An Extraction Method of Urban Ecological Types Based on Object-oriented Classification

A Case Study on Wuhan City

Mengmeng Wu
University of Chinese Academy of Sciences
Institute of Remote Sensing and Digital Earth
Chinese Academy of Sciences
Beijing, China

Weili Jiao, Wei Wang, Huichan Liu, Tengfei Long
Institute of Remote Sensing and Digital Earth
Chinese Academy of Sciences
Beijing, China
wljiao@ceode.ac.cn

Abstract—**Combining SPOT5 multispectral and panchromatic data of Wuhan city, object-oriented method of land cover classification is used to extract the urban ecological types, such as water, vegetation, bare land and impervious surface (including building, road, and other artificial surface) in this paper. The first fundamental step is image segmentation, and then object features that can distinguish each ecological type are selected to extract urban ecological types progressively in this study. After the classification, an accuracy assessment is carried out and the overall accuracy is 94.75%, which can meet the needs of subsequent analyses to Wuhan city.**

Keywords—**Object-oriented, urban ecological types extraction, image segmentation, object feature selection.**

I. INTRODUCTION

Land cover classification is the foundation of many works like the evaluation of land resources, land use planning and land cover change. In general, there are mainly two categories of methods in land classification: pixel-based method and object-based method. Pixel-based method is based on pixels, while the object-oriented method is based on objects and it can take advantage of not only the spectral characteristics, but also the features like shape index, texture, spatial information and context information. In recent years, object-oriented method has been widely used in the information extraction of land cover, especially in the classification of high-resolution remote sensing images, such as SPOT5, IKONOS, QuickBird, etc. Many researchers have studied the object-based method in identifying urban ecological types and get better results than pixel-based methods like maximum likelihood rules[1][2][3][4]. There are mainly two aspects in object-oriented land classification: image segmentation and object feature selection. In this study, a step-by-step method based on object-oriented classification is used to extract ecological types of Wuhan. Firstly, some preprocessing for remote sensing image is needed. Secondly, segments the image properly, and then features that can distinguish different land covers are selected to extract the urban ecological types.

II. STUDY AREA AND DATA

The study area is Wuhan municipal districts, China. Wuhan, which is located in the middle area of China, is the economic and geographic center (Fig.1). The remote sensing data used in this study are SPOT5 multispectral and panchromatic images captured in August 10th, 2010.

III. STUDY METHODS

The goal of the study is to extract four ecological types of Wuhan municipal districts: water, vegetation, bare land and impervious surface. Firstly, the geometric corrections were done for the multispectral and panchromatic images with ground control points. Then, the Pansharping method was applied to the multispectral and panchromatic images to get the fusion image with 2.5m spatial resolution. Figure 2 shows a subset of the fusion image.

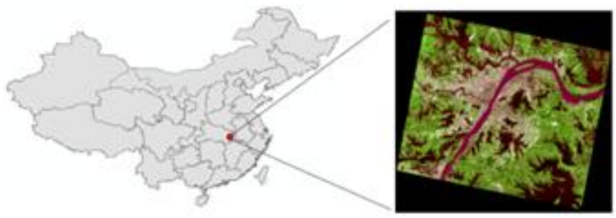


Fig.1. The study area

A. Image Segmentation

Image segmentation is the first fundamental step in object-oriented image analysis, as these objects resulting from this process form the basis of an object-based image classification. In this study, image segmentation is performed with the multi-resolution segmentation (MRS) algorithm by the eCognition Developer 8. The MRS algorithm uses a “bottom-up” image segmentation approach that begins with pixel sized objects which are iteratively grown through pair-wise merging of neighboring objects based on several user-defined parameters (scale, shape, compactness) that are weighted together to a homogeneity criterion; together, these parameters define a “stopping threshold” of within-object homogeneity based on underlying input layers, and thus define the size and shape of resulting image objects [2][3]. In this study, after many experiments, the segmentation parameters are set as scale 20, shape 0.1, and compactness 0.5. A subset of the image after segmentation is shown in Figure 3.

B. Classification Rules

The spectral profiles of different land types are shown in Figure 4. It is obvious that water and shadows have lower values in band4 (SWIR) than other land types. Therefore, SWIR can extract water and shadows. To exclude shadows, this study has selected two features: NDWI [5] and the number of pixels of an object. To extract vegetation, NDVI has been selected, which is generally used in vegetation extraction. But for farmland without vegetation because of seasonal reason, NDVI is useless. On the other hand, farmland without vegetation is similar to bare land in appearance. This study has selected standard deviation (StdDev.) together with band 3 to extract farmland and bare land. When water, vegetation, farmland and bare land are extracted respectively, the remains in image are impervious surface. However, some roads are set as vegetation wrongly because of the influence of plants beside roads. NDBI [6] and length/width of an object have been used to extract these roads. All of the features have been used in this study and their value ranges for different land cover types are shown in Table 1. The flow chart of the algorithm of urban ecological type extraction is shown in Figure 5. The effect of excluding shadows is shown in Figure 6. And a subset of the classification result is shown in Figure 7.

Fig.2. Subset of the fusion image

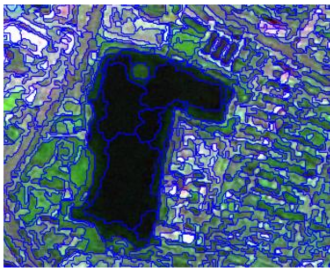


Fig.3. Subset of the image after segmentation

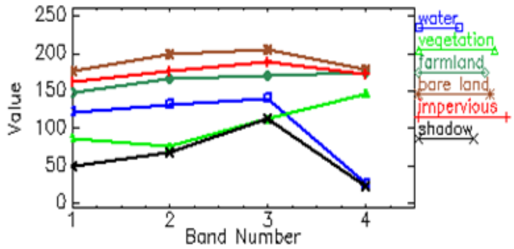


Fig.4. Spectral profiles for different land types

Table 1 Features selected in this study and value ranges for different land cover types

Feature	*Feature description*	*Value range of features for different land types*
Band4	Mean value of an object in SWIR	Water[26.72,51.42] Shadows[21.78,67.24] others[94.27,230.29]
NDWI	(Green-NIR)/(Green+NIR)	Water[-0.13,0.067] Shadows[-0.33,-0.21]
Number of pixels	Number of pixels of an object	Number of pixels of water is mostly bigger than 100.
NDVI	(NIR-Red)/(NIR+Red)	NDVI of vegetation is mostly bigger than 0.12.
Std.Dev.	Standard deviation of an object’s layer values	Farmland [22.73,32.74] Impervious[47.89,94.16] Bare land[14.61,30.85]
Band3	Mean value of an object in NIR	Farmland[98.48,144.32] Bareland1[60.69,226.18]
NDBI	(SWIR-NIR)/(SWIR+NIR)	Vegetation[0.02,0.17] Road[-0.17,-0.056]
L/w	Length/width	L/W of road is mostly bigger than 5.0.

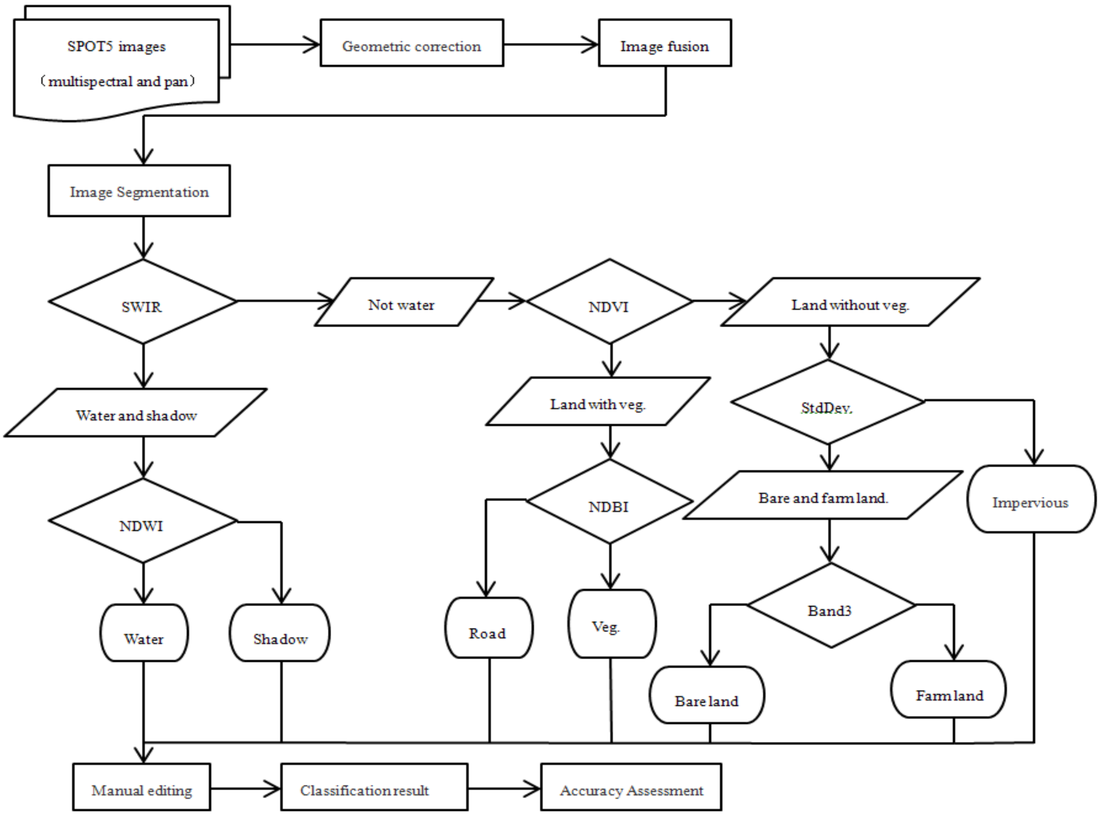
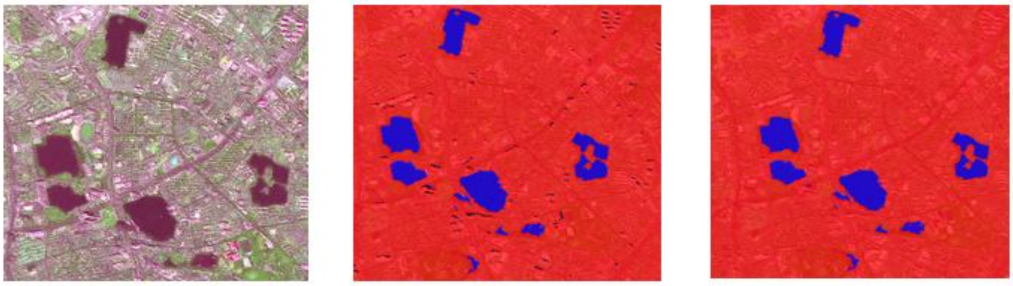
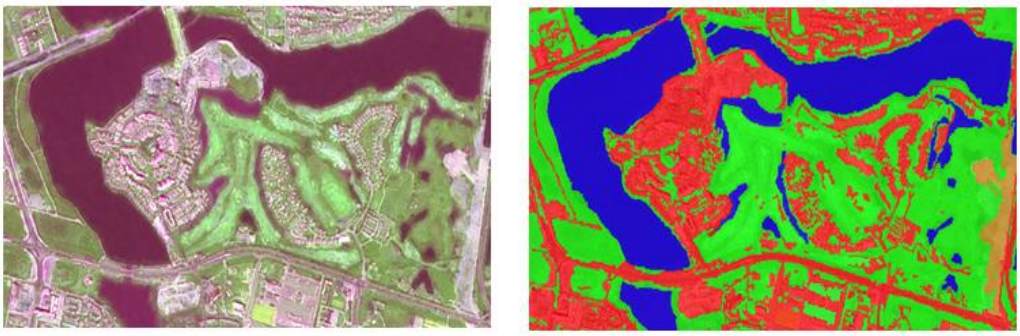


Fig.5. The flow chart



(a) (b) (c)

Fig.6. (a) Subset of fusion image (b) Using SWIR to extract water, blue=water, black=shadow, red=not water (c) After using NDWI to exclude shadows



(a) (b)

Fig.7. (a) Subset of fusion image (b) Object-oriented classification result, blue=water, green=vegetation, red=impervious surface, brown=bare land

Table 2 Error matrix, producer's accuracy and user's accuracy

Classified Data	***Vegetation***	***Water***	***Impervious Surface***	***Bare Land***	***Total***	***Producer's Accuracy***	***User's Accuracy***
Vegetation	142	3	2	0	147	92.21%	96.60%
Water	0	102	0	0	102	97.14%	100.00%
Impervious surface	9	0	96	3	108	96.97%	88.89%
Bare Land	3	0	1	39	43	92.86%	90.70%
Total	154	105	99	42	400		
Overall classification accuracy=94.75% and overall kappa statistics =0.9264.							

C. Accuracy Assessment

Combining with the fieldwork in Wuhan and referring a higher spatial resolution remote sensing image in August, 2010 in Google Earth, 400 points were selected randomly to check the accuracy. The overall accuracy is 94.75% and the kappa statistics is 0.9264(see Table 2). Water has the highest producer's accuracy (97.14%) and user's accuracy (100.00%). The reason is that water is greatly different from other land types in SWIR. The second highest producer's accuracy is produced by impervious surface (96.97%) and the second highest user's accuracy is produced by vegetation (96.60%). The two lowest user's accuracy are produced by impervious surface (88.89%) and bare land (92.86%), and most of the misclassification is set as vegetation.

Ⅳ. CONCLUSION

In this research, object-oriented method is used to get the ecological types of Wuhan municipal districts. This paper introduces the main procedures of the classification: image segmentation and object feature selection. With the accuracy 94.75% and the kappa statistics 0.9264, the classification result can satisfy the following analyses of ecological environment in Wuhan city. And the method used in this study to extract water, vegetation, impervious surface and bare land can be applied to other areas.

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