Comparison of Pixel-based and Object-oriented Knowledge-based Classification Methods Using SPOT5 Imagery

Minjie Chen[a], Wei Su[a], Li Li[a], Chao Zhang[a,*], Anzhi Yue[a], Haixia Li[a]
[a] College of Information & Electrical Engineering, China Agricultural University, Beijing, 100083, P.R. CHINA
*Corresponding author: Chao Zhang (Dr.) Tel: +86-10-62737855, Email: zhangchao_bj@163.com

Abstract: - Land cover mapping is very important for evaluating natural recourses, understanding the societal and business activities. The remote sensing techniques provide effective and efficient methods to create such maps. To high spatial resolution imagery such as SPOT5 imagery, the land cover classification precision will be improved with the knowledge, Digital Elevation Model (DEM) data and the spatial information such as texture and. Both the pixel-based classification method based on the knowledge rule and the object-oriented fuzzy classification methods have been studied in this paper using SPOT5 high spatial resolution imagery. Some GIS dataset and the texture are integrated into the two knowledge-based classifications in this paper. And the result of accuracy assessment indicates that the two classifications can catch good classification precision, but the objected-oriented classification method does better. Besides, the shape and context information can be used fully to distinguish the roads from the buildings with the objected-oriented fuzzy classification method, which is hard to accomplish in pixel-based classification. Furthermore, the objected-oriented classification method is more suitable in land cover mapping due to its meaningful objects.

Key-Words: SPOT5 imagery, Texture, DEM, Pixel-based, Object-oriented, Knowledge-based rules

1. Introduction

Land cover information is vital input for various developmental, environmental and resource planning applications in regional as well as global scale processing models[1].Land cover serves as an important source of information for both the scientific and business communities, and remote sensing is a cost-effective method to gather the land-cover information[2].Our ability to analyze remote sensing image data is important because it allows changes in the earth's surface to be monitored as they occur[3].Deriving land-cover information from remote sensing imagery, however, can be a difficult task depending on the complexity of the landscape and the spatial and spectral resolution of the imagery being used. Improving the accuracy of land-cover classifications is thus a fundamental research topic in the field of remote sensing[4].

Over regional scales, Land use maps are typically produced from remotely sensed image analysis using moderate resolution satellite imagery such as Landsat TM [5-7]. While these products are useful for producing coarse-scale classifications, they are inadequate for detailed mapping (e.g., species-level vegetation or buildings) [8]. Land use maps require finer details, and utilize either photo interpretation or image processing of high resolution images [9-10]. High spatial resolution imageries are increasingly accessible to municipal governments, land management agencies, and other communities because of their clear visual effects and rich texture information. But the high resolution imageries usually lack enough spectral information because of the relationship of the spatial and spectral resolution. Therefore, it is important to develop the accurate approaches that are suitable for the classification for high spatial resolution images.

Since remote sensing images consist of rows and columns of pixels, conventional land-cover mapping has been based on a per-pixel basis[11]. Pixel-based classification uses multi-spectral classification techniques that assign a pixel to a class by considering the spectral similarities with the class or with other classes [12].

While high spatial resolution remote sensing provides more information than coarse resolution imagery for detailed mapping, increasingly finer spatial resolution produces challenges for conventional pixel-based techniques such as Iterative Self-Organizing Data Analysis Technique (ISODATA) and Maximum Likelihood Classifier (MLCM) [13]. In recent years, knowledge-based remote sensing information extraction model has been rapid developed; this method takes knowledge as assistant information to participate in the classification process, to effectively improve the accuracy of classification [14].

Object-oriented classification approach is a new method employed in recent years, it not only relies on the spectral characteristics of the features when utilized, but more their geometric and structural information, and furthermore integrates multi-source remote sensing data for analysis[15]. Image segmentation is a preliminary step in object-oriented image classification[16]. Object-based classifiers can be used by segmenting an image into objects of similar neighboring pixels, pixels are therefore aggregated into image objects by segmentation, which is defined as the division of remotely sensed images into discrete regions or objects that are homogenous with regard to spatial or spectral characteristics [17]. Image objects are therefore basic unites in an image, where each pixel group is composed of similar digital values, and possesses an intrinsic size, shape, and geographic and/or ecological relationship within the real-world scene component it models[18-19]. Object-oriented classification approach can use levels to express the classification task according to the knowledge[20]; therefore, object-oriented classification approach is a knowledge-based method too.

Many researchers have used these methods to successfully map features [21-27]. For example, Volker Walter employed the object-oriented method to realize the change detection, and study further measures to enable the distinction between more land-use classes[23]. Cao, X. et al. employed the Fractal Net Evolution Approach (FNEA) to get objects and a multi-level object-oriented classification to classify the QUICKBIRD image of Shenzhen city[25]. Wang, L. et al. utilized an object-based classification to compare underlying texture in both panchromatic and multispectral bands[26].

Knowledge-based classification can be used in both pixel-based and object-oriented methods, but few researches have compared the analysis result and classification accuracy between them. Therefore, the objectives of this paper are to find a suitable strategy for the knowledge-based classification for SPOT 5 imagery in the pixel-based and object-oriented methods (i), and (ii) evaluate the performance of these two methods in surface urban-suburban areas mapping.

2. Study area and dataset

This study focused on a small region (approximately 25.5 square kilometer) in Liangxiang Town, Fangshan District, Beijing, China (Fig. 1).The area covers both urban and suburban landscapes, and land cover information varies from highly impervious in the residential community to absolutely pervious farmland. The variety of land use and land cover types makes it ideal for this study. Additionally, high spatial resolution imagery was available in this area.

Fig. 1. Location and SPOT 5 imagery (2.5m) subset of Study Area (Liangxiang town, Fangshan district, Beijing, China)

High resolution SPOT 5 imagery, DEM, and other ancillary data were used to aid in the classification. The SPOT 5 imagery data were collected on September 26, 2006, including four 10 m resolution, multi-spectral bands and a 2.5 m resolution panchromatic band.

The DEM data utilized in this study was acquired in 2004, with the resolution of 10m. Additionally, a SPOT 5 2.5 m resolution true color Digital Orthophoto Map (DOM) image of Fangshan District, Beijing acquired in 2004, which would be used as the reference image in the geometric calibration, and a land-use map of Fangshan District, Beijing, 2004 was used to assistant interpretation as ancillary data too.

3. Methodology

The methodology involved pre-processing the image, the engagement of classification in the pixel-based classification, building an object-oriented model and assessing the accuracy of the two kinds of methods.

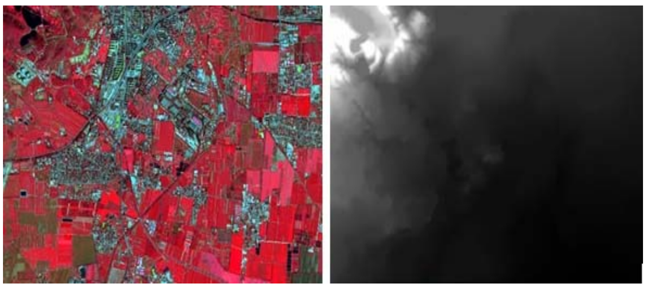


Fig.2. the fused SPOT5 imagery and the DEM data

The SPOT5 multi-spectral imagery and panchromatic imagery were fused together, after they were both geometric calibrated by the SPOT5 DOM data respectively, with the RMSE both less than one pixel. The fused image contained three bands (i.e., Near Infrared (NIR), Red(R), and Green (G)), with both the rich spectral information and textural feature. Both the fused SPOT5 imagery and the DEM dataset (Fig.2) were utilized in both the pixel-based decision tree classification and object-oriented classification approaches.

3.1 Pixel-based classification

Based on literature researches, field knowledge, and the land-use map of Fangshan District, Beijing in 2004, the following five land use classes were identified: (1) farmland, (2) woodland, (3) construction land, (4) bare soil and (5) water body.

3.1.1 Spectrum-based decision tree classification

Normalized Difference of Vegetation Index (NDVI), which was derived from the red and near-infrared(NIR) bands[28], which is a very useful feature for the differentiation of vegetation and non-vegetation[29]. NDVI is defined as:

$$NDVI = \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red}} \quad (1)$$

Where ρ_{nir} and ρ_{red} respectively represent NIR and red reflectances.

An NDVI layer was created firstly, and the spectral and NDVI information of the five classes (i.e., farmland, woodland, construction land, bare soil and water body) was obtained through the samples of different land cover classes. Thence, the five average spectral response curves (Fig.3) and five NDVI curves of the five classes were delineated.

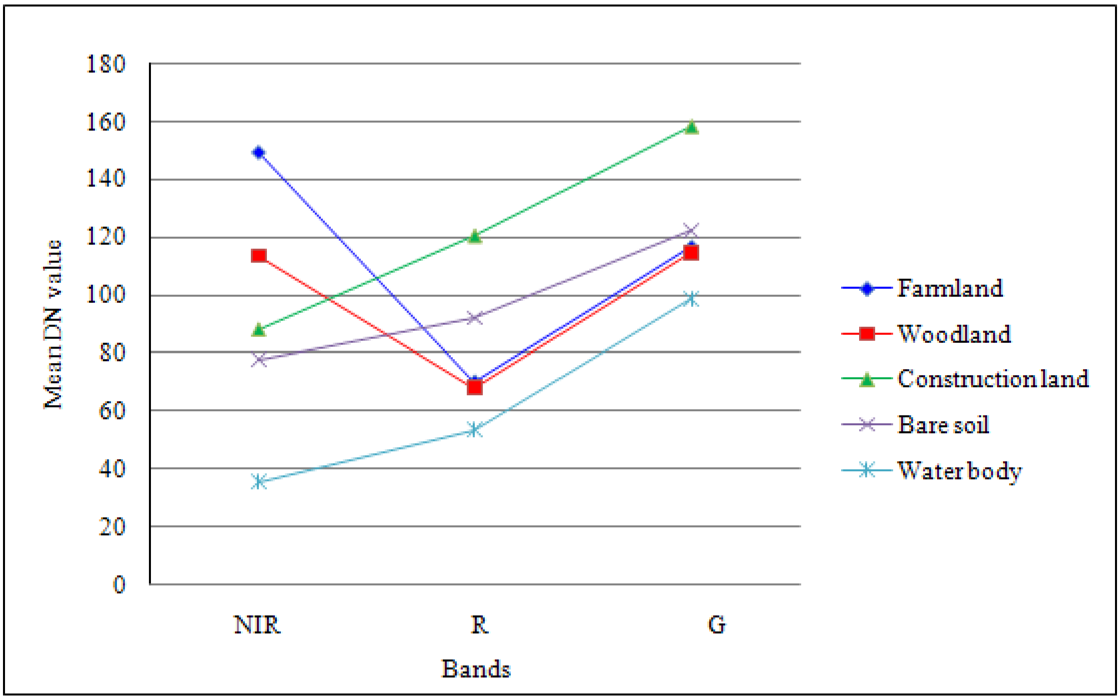


Fig.3 The average spectral response curves of the five classes

According to the above statistics, some thresholds for the decision tree classification were found, and a decision tree classification strategy based on spectrum was proposed (Fig. 4). First of all, base on the characteristics of the water body on this area, two features were proposed as the threshold value to identify water body (R>NIR and R<63) and other objects. Secondly, NDVI was applied to distinguish between vegetation (NDVI > 0) and bare soil and Construction lands. Finally, the construction land and bare soil were distinguished with a G value of 146.

In addition, according to the spectral response curves, the near-infrared spectral average of the farmland was larger than that of woodland, but the NDVI range of farmland covered that of the woodland. Through some further analysis of the near-infrared band of the farmland and woodland, the spectral overlap effect between the two classes was very serious in the near-infrared spectral band and other bans, and if distinguishing between farmland and woodland only using spectral information it will lead to quite a high error rate, so farmland and woodland classes didn’t be distinguished here.

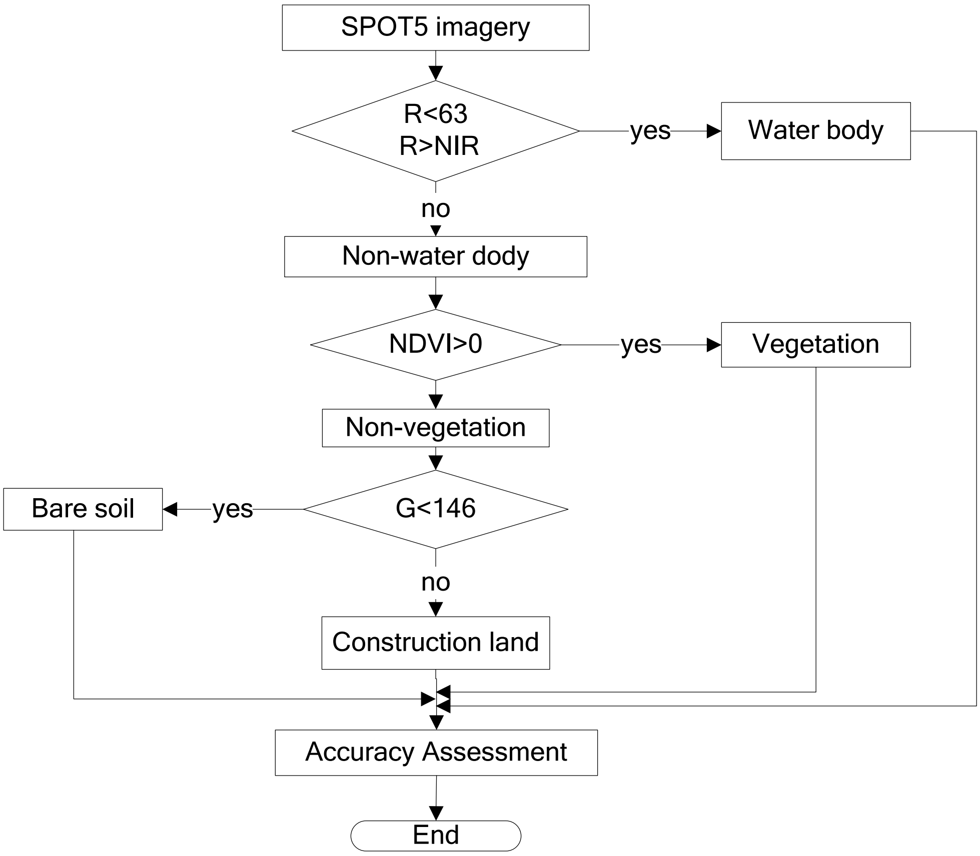


Fig.4 The workflow chat of the spectrum-based classification

3.1.2 DEM and texture feature-combined decision tree classification

Classification only utilizing the spectrum is always limited; therefore, other data sources are always employed to improve the accuracy.

The DEM dataset was applied to distinguish the woodlands and farmlands after the foundation that the vast majority of woodlands were in the upper left corner of the study area which is just a small hill, in addition to a very small part of the trees scattered around the Construction lands. The slope data of the study area is created with 10 m spatial resolution from the DEM. The woodland is these pixels with the slope value greater than 2.2 degree.

Gray level co-occurrence matrix (GLCM) is a popular and important method of calculation to get texture statistical information, and homogeneity is a significant criterion derived from GLCM, it is used to measure the degree of local homogeneity. In this study, a 9 * 9 window was chosen to determine the homogeneity index (Fig.5) of all pixels through some repeated tests. In the homogeneity image, a higher brightness indicates a higher homogeneity index. Based on several repeated experiments and field work knowledge, a threshold value was applied to homogeneity index to discriminate water body (homogeneity > 0.65) and shadow ,and another threshold value of homogeneity index was employed to distinguish bare soil (homogeneity > 0.44)and construction land.

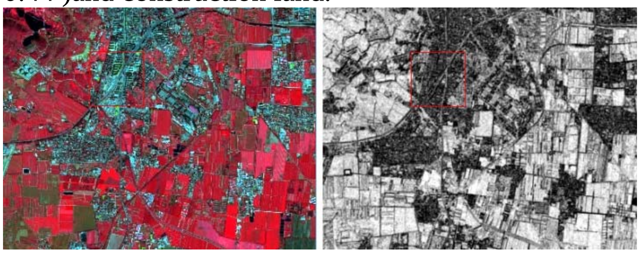


Fig.5. The fused SPOT5 imagery and the homogeneity layer

A knowledge base of classification rules, combining features of DEM data and texture characteristics to an improved decision tree was created to classify each pixel into one of the five classes (Fig.6).

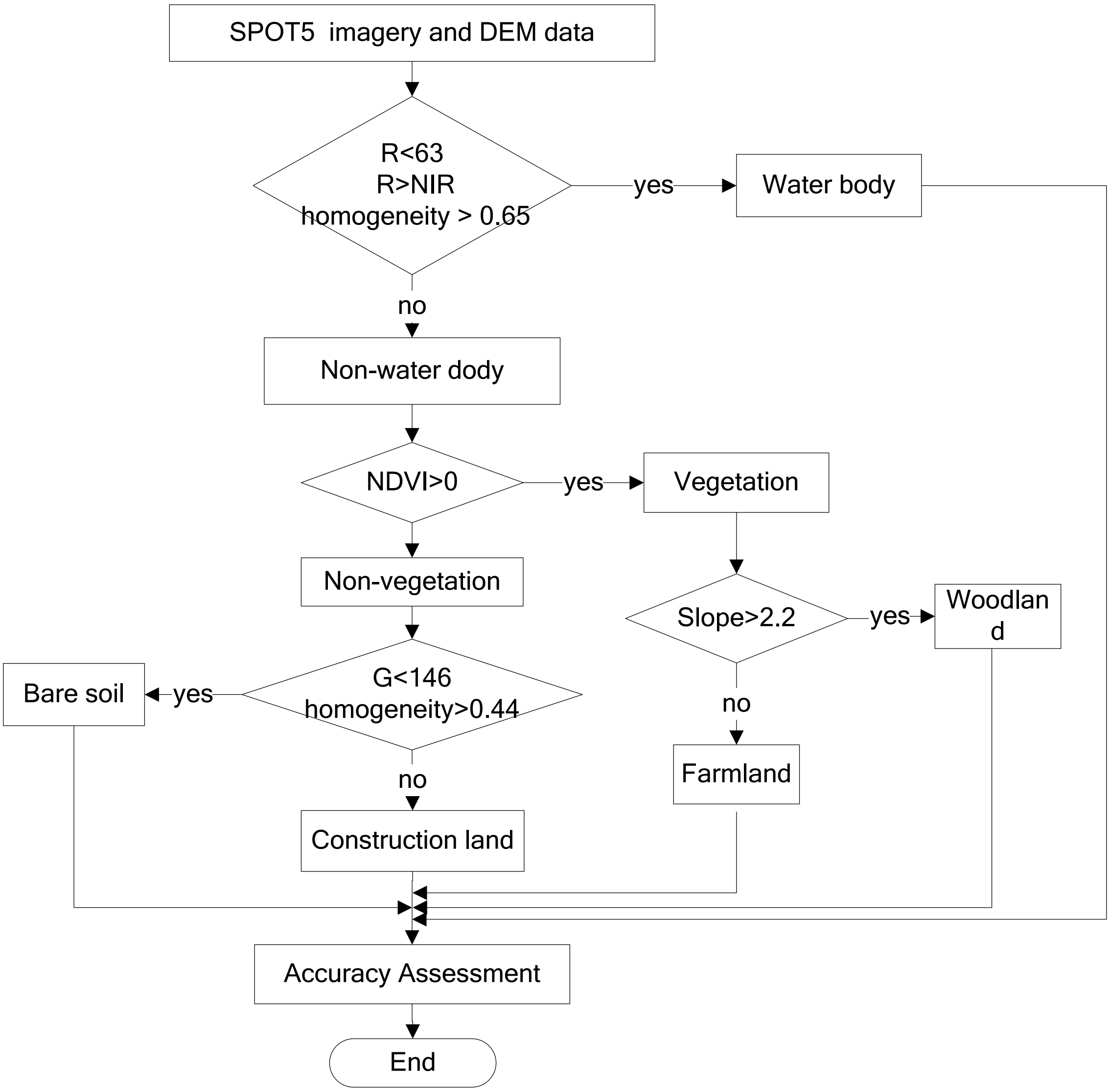


Fig.6. The workflow chat of the DEM data and texture feature-combined classification

3.1.3 Maximum likelihood method classification

The Maximum likelihood classification method (MLCM) classification was implemented using the fused SPOT5 imagery. The maximum likelihood decision rule is still one of the most widely used supervised classification algorithms[30], it has proven to be the most robust classifier in the field of Remote Sensing, as long as spectral information in each class meets the normal distribution criteria[31]. But it was reported that per-pixel Maximum Likelihood classification was limited by only utilizing spectral information without considering texture and contextual information[11].

3.2 Object-oriented classification

3.2.1 Concepts of object-oriented image analysis

Object-oriented classification is an image analysis method with image objects as the basic units. Segmentation represents the first step of any object-oriented image analysis, the adjacent pixels are aggregated into different image objects by the pixel spectral and shape characteristics through the segmentation process. With this approach, image objects not only have spectral properties but also region-based measure such as shape, texture, structure, size and context. A complete tool for object-oriented image analysis with various segmentation algorithms are provided in the commercial software Definiens developer 7.0[32]. The main segmentation parameters are scale parameters, the single layer weights and the mixing of the heterogeneity criterion concerning tone and shape[33]. The segmentation can be applied with different scale parameters to form a hierarchical network of image objects. In this way, the relationships between image objects defined at different scales can be used for classification.

To perform a classification, appropriate classes need to be defined. During classification, the image objects are analyzed according defined criteria and assigned to classes that best meet the defined criteria[5]. Within object-oriented analysis, spectral, textural, contextual and scale information can be integrated into the classification hierarchical rule set, or to the classification feature space of supervised classifications. This information is expected to increase the quality of classifications.

3.2.2 Object-oriented classification

In the object-oriented classification experiment, the DEM data and the imagery were organized; therefore, there were four layers. The near Infrared band (NIR), the green band (R), the red band (G) and the DEM data were set as layer 1, layer 2, layer 3, and layer 4 respectively.

Segmentation is the first step in any object-oriented image analysis. Humans can visually group similar pixels into meaningful objects based on the spatial arrangement and pixel color. Segmentation acts to simulate this behavior by both creating meaningful image objects and providing object topology[34]. According to the characteristics of the experimental data, we used two levels to extract ground objects(Table 1).The weight value of layer 1, layer 2, and layer 3 were all 1 , and that of layer 4 was 0 due to its lower resolution in both two levels. Therefore, the image objects in Level 1 became the super-objects of those in Level 2. The first level (Level 1) would be used to describe the macroscopic and large entities, such as woodland and water body, and the second level (Level 2) was used to describe the microscopic details of the roads and buildings.

The process of this object-oriented image analysis was similar to the DEM data and texture feature-combined decision tree classification (Fig. 7).In this study, ‘NDVI’ and ‘R-NIR’ were two customized features:

$$\mathrm{R-NIR} = \rho_{\mathrm{red}} - \rho_{\mathrm{nir}} \quad (2)$$

The distinction of buildings and roads here was implemented in Level 2. The classified large image objects in Level 1 were applied to small image objects in Level 2. Two boundaries were used to refine the class ‘road’ and discriminate between the classes of roads and buildings. These two features used to define ‘road’ were “length/width” and “length”, and the ‘building’ class was extracted by inverting the “road”.

Table 1 Segmentation parameters

Segmentation level	Segmentation parameters				
	Scale parameter	Homogeneity criterion			
		Color parameter	Shape parameter	Shape settings	
				smoothness	compactness
Level 1	70	0.9	0.1	0.5	05
Level 2	50	0.7	0.3	0.5	0.5

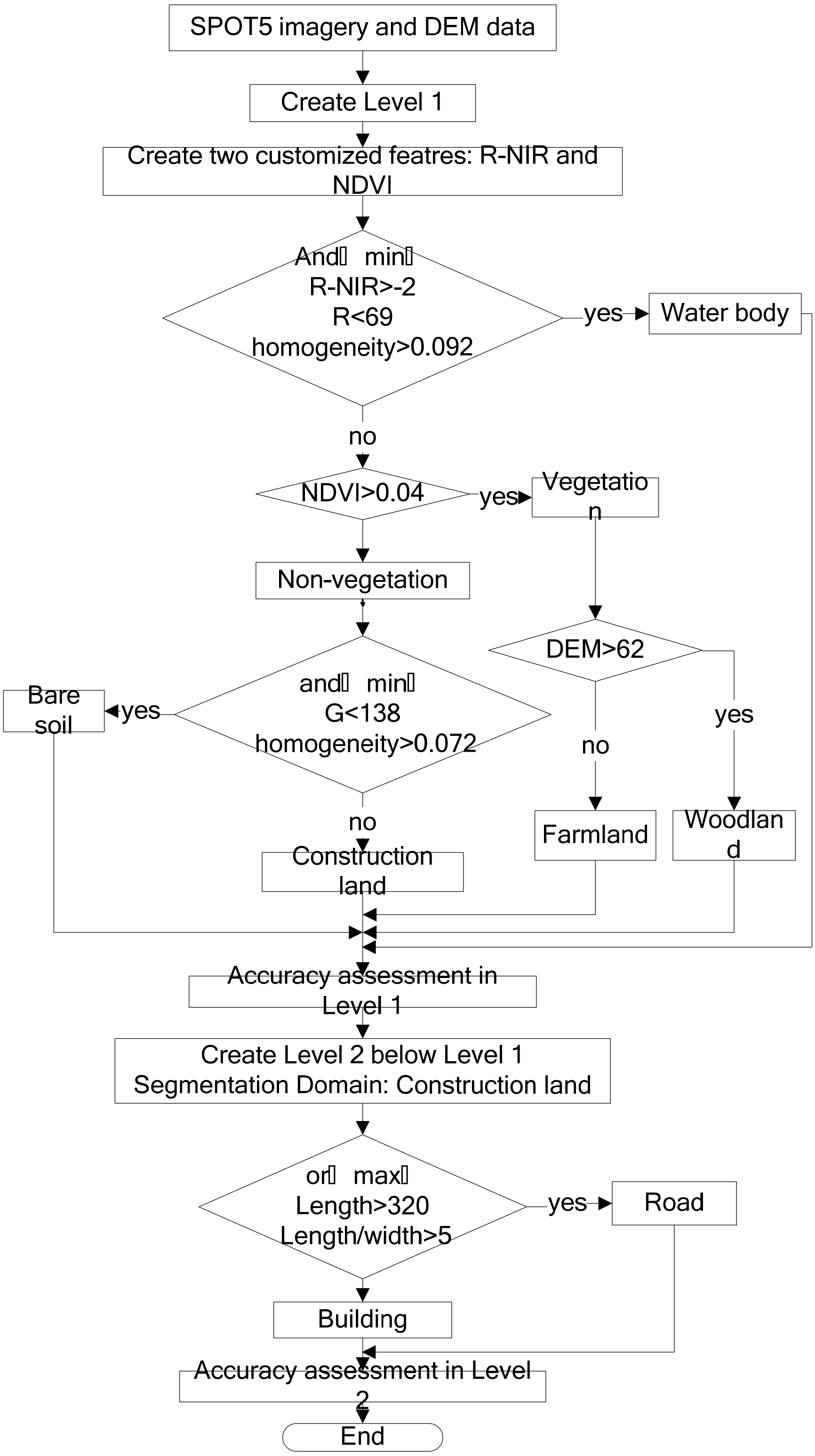


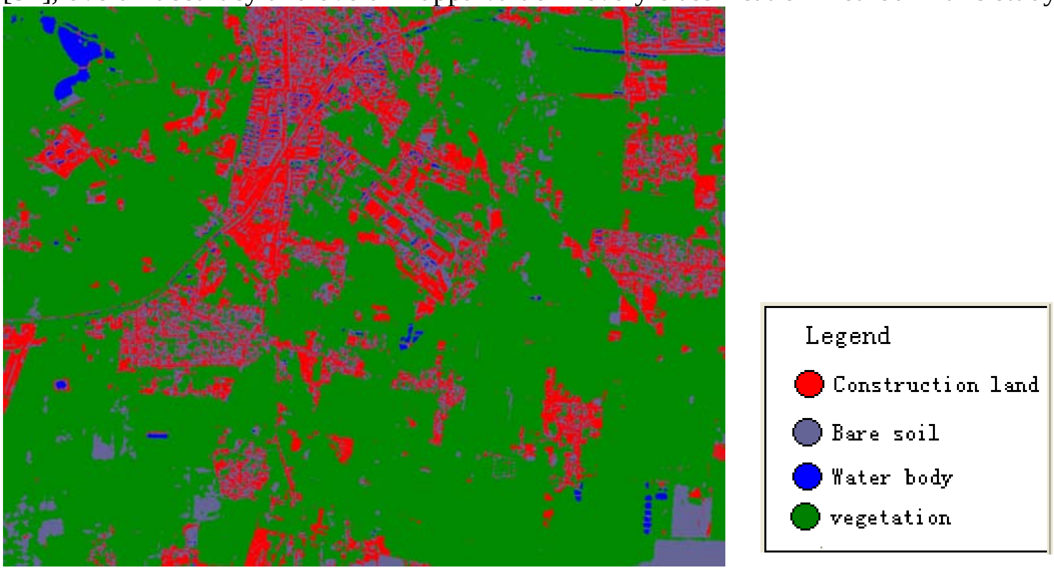
Fig.7. The workflow chart of Object-oriented fuzzy classification

3.3 Accuracy assessment

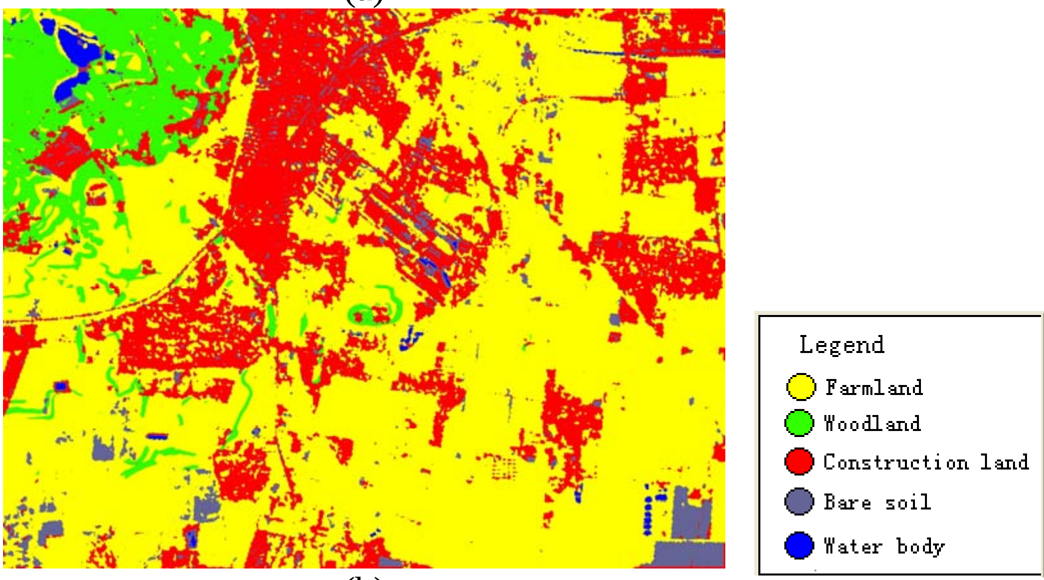
Classification accuracy was measured for both classification methods using a standard error matrix[35]. We purposefully used identical error assessment techniques to evaluate all of the five classifications. An accuracy assessment of the classification results was performed using reference data created from visual interpretation of the fused image data and the land use map in 2004. The accuracy assessment was carried out on the classification results for the classes. The accuracy assessment reports overall accuracy and Kappa coefficient and accuracy statistics for each class[36].The overall kappa coefficient represents a measure of agreement between the classes represented in the image.

4. Results and discussion

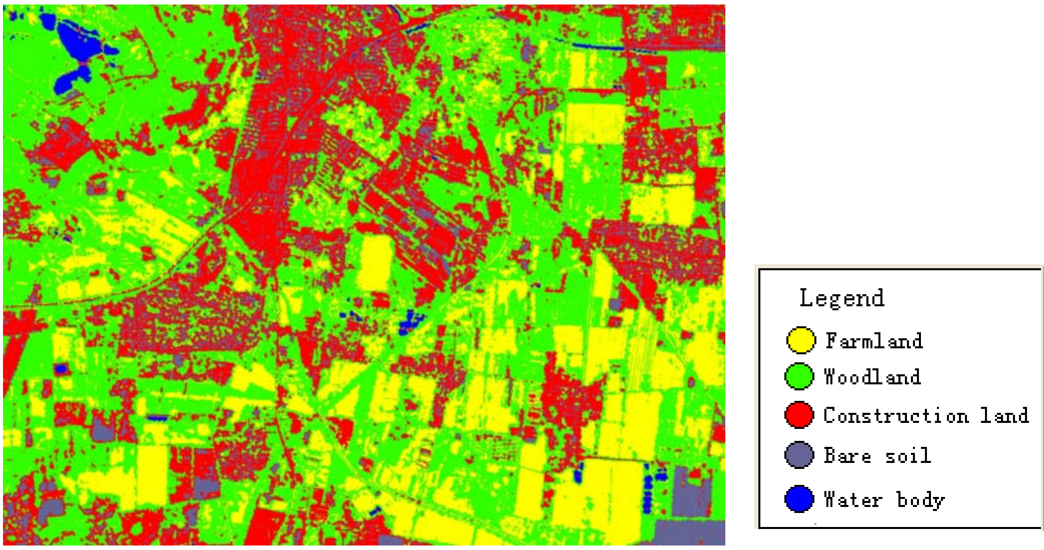
Fig.8 shows both the pixel-based and object-oriented classifications, and Table 2 shows the producer's accuracy (which measures omission error), user's accuracy of each class (which measures commission error) [37], overall accuracy and overall kappa value in every classification method in this study.



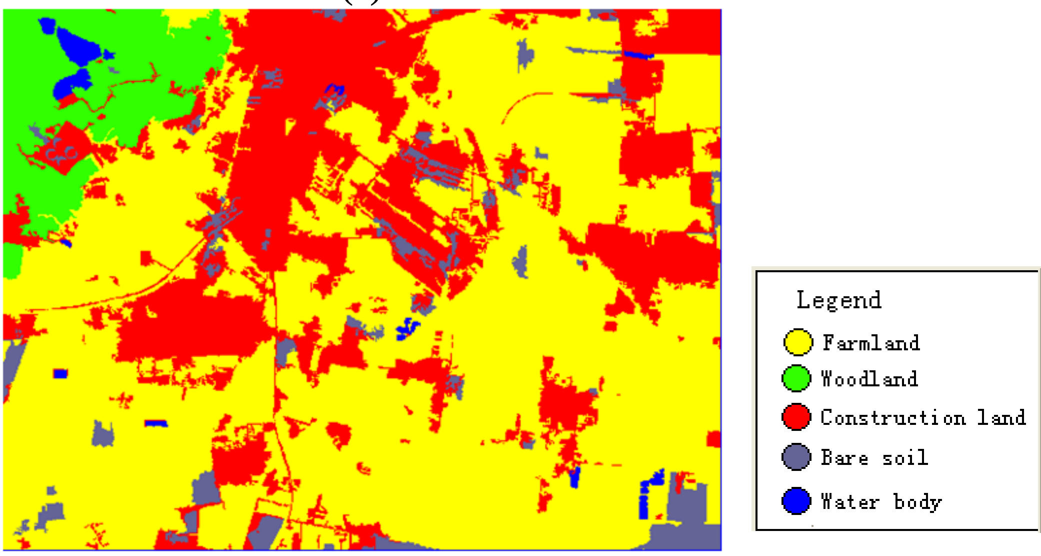
(a)



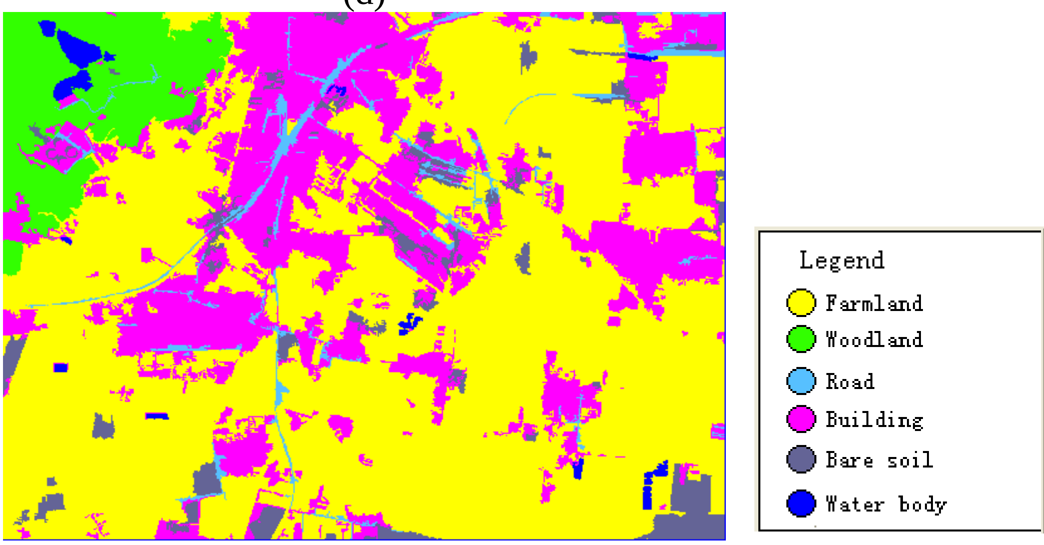
(b)



(c)



(d)



(e)

Fig.8 (a-c)Pixel-based classification. (a)Spectrum-based decision tree classification. (b)DEM data and texture feature-combined decision tree classificationl. (c)Maximum likelihood method classification. (d)Object-oriented classification (Level 1).(e) Object-oriented classification (Level 2).

Table 2 Accuracy matrices for all classification methods

Methods	Classes	Producer's accuracy (%)	User's accuracy (%)	Overall accuracy (%)	Kappa coefficient
Spectrum-based decision tree classification	Vegetation	99.90	96.76	81.9496	0.7265
	Construction land	57.12	99.46		
	Bare soil	97.37	28.84		
	Water body	94.34	83.33		
DEM data and texture feature-combined decision tree classification	Farmland	95.14	93.45	93.1479	0.9011
	Woodland	89.42	88.83		
	Construction land	91.17	99.25		
	Bare soil	96.92	78.03		
	Water body	93.83	99.96		
Maximum likelihood method classification	Farmland	63.20	96.39	77.7990	0.7010
	Woodland	93.30	48.37		
	Construction land	84.23	94.47		
	Bare soil	96.60	56.63		
	Water body	97.88	99.83		
Object-oriented classification(Level 1)	Farmland	99.21	95.85	96.42	0.9431
	Woodland	93.53	96.00		
	Construction land	99.00	97.82		
	Bare soil	86.80	97.48		
	Water body	85.08	100		
Object-oriented classification(Level 2)	Road	77.68	90.77	93.88	0.9068
	Building	88.17	84.28		

The DEM data and texture feature-combined decision tree classification method provides an 11.20% higher overall accuracy and a 0.1746 higher kappa coefficient than the spectrum-based decision tree classification approach (Fig.8a, b & Table 2). Particularly, the former provides a significantly higher user's accuracy in the bare soil with an increase of 49.19%, and the producer's accuracy of the construction land is 34.05% higher correspondingly. This is largely due to the integration of texture feature in the combined decision tree classification method.

The maximum likelihood classification method caught the worst classification and accuracy (Fig.8c & Table 2) of these approaches, especially the farmland and woodland classes. This is consistent with other studies, because the farmland and woodland classes are very similar in the spectrum and therefore greatly difficult to avoid the spectral overlapping effect.

The object-oriented classification approach yields a higher accuracy, with an overall accuracy of 96.42%, a Kappa coefficient of 0.9431 than all of the above approaches. This approach also provided higher user's accuracy for each class and obtains a slightly better accuracy than the DEM data and texture feature-combined decision tree classification method based on pixels (Table 2); but differences are obvious between the two products in the visual interpretation: the object-oriented result is a more spatially cohesive map, with none of the spurious pixel effect found in the pixel-based product, and it avoids the "Salt and Pepper" effect extremely good ,which is inevitable in the pixel-based classification for the high resolution imagery (Fig.8d,e).

Moreover, roads and buildings can be separated well in the object-oriented method (Fig.8e), and the accuracies for them are relatively high (Table 2). Relatively accurate results have been obtained in mapping the two classes thanks to the integration of shape information obtained in the object-oriented approach but not in pixel-based approach. It's hard to discriminate between the class 'road' and 'building' in the pixel-based methods because of the similar spectrum of them and we can't get the shape information of one pixel, but it can be accomplished in the object-oriented method.

In heterogeneous areas such as urban areas, conventional pixel-based classification approaches have very limited applications because of the very similar spectral characteristics among different land cover types (e.g., construction land and roads), and high spectral variation within the same land cover class. As demonstrated in this study, the knowledge-based classification (both pixel-based and object-oriented methods) integrated with the GIS data provided effective means of classifying this type of imagery. But grouping pixels to objects in the object-oriented classification method decreases the variance within the same land cover type by averaging the pixels within the objects, which prevents the significant “Salt and Pepper” effect in pixel-based classification[38]; and furthermore, as we are dealing with ‘‘meaningful’’ objects, instead of pixels, we are able to employ spatial relations, object features, and expert knowledge to the classification. The object-oriented approach provides a convenient way to incorporate ancillary data for classification, which sometimes can greatly improve the classification of certain classes. For instance, the use of DEM data in this study was very helpful for the separation of woodlands and farmlands; although it can be participated in the pixel-based method too, it’s hard to utilize the data directly. Therefore, the object-oriented classification approach will be more suitable for the needs of mapping when dealing with the high resolution imageries.

In a word, the object-oriented method in classification had an advantage over the pixel-based one by supplying the opportunity to combine spatial and spectral information into classification which enhanced the accuracy. The object-oriented classification approach presented in this paper proved to be very effective for classifying urban-suburban land cover classes from high resolution multispectral imagery. As the cover classes employed in this study are commonly found in urban-suburban areas, the knowledge base of classification rules developed for this study could potentially be applied to other similar areas. Moreover, the class hierarchy developed in this study is very flexible.

However, because object-based classifications generate various features, assessment of those features properties should also be implemented. This has not been attempted here, but will be in the future.

5. Conclusion

This study demonstrated the potential use of the knowledge-based approaches in both pixel-based and objected-oriented classification method as a tool for effectively classifying urban-suburban areas, and furthermore, the objected-oriented approach is more suitable on the high resolution imagery. The GIS data and other ancillary data integrated in the classification can improve the accuracy effectively. An object-oriented model was developed for accurately classification on the study area using an SPOT5 fused imagery, it avoided the “Salt and Pepper” effect very well which is inevitable in the pixel-based method, and differentiate the similarly spectral objects such as roads and buildings by the shape and context and semantic information effectively.

Acknowledgements

This research is funded by the National High Technology Research and Development Program of China titled The technique of the patch-oriented culture type precision recognition and its application (contract number: 2007AA12Z181). All authors would like to appreciate many experts from Research Institute of Forest Resource Information Techniques of Chinese Academy of Forestry, Institute of Remote Sensing Applications of Chinese Academy of Sciences, China Land Surveying and Planning Institute for their co-operation and support.

Reference:

[1] Kandrika, S., and Roy, P. S., Land use land cover classification of Orissa using multi-temporal IRS-P6 awifs data: A decision tree approach, *International Journal of Applied Earth Observation and Geoinformation,* Vol.10, No.2, 2008, pp.186-193.

[2] Tseng, M.-H., Chen, S.-J., Hwang, G.-H. *et al.*, A genetic algorithm rule-based approach for land-cover classification, *ISPRS Journal of Photogrammetry and Remote Sensing,* Vol.63, No.2, 2008, pp.202-212.

[3] Roiger, R. J., and Geatz, M. W., *Data Mining: A Tutorial-Based Primer*, Boston: Addison Wesley, 2003.

[4] Song, M., Civco, D. L., and Hurd, J. D., A competitive pixel-object approach for land cover classification, *International Journal of Remote Sensing,* Vol.26, No.22, 2005, pp.4981-4997.

[5] Alberti, M., Weeks, R., and Coe, S., Urban land-cover change analysis in Central Puget Sound, *Photogrammetric Engineering and Remote Sensing,* Vol.70, No.9, 2004, pp.1043-1052.

[6] Hollister, J. W., Gonzalez, M. L., Paul, J. F. *et al.*, Assessing the accuracy of national land cover dataset area estimates at multiple spatial extents, *Photogrammetric Engineering and Remote Sensing,* Vol.70, No.4, 2004, pp.405-414.

[7] Chen, J., Luo, M., Li, L. *et al.*, Comparation and analysis methods of moderate -resolution satellite remote sensing image classification, *WSEAS Transactions on Computers,* Vol.7, No.7, 2008,

pp.877-886.

[8] Harvey, K. R., and Hill, G. J. E., Vegetation mapping of a tropical freshwater swamp in the Northern territory, Australia: A comparison of aerial photography, Landsat TM and SPOT satellite imagery, *International Journal of Remote Sensing,* Vol.22, No.15, 2001, pp.2911-2925.

[9] Benediktsson, J. A., Pesaresi, M., and Arnason, K., Classification and feature extraction for remote sensing images from urban areas based on morphological transformations, *IEEE Transactions on Geoscience and Remote Sensing,* Vol.41, No.9 PART I, 2003, pp.1940-1949.

[10] Ehlers, M., Ga?hler, M., and Janowsky, R., Automated analysis of ultra high resolution remote sensing data for biotope type mapping: New possibilities and challenges, *ISPRS Journal of Photogrammetry and Remote Sensing,* Vol.57, No.5-6, 2003, pp.315-326.

[11] Dean, A. M., and Smith, G. M., An evaluation of per-parcel land cover mapping using maximum likelihood class probabilities, *International Journal of Remote Sensing,* Vol.24, No.14, 2003, pp.2905-2920.

[12] Casals-Carrasco, P., Kubo, S., and Babu Madhavan, B., Application of spectral mixture analysis for terrain evaluation studies, *International Journal of Remote Sensing,* Vol.21, No.16, 2000, pp.3039-3055.

[13] Cleve, C., Kelly, M., Kearns, F. R. *et al.*, Classification of the wildland-urban interface: A comparison of pixel- and object-based classifications using high-resolution aerial photography, *Computers, Environment and Urban Systems,* Vol.32, No.4, 2008, pp.317-326.

[14] Baltsavias, E. P., Object extraction and revision by image analysis using existing geodata and knowledge: Current status and steps towards operational systems, *ISPRS Journal of Photogrammetry and Remote Sensing,* Vol.58, No.3-4, 2004, pp.129-151.

[15] Barrile, V., and Bilotta, G., Object-oriented analysis applied to high resolution satellite data, *WSEAS Transactions on Signal Processing,* Vol.4, No.3, 2008, pp.68-75.

[16] Yan, G., Mas, J. F., Maathuis, B. H. P. *et al.*, Comparison of pixel-based and object-oriented image classification approaches - A case study in a coal fire area, Wuda, Inner Mongolia, China, *International Journal of Remote Sensing,* Vol.27, No.18, 2006, pp.4039-4055.

[17] Ryherd, S., and Woodcock, C., Combining spectral and texture data in the segmentation of remotely sensed images, *Photogrammetric Engineering and Remote Sensing,* Vol.62, No.2, 1996, pp.181-194.

[18] Hay, G. J., Marceau, D. J., Dube, P. *et al.*, A multiscale framework for landscape analysis: Object-specific analysis and upscaling, *Landscape Ecology,* Vol.16, No.6, 2001, pp.471-490.

[19] Benz, U. C., Hofmann, P., Willhauck, G. *et al.*, Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information, *ISPRS Journal of Photogrammetry and Remote Sensing,* Vol.58, No.3-4, 2004, pp.239-258.

[20] Laliberte, A. S., Fredrickson, E. L., and Rango, A., Combining decision trees with hierarchical object-oriented image analysis for mapping arid rangelands, *Photogrammetric Engineering and Remote Sensing,* Vol.73, No.2, 2007, pp.197-207.

[21] Grenier, M., Labrecque, S., Garneau, M. *et al.*, Object-based classification of a SPOT-4 image for mapping wetlands in the context of greenhouse gases emissions: The case of the Eastmain region, Que?bec, Canada, *Canadian Journal of Remote Sensing,* Vol.34, No.SUPPL. 2, 2008.

[22] Barlow, J., Martin, Y., and Franklin, S. E., Detecting translational landslide scars using segmentation of Landsat ETM+ and DEM data in the northern Cascade Mountains, British Columbia, *Canadian Journal of Remote Sensing,* Vol.29, No.4, 2003, pp.510-517.

[23] Walter, V., Object-based classification of remote sensing data for change detection, *ISPRS Journal of Photogrammetry and Remote Sensing,* Vol.58,

No.3-4, 2004, pp.225-238.

[24] Esch, T., Roth, A., and Dech, S., Analysis of Urban land use pattern based on high resolution radar imagery. pp. 3615-3618.

[25] Cao, X., and Ke, C. Q., Land use classification with QUICKBIRD image using object-oriented approach. pp. 3255-3258.

[26] Wang, L., Sousa, W. P., Gong, P. *et al.*, Comparison of IKONOS and QuickBird images for mapping mangrove species on the Caribbean coast of Panama, *Remote Sensing of Environment,* Vol.91, No.3-4, 2004, pp.432-440.

[27] Su, W., Zhang, C., Luo, M. *et al.*, Object oriented implementation monitoring method of zone feature in land consolidation engineering using SPOT 5 imagery, *WSEAS Transactions on Computers,* Vol.7, No.7, 2008, pp.847-856.

[28] Jensen, and J.R., *Remote Sensing of the Environment: An Earth Resource perspective*, Upper Saddle River, NJ,USA: Prentice Hall, 2000.

[29] De Fries, R. S., Hansen, M., Townshend, J. R. G. *et al.*, Global land cover classifications at 8 km spatial resolution: The use of training data derived from Landsat imagery in decision tree classifiers, *International Journal of Remote Sensing,* Vol.19, No.16, 1998, pp.3141-3168.

[30] Wu, W., and Shao, G., Optimal combinations of data, classifiers, and sampling methods for accurate characterizations of deforestation, *Canadian Journal of Remote Sensing,* Vol.28, No.4, 2002, pp.601-609.

[31] Bischof, H., Schneider, W., and Pinz, A. J., Multispectral classification of Landsat-images using neural networks, *IEEE Transactions on Geoscience and Remote Sensing,* Vol.30, No.3, 1992, pp.482-490.

[32] AG, D., *Definiens Professional 7 User Guide.*, Munchen, Germany: Definiens AG, 2007.

[33] Addink, E. A., De Jong, S. M., and Pebesma, E. J., The importance of scale in object-based mapping of vegetation parameters with hyperspectral imagery, *Photogrammetric Engineering and Remote Sensing,* Vol.73, No.8, 2007, pp.905-912.

[34] Hay, G. J., Blaschke, T., Marceau, D. J. *et al.*, A comparison of three image-object methods for the multiscale analysis of landscape structure, *ISPRS Journal of Photogrammetry and Remote Sensing,* Vol.57, No.5-6, 2003, pp.327-345.

[35] Congalton, R. G., and Green, K., *Assessing the accuracy of remotely sensed data: principles and practices*, New York: Lewis Publishers, 1999.

[36] Congalton, R. G., and Mead, R. A., A quantitative method to test for consistency and correctness in photointerpretation, *Photogrammetric Engineering & Remote Sensing,* Vol.49, No.1, 1983, pp.69-74.

[37] Foody, G. M., Status of land cover classification accuracy assessment, *Remote Sensing of Environment,* Vol.80, No.1, 2002, pp.185-201.

[38] Laliberte, A. S., Rango, A., Havstad, K. M. *et al.*, Object-oriented image analysis for mapping shrub encroachment from 1937 to 2003 in southern New Mexico, *Remote Sensing of Environment,* Vol.93, No.1-2, 2004, pp.198-210.