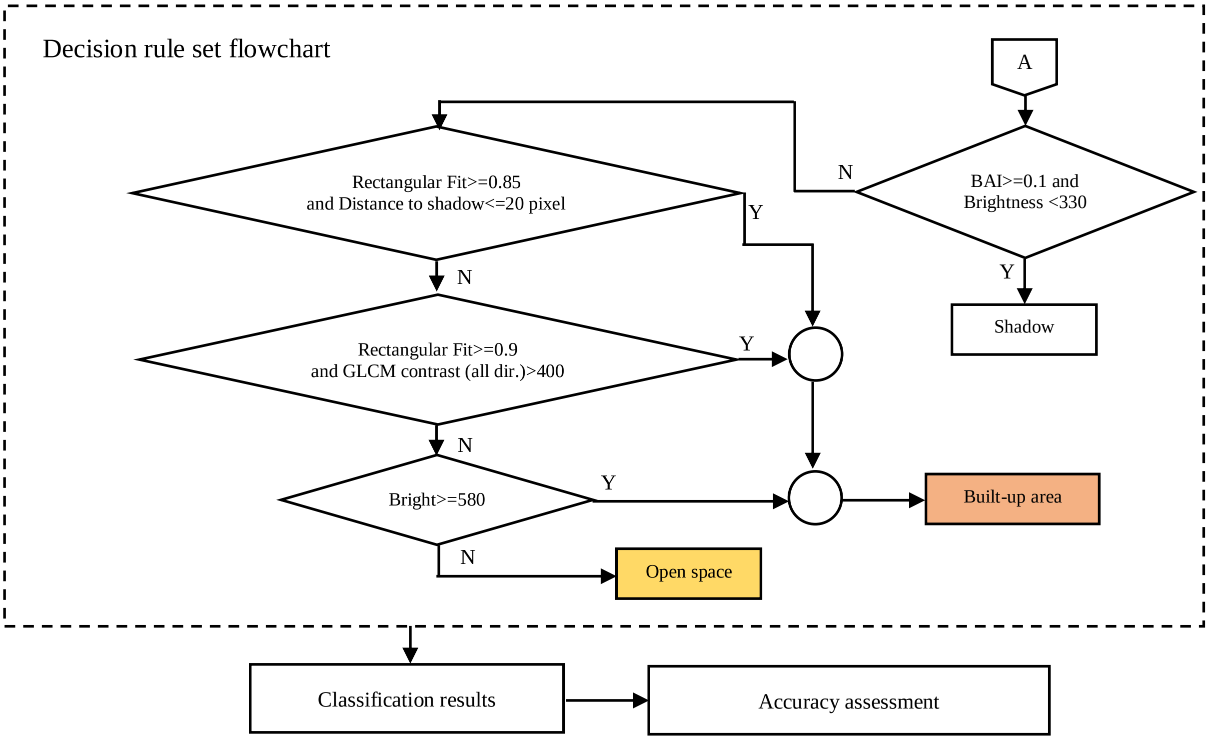

Figure 2. A flowchart of the decision rule set and all processes in this study. (Cont.)

3.4 Accuracy Assessment

Accuracy assessment is an important factor used to evaluate classification efficiency and usefulness of the output. It expresses the degree of correctness of the classification resulting from a comparison with the actual ground features (ground truth). In this study, the testing area was sampled by visualizing the combination of systematic and stratified random sampling methods, which distributes to cover in our study area and all classes of land use in this study.

4. RESULTS AND DISCUSSION

There are two types of results presented here. The first part shows a comparison of the image segmentation result in a different scale and parameters. The second part describes the accuracy assessments of object based hierarchical classifications.

4.1 Image Segmentation Results

The best image level segmentation was obtained for each observed object by experimentation to find the best composition of each segmentation parameter, First segmentation was the best composition to identify road, water body and vegetation including urban trees and grass (Figure 3a), second and third segmentation was used to classify built-up area and open space (Figure 3b and c).

(a) 1stsegmentation (b) 2ndsegmentation (c) 3rdsegmentation

Figure 3. Image segmentation result

4.2 Classification Result and Accuracy Assessment

According to early method that application of image segmentation and classification, the result of land use classified presented in Figure 4. Because shadow and dark object are not a real land use class. Therefore, we were reclassified shadow into built-up area later. The classification result shows that six land use classes include vegetation, grass, water, road, open space and built-up area are have been successfully classified and area of each land use classes is shown in Table 3 as below.

Table 3. Area of each land use classes.

Land use classes	Area (square kilometers)	Area (%)
Vegetation	24.66	68.42
Grass	0.95	2.64
Water	1.80	4.99
Road	0.65	1.80
Open space	2.00	5.55
Built-up area	5.98	16.59
Total	36.04	100

Accuracy assessment was made by comparing land use classification from object based hierarchical classification and samples of the testing area. It present to land use class specific producer and user's accuracy, overall accuracy and Kappa coefficient was successively computed after generating a confusion matrix. Classification accuracy is shown in Table 4.

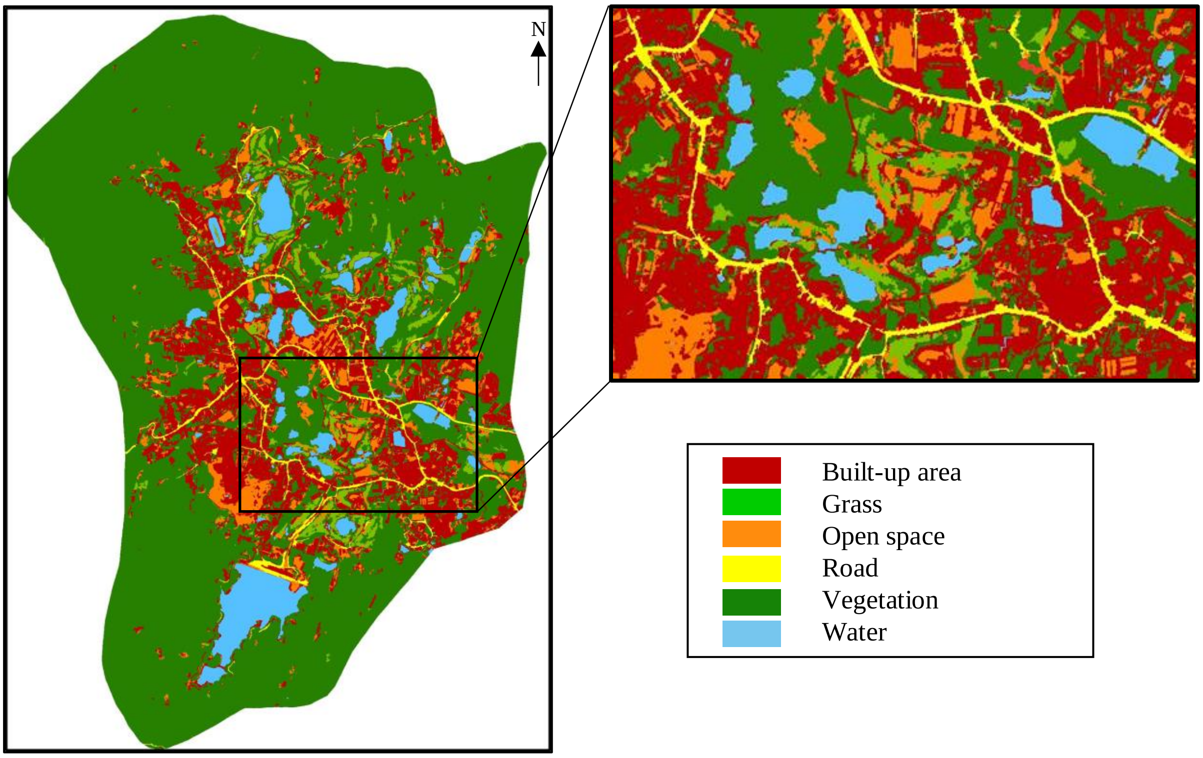

Figure 4. Land use classification result

The classification results show an overall accuracy of 87.61% and a Kappa coefficient of 0.84 (Table 4). Overall, there was more than 85% of classification accuracy are in terms of producer's accuracy for all of the different classes. For some classes, accuracy was essentially complete for four classes including water, vegetation, grass and built-up area with highest for water (99.5%).

Table 4. Confusion or error matrix of land use classification (classification accuracy).

Reference / Classified	Vegetation	Grass	Water	Road	Open Space	Built-up area	Total
Vegetation	**21,368**	568	0	196	1,650	323	24,105
Grass	194	**8,346**	0	0	0	0	8,540
Water	0	0	**37,408**	0	0	0	37,408
Road	0	0	0	**8,192**	510	69	8,771
Open space	0	232	0	424	**8,657**	491	9,804
Built-up area	192	105	187	2,080	5,593	**6,663**	14,820
Total	21,754	9251	37,595	10,892	16,410	7,546	103,448
Producer's acc. (%)	98.22	90.22	99.50	75.21	52.75	88.30	
User's acc. (%)	88.65	97.73	100	93.40	88.30	44.96	
Overall accuracy (%)	87.61						
Kappa coefficient	0.84						

Built-up area, open space and road was still difficult to identify. However, we found we could reduce this problem using the NDBSI and BAI indices. The Coastal index (which uses new wavebands) was founds to be very important for discrimination of open space from other land cover such as gray roof. Class related features such as the distance to shadow is significant for distinguishing the built-up area from some special land cover classes, for example, open space with higher water content on the surface (such as rainwater covered wasteland).

NDVI performs the best for distinguishing vegetation objects and non-vegetation objects. NDWI can be used for effectively extracting water bodies from land areas. NDBSI and BAI are very significant for extracting open space areas from built-up areas.

There are lower classification accuracies for open space and road. Open space was classified with only 52.75% of producer's accuracy. This shows that most of the open space objects could not be extracted from built-up areas. Road was classified with 75.21% of producer's accuracy mainly due to the use of the length value as a useful identifier for road making the segmentation result suitable for extracting roads. Nevertheless, some road was confused with open space and built-up objects, particularly short laneways and short roads

Grass was classified with only 90.22% of producer's accuracy and 97.73% of user's accuracy. The result shows the significance of the NDVI and GLCM homogeneity features as being the most appropriate methods for distinguishing grass from other vegetation.

5. CONCLUSIONS

Our results lead to the conclusion that spectrally similar classes like vegetation and grass, built-up area and open space, water and shadow (or dark object) can be better discriminated when the additional bands of the WorldView-3 sensor such as Coastal and Near-IR2 are used throughout the object-based classification method.

Built-up area and road were effectively distinguished with multi-scale object oriented classification technique. Because of the same scale of image segmentation (≈ 0.5-2 m) the method is still not suitable for all urban ground features because many human-made features are about the same scale as the pixel size.

The new Normalized Difference Bare Soil Index (NDBSI) feature based on band 1 (coastal) and band 2 (blue) was successfully used to better identify open space and bare soil. Class related features such as the distance to the shadow is significant for identifying the built-up area from some special land use class, for example some open space with higher water content on the surface.

Nevertheless, only MS bands of the WV-3 data were classified in the study. There is still more potential to classify other classes in urban areas based on WorldView-3 image, such as small built-up and impervious surfaces, when the Panchromatic band will be integrated with the MS band, since built-up and urban features maybe be more accurately identified from higher spatial resolution images than currently available.

ACKNOWLEDGEMENTS

This research is based in part upon a Masters in Technology and Environmental Management project entitled "Classification of Impervious Surface in Urban Area for Water Management". We are grateful to the Faculty of Technology and Environment, Prince of Songkla University, Phuket Campus for financial support during the realization of this project. We wish to thank Geo-Informatics and Space Technology Development Agency (Thai Public Organization) and Land Development Department of Thailand's Ministry of Agriculture and Cooperatives for their data support. We would like to gratefully and sincerely thank Dr. Chanida Suwanprasit and Dr. Raymond J. Ritchie for their guidance, teaching and constant reassurance.

REFERENCES

Belgiu, M., Dr Guţ, L., and Strobl, J., 2014. Quantitative evaluation of variations in rule-based classifications of land cover in urban neighbourhoods using WorldView-2 imagery. ISPRS journal of photogrammetry and remote sensing, 87, pp. 205-215.

Carvalho, M. V. A., Kux, H. J. H., and Florenzano, T. G., 2012. Urban Land Cover Classification With Worldview-2 Images Using Data Mining and Object-Based Image Analysis. Proceedings of the 4th GEOBIA, Rio de Janeiro, Brazil, pp. 431-436.

Chust, G., Ducrot, D., and Pretus, J. L., 2004. Land cover mapping with patch derived landscape indices. Landscape and Urban Planning, 69, pp. 437-449.

Dams, J., Dujardin, J., Reggers, R., Bashir, I., Canters, F., and Batelaan, O., 2013. Mapping impervious surface change from remote sensing for hydrological modeling. Journal of Hydrology, 485, pp. 84-95.

Definiens, A., 2007. Definiens developer 7 reference book. Definiens AG Publ., München, pp. 11-27.

DigitalGlobe, 2014. WorldView-3 spacecraft information and specifications, Retrieved September 4, 2015, from https://www.digitalglobe.com/resources/satellite-information.

Gong, P., Marceau, D. J., and Howarth, P. J., 1992. A comparison of spatial feature extraction algorithms for land use classification with SPOT HRV data. Remote Sensing of Environment, 40, pp. 137-151.

Kong, C., Xu, K., and Wu, C., 2006. Classification and extraction of urban land use information from high-resolution image based on object multi features. Journal of China University of Geosciences 17(2), pp. 151-157.

Lackner, M., and Conway, T. M., 2008. Determining land-use information from land cover through an object oriented classification of IKONOS imagery. Canadian Journal of Remote Sensing 34(2), pp. 77-92.

Lo, C. P., and Choi, J., 2004. A hybrid approach to urban land use/cover mapping using Landsat 7 Enhanced Thematic Mapper Plus (ETM+) images. International Journal of Remote Sensing, 25, pp. 1687-2700.

Rogan, J. and Chen, D., 2004. Remote sensing technology for mapping and monitoring land-cover and land-use change. Progress in Planning, 61, pp. 301-325.

Shahi, K., Shafri, H. Z. M., Taherzadeh, E., Mansor, S., and Muniandy, R., 2015. A novel spectral index to automatically extract road networks from WorldView-2 satellite imagery. The Egyptian Journal of Remote Sensing and Space Science, 18(1), pp. 27-33.

Thapa, R. B. and Murayama, Y., 2009. Urban mapping, accuracy, & image classification: A comparison of multiple approaches in Tsukuba City, Japan. Applied Geography, 29(1), pp. 135-144.

Verbeiren, B., Van de Voorde, T., Canters, F., Binard, M., Cornet, Y., and Batelaan, O., 2013. Assessing urbanisation effects on rainfall-runoff using a remote sensing supported modelling strategy. International Journal of Applied Earth Observation and Geoinformation, 21, pp. 92-102.

Zhou, X., Jancso, T., Chen, C., and Verone, W. M., 2012. Urban Land Cover Mapping Based on Object Oriented Classification Using WorldView 2 Satellite Remote Sensing Images. International Scientific Conference on Sustainable Development & Ecological Footprint, Sopron, Hungary.