APPLICATION OF HIGH RESOLUTION SATELLITE IMAGERY FOR WETLANDS COVER CLASSIFICATION USING OBJECT-ORIENTED METHOD

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ABSTRACT:

Wetlands are considered an integral part of the global ecosystem, the development of the remote sensing technology makes us obtain very abundant information of wetlands, especially with the appearance of high resolution satellite imagery which extends the visual field of the wetlands. The aim of this study is to explore the viability of applying high resolution satellite imagery for inland limnetic wetlands cover classification using object-oriented method. Thesis discussed the selection of best segmentation scale during segmentation procedure using statistical, trial and error method, determined the separability of each wetlands cover structural class using each texture band through z-test method, and a high accuracy of classification result was acquired at last through test.

1. INTRODUCTION

Convention on Wetlands of International Importance Especially as Waterfowl Habitat defined wetlands as areas of marsh, fen, peatland or water, whether natural or artificial, permanent or temporary, with water that is static or flowing, fresh, brackish or salt, including areas of marine water the depth of which at low tide does not exceed six metres. Wetlands are considered an integral part of the global ecosystem as they prevent or reduce severity of floods, feed groundwater aquifers and provide a unique habitat for flora and fauna (Mitsch & Gosselink, 1993). Lots of wetlands around the world are protected and monitored by various agencies because of their important role. But their dynamic hydrological characteristics and frequently complex terrain means wetlands are often difficult to monitor in situ. In addition, many wetlands are situated in remote locations with limited access and may cover extensive areas (Jessika & Alain, 2005). Then the use of remote sensing technology for the mapping, identification, inventory and classification of the wetlands has been a common application of satellite imagery (MacDonald, 1999; Lyon, 2001). The development of the remote sensing technology makes us obtain very abundant information of wetlands, especially with the appearance of high resolution satellite imagery which extends the visual field of the wetlands. But the challenge that faces us is how to make use of the data effectively and obtain more useful wetlands information through imagery processing.

As one of the main imagery processing technologies, the satellite imagery classification has made considerable progress, and classification using object-oriented method is being studied emphatically. Object-oriented analysis provides an alternative methodology to per-pixel based analysis (de Koket al., 1999) by developing region-growing image analysis techniques using a combination of the shape, size, texture and spectral data of the regions to classify image data (Chubey et al., 2006; Hay et al., 2005; McKeown, 1988; Johansen & Phinn, 2006a; Wulder et al., 1998). In addition, the compactness and context information with adjacent image regions can also provide important information that can be related to the classification (Blaschke and Hay, 2001; Blaschke and Strobl, 2001). And some accessorial geographic information such as elevation and soil distribution etc. can also be added to classification. In object-oriented method, the image regions are called as objects with kinds of information that is used to classify. In this research, shape, size, texture, spectral, compactness and context information were used to classify the wetlands cover together using object-oriented method.

Lots of former studies on classification of satellite imagery using object-oriented method have been carried out. Some studies focused on applying low and middle resolution satellite imagery such as Landsat ETM, Landsat TM, NOAA AVHRR, Terra ASTER, etc. for classification using object-based method (Argialas et al., 2006; Hurd et al., 2006; Lewinski, 2006; Gitasa et al., 2004). And some studies applied high resolution satellite imagery such as Spot, Ikonos, Quickbird, Airborne imagery for classification and change detection using object-based method (Desclée et al., 2006; Mathieu et al., 2007; Stow et al., 2007; Walter, 2004; Lalibertea et al., 2004; Johansen, 2007). Though application of satellite imagery for land cover classification using object-oriented method have been carried out largely, the application of high resolution satellite imagery for inland limnetic wetlands cover classification using object-oriented method is few. The aim of this study is to explore the viability of applying high resolution satellite imagery for inland limnetic wetlands cover classification using object-oriented method.

2. STUDY AREA AND DATA

Study area locates at Jingyue economical development zone, Changchun city in Jilin province, China (Figure 1). The natural scenery of study area is very beautiful, and contains lots of landscape types such as water, grass, trees, road and residential area, which is suitable for the classification test.

Test selects Quickbird satellite imagery as the data of classification because it is representative for the high resolution satellite imagery. A Quickbird imagery (Figure 1) was acquired on September 29, 2006 for the study area. The imagery is composed by four spectral bands B (Blue Band), G (Green Band), R (Red Band), NIR (Near Infrared Band) with a 2.4 m resolution and one panchromatic band with a 0.6 m resolution.

GPS points, topographic maps and vegetation maps will be together used to assess the accuracy of classification results.

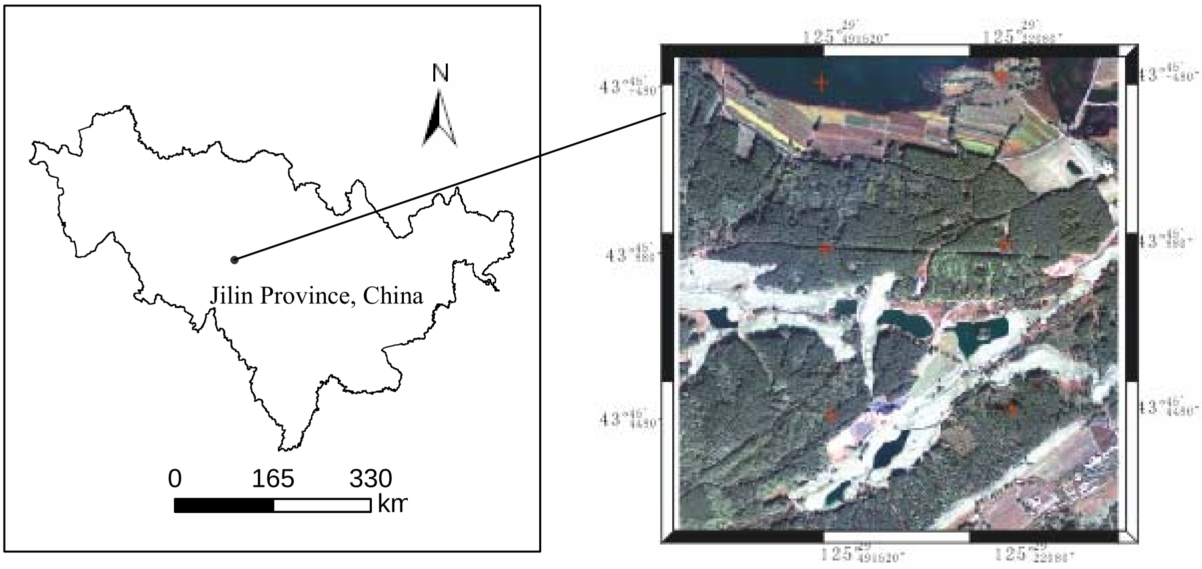

Figure 1. Location of study area and satellite imagery data

3. METHODS

Wetlands cover classification using object-oriented method needs three main steps to be finished: segmentation, classification and accuracy assessment.

3.1 Segmentation

Image segmentation is a prerequisite to classification, which is the subdivision of an image into separated regions. Those image regions resulting from segmentation represent image object primitives, serving as information carriers and building blocks for further classification or other segmentation processes (eCognition User Guide, 2002). Segmentation procedure has the objective, to provide the primitive objects, in order to apply higher level knowledge in a later step and classify the primitives into semantic objects (Argialas & Tzotsos, 2006). The purpose of the segmentation is to generate elementary imagery objects, which are primary processing units in imagery classification process.

The segmentation procedure is controlled by the user-specified scale (size) or resolution of the expected objects (Dekok et al. 1999) and the output segment sizes depend therefore on image heterogeneity and are regulated by a so-called scale factor (Baatz et al., 2001). Different segmentation scale can affect the classification result, if the features in image are large, but with a small segmentation scale, the noises in image will be not classified to according classes, then reduces the accuracy of classification; if the features in image are small, but with a large segmentation scale, some small features will be merged in the segmentation results (objects), then affect the accuracy of classification. Selection of the best segmentation scale becomes a key problem during segmentation procedure.

Some researchers have been working on the scale problem in object-oriented image analysis. Based on methods and approaches in pixel-based image analysis, Huang (2003) developed several results which focus on scaling and scale choose in object-oriented image analysis. Zhang and Maxwell (2006) presented a fuzzy logic approach to the determination of suitable object segmentation parameters leading to an improved object-oriented classification result; A hierarchical image segmentation approach was adopted to extract the objects from multi-temporal Landsat images over Zimbabwe by Gamanya et al. (2007). Study used the objects max area method (Huang, 2003) and a trial and error procedure with eCognition software to determine the optimal scale during segmentation.

3.2 Classification and accuracy assessment

According to the test area practical conditions, seven classes forest1, forest2, grass, water, resident area, road and cultivated land became the aim of classification (figure 2). And a fusion matrix was developed to determine the classification accuracy of classification at last.

4. RESULT AND DISCUSSION

4.1 Texture band analysis

Wetlands cover classification using object-oriented method involves kinds of original input data such as spectral bands, indices deviated from spectral bands, texture characteristics calculated for some data source and some correlative geographical information. For this classification, four spectral bands B (Blue Band), G (Green Band), R (Red Band), NIR (Near Infrared Band), two vegetation indices NDVI (Normalized Difference Vegetation Index) and EVI (Enhanced Vegetation Index), one transformation PC1 (Principal Components one), one water index NDWI (Normalized Difference Water Index), and five grey-level texture cooccurrence measures were calculated for all of them: variance; homogeneity; contrast; dissimilarity and entropy. All the data were included as they were found useful for analysis of classes variability by former researchers (Johansen & Phinn, 2006b; stow, et al., 1998; Johansen, 2007; McFeeters, 1996).
This study took the Z-test method that was used by Kasper Johansen, et al. (2007) to determine the separability of each

wetlands cover structural class using each texture band. To do this, all pixel values within each subset were compared using the z-test to identify the texture measure that provided the largest statistically significant difference between the wetlands cover structural classes (Johansen, 2007). Formula 1 was applied for calculating the z statistics (Zarf, 1984).

$$z = \frac{(\mu_1 - \mu_2)}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \tag{1}$$

Where n_1 and n_2 : The number of samples;

μ_1 and μ_2 : Mean pixel values of two different texture bands;

s_1 and s_2 : The sample standard deviation of corresponding means.

The result of selected texture measures and their image band derivative used to optimize discrimination between classes in classification is show in table 1.

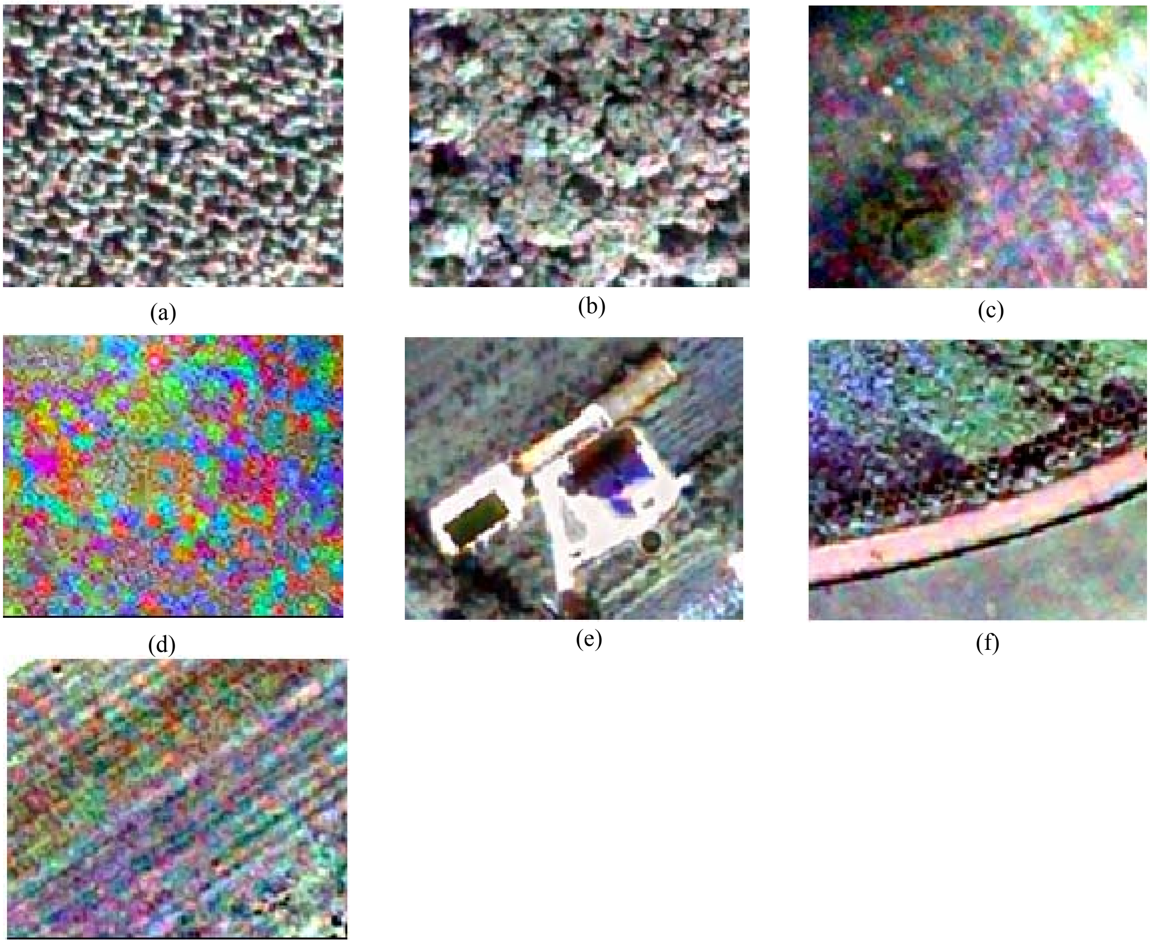

Figure 2. Classification system of study area.
(a) forest1, (b) forest2, (c) grass, (d) water, (e) resident area, (f) road, (g) cultivated land.

4.2 Selection of segmentation scale

The principle of objects max-area method is: when the segmentation scale being magnified gradually, the sizes of image objects are not point-blank increased, the sizes of some image objects keep stable within certain scale range. The graph that shows the relationship of objects max-area and segmentation scale is ladder like increased (figure 3). Each flat is the appreciate scale range for one class (Huang, 2003).

Discrimination of classes	Source bands	Texture
Forest1 - forest2	NIR	Variance
Forest1 – grass	NDWI	Homogeneity
Forest1 – resident area	Red	Variance
Forest1 – water	NIR	Homogeneity
Forest1 –cultivated land	NIR	Homogeneity
Forest1 – road	Red	Contrast
Forest2 – grass	NDWI	Entropy
Forest2 – resident area	Red	Contrast
Forest2 – water	NIR	Entropy
Forest2 –cultivated land	NIR	Entropy

Forest2 – road	Blue	Contrast
Grass – resident	Green	Contrast
Grass – water	NIR	Entropy
Grass –cultivated land	NIR	Homogeneity
Grass – road	Green	Contrast
Resident – water	NIR	Homogeneity
Resident –cultivated land	NIR	Homogeneity
Resident – road	Blue	dissimilarity
Water –cultivated land	NIR	Contrast
Water – road	Green	Contrast
Cultivated land – road	Green	Contrast

Table 1. Result of texture band analysis

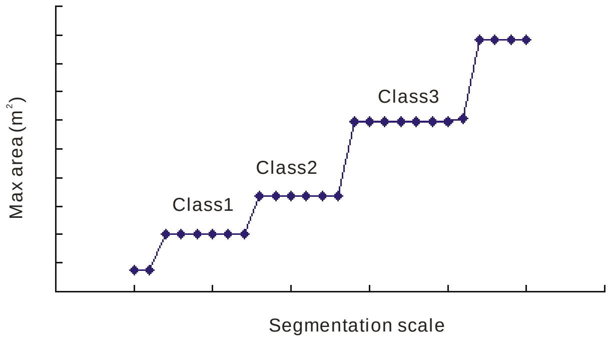

Figure 3. Sketch map of objects max area method

Took four spectral bands B (Blue Band), G (Green Band), R (Red Band) and NIR (Near Infrared Band) as the segmentation test data, through the experience of changing scale parameter with Ecognition, gained the relationship of segmentation scale and objects max area (figure 4). In figure 4, there were only two classes water and forest could be found, which meant that water and forest were the two main landscape types at test area. The graph reflected the relationship of water, forest objects max-area and segmentation scale, though other classes couldn't be found. Then scale parameter 50 was determined to carry out

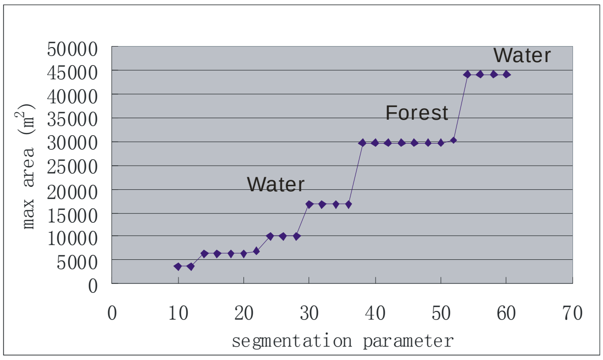

Figure 4. Relationship of scale and objects max area

segmentation for forest, and 80 was determined to carry out segmentation for water. The segmentation scales for other classes were determined though a trial and error procedure.

	Scale	Color	Shape	Compactness	Smoothness
Level 3	80	0.7	0.3	0.4	0.6
Level 2	50	0.9	0.1	0.7	0.3
Level 1	20	0.7	0.3	0.3	0.7

Table 2. Segmentation parameters system

At last, a multi-resolution segmentation parameters system (eCognition User Guide, 2002) or hierarchical network of segments (Baatz & Schaepe, 2000) was established with eCognition software, which consisted of three levels (table 2). The size of the segments decreases from level 3 (coarse) to level 1 (fine). The aim of doing this was that different segmentation scales were proper for certain classes: Level 1 was proper for segmentation for resident area and road classes. Level 2 was proper for segmentation for forest1, forest2, cultivated land and grass classes, Level 3 was proper for segmentation for water.

Type	Forest1	Forest2	Grass	Cultivated land	Water	Resident area	Road	Sum	user's accuracy
Forest1	89	1	0	0	0	0	0	90	98.9%
Forest2	4	33	0	5	0	0	0	42	78.6%
Grass	0	1	57	1	0	0	0	59	96.6%
Cultivated land	1	1	0	88	0	0	0	90	97.8%
Water	0	0	0	0	16	0	0	16	100%
Resident area	0	0	0	0	1	48	1	50	96%
Road	0	0	0	1	0	2	50	53	94.3%
Sum	94	36	57	95	17	50	51	381	
producer's accuracy	94.7%	91.6%	100%	92.6%	94.1%	96%	98%		
	Total =95.25%	Kappa =0.9427							

Table 3. Accuracy assessment on classification using oriented-object in study area

4.3 Classification

“Membership Functions” and “Nearest Neighbour” classifiers were together used to carry out classify with eCognition software, water objects were distinguished by defining a membership functions that could discriminate water from other classes objects on level 1. Forest1, forest2, grass and cultivated land objects were distinguished by defining feature space that could discriminate them on level 2, which was realized through defining samples that represented different classes. Resident area and road were also distinguished by defining feature space that could discriminate them on level 3. At last, 400 sample points with attributes were selected to assess the accuracy of classification. The result was showed in table 3.

5. CONCLUSION

The study results proved the viability of applying high resolution satellite imagery for inland limnetic wetlands cover classification using object-oriented method. The total accuracy of classification reached 95.25%, which is satisfied. Through a test about the selection of best segmentation scale during segmentation procedure, study found that max area method couldn’t reflect all the classification objects, a combination of statistical, trial and error method was necessary for selection of segmentation scale.

Though there are lots of original input data for classification, it is an important step to discard irrelevant and redundant features that may affect classifier performance and efficiency among those data. Study considered the separability of each wetlands cover structural class using each texture band through z-test method and gained a results that reflected selected texture measures and their image band derivative used to optimize discrimination between classes in classification. Optimal combination of bands used to segment and classify will be further discussed by work team.

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