OBJECT-ORIENTED CLASSIFICATION FOR LAND COVER MAPPING BASED ON ASTER DATA FOR BEIJING

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1. INTRODUCTION

The work present in this paper is part of 100 cities project, which focuses on the intense and frequent monitoring of major cities worldwide. For a metropolis like Beijing, whose land use and land cover is changing dramatically, it is very important to map accurate and up-to-date information of land cover. This paper developed an effective classification scheme and mapping workflow for mapping Beijing's land cover based on ASTER data and the object-oriented classification. Multi-source data were applied in this study. The mountain area in the northwest Beijing was identified with elevation data. The boundary of Beijing is also imported as thematic layer to assist area statistics of classification result as an administrative unit. eCognition, Erdas and ArcGIS work together, play to their own strong point and make up of an effective system to improve the efficiency of mapping significantly. The accuracy assessment of classification showed the developed workflow in this paper could provide results with an acceptable accuracy.

2. DATA

The dataset consists of 14 scenes of ASTER Level-1B data most of which acquired between May and August in 2001, which are optimum months for land cover classification. They are almost the earliest ASTER data which can be downloaded from NASA's EOS Data Gateway (EDG) and can be stitched into a whole 0-cloud-coverage Beijing municipality. The digital elevation data (DEMs) provided by the NASA Shuttle Radar Topographic Mission (SRTM) were applied to identify the mountain area surrounds Beijing. It is available as 3 arc second (approx. 90m resolution) DEMs. Meanwhile, the Google earth data is also used to help selecting the test area to verify the accuracy of classification.

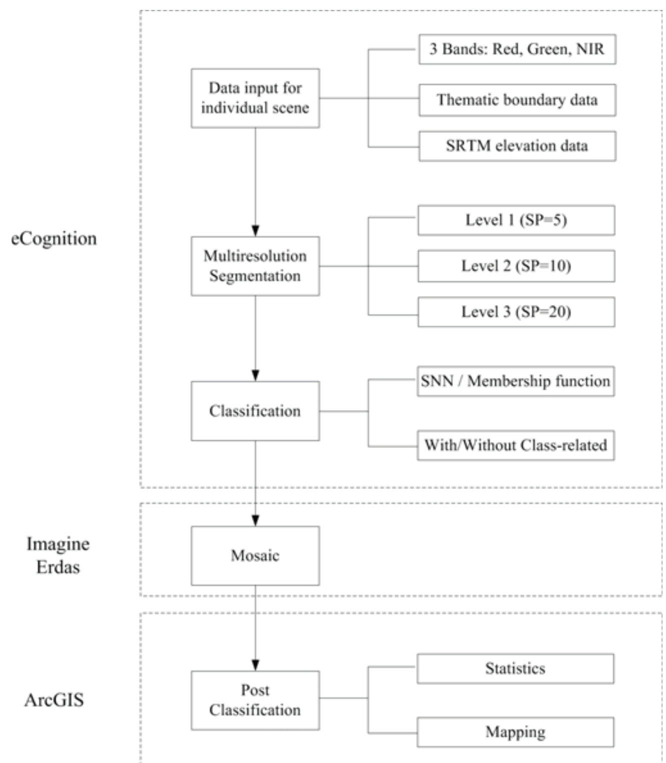


Figure 1:Workflow for land cover mapping

3. METHODS

The main stages for land cover mapping can be generalized as 3 steps: segmentation, classification and mosaic. The key work is to define the appropriate class parameters or rule-set for a best description of the desired output classes. For the difference of tone and land cover among different time-phase data, the 14 scenes of image were classified using the built knowledge-base independently. The data acquired on the same day can be classified with the same parameter of the knowledge-base, moreover, the data acquired on the different date can also classified with the built knowledge-base only adjusting several parameters e.g. threshold value of membership functions. The workflow for land cover mapping based on ASTER 15m data and eCognition's object-based method was built (figure 1). In this workflow, eCognition, Erdas and ArcGIS work together, play to their own strong point and make up of an effective system. Table 1 shows the selected features and rule set for recognition each class. The principle of feature selection is always trying to describe a class with as few features as possible. The use of too many features in one class description causes an immense increase of overlaps in the feature space, complicates classification and reduces transparency significantly.

Classes	**Features used in the rule base**
Water	Mean NIR or(max) Ratio Green or(max) Rel. area of water(Level 1)
Mountain	Existence of Mountain(Level 3) super-objects
Vegetation	NDVI
Urban Green Space • Low Vegetation • High Vegetation	Rel. border to Impervious neighbor-objects or (max) Thematic attributes ID = downtown
Farmland	Inverted similarity as class Urban Green Space
Bare Soil	Rel. area of Bare Soil (Level 1) sub-objects
Impervious Surface • Low impervious • Medium impervious • High impervious	Rel. area of Impervious Surface (Level 1) sub-objects

Table 1: Rules used for separation classes

4. RESULT AND DISCUSSION

Once the classification scheme was built, the classification process is handy and flexible. According to the method illustrated above, 14 scenes of Beijing's ASTER image were classified with a division into 9 classes based on eCognition's object-based image analysis. The classification result is given in figure 2. A classification is not complete until its accuracy is assessed. Classification evaluation gives evidence of how well the generated or used classifier is capable of extracting the desired objects from the image. For this purpose, a comparison is made between classified data and test samples. Test samples were selected by reference to the ancillary data of Google Earth satellite data. Afterwards, eCognition compared the classification result to the test samples automatically. Error matrix for each scene was calculated individually. Figure 3 showed the confusion matrix for scene 10. The overall accuracy and Kappa statistics are presented. The big advantage of the kappa coefficient over overall accuracy is that kappa takes chance agreement into account and corrects for it. Chance agreement means here the probability that classification and reference classification agree by mere chance. Given that a classification is considered satisfactory when its overall accuracy is more than 70-75% and its Kappa coefficient is more than 65%.

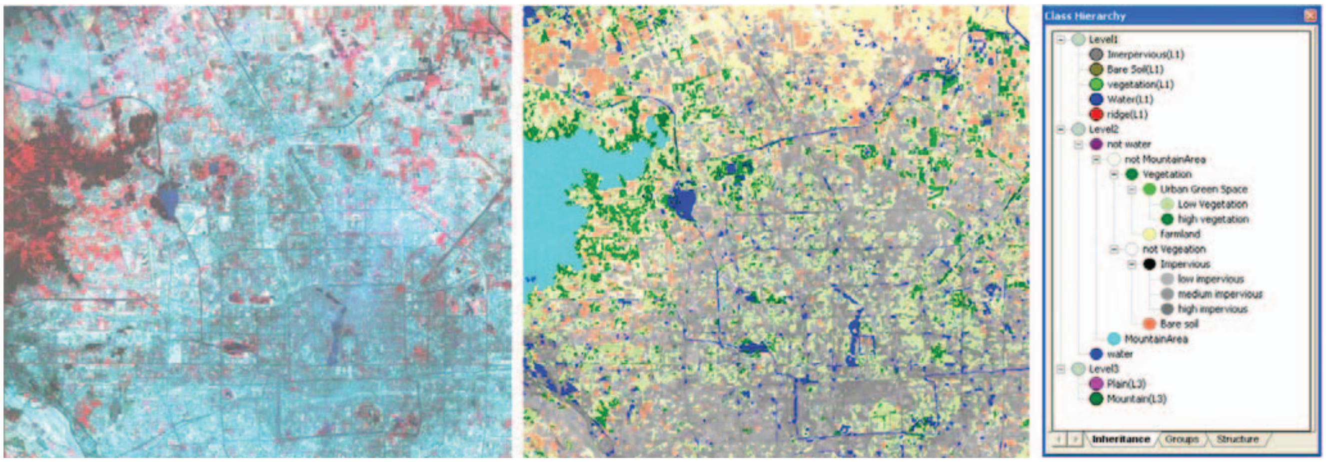
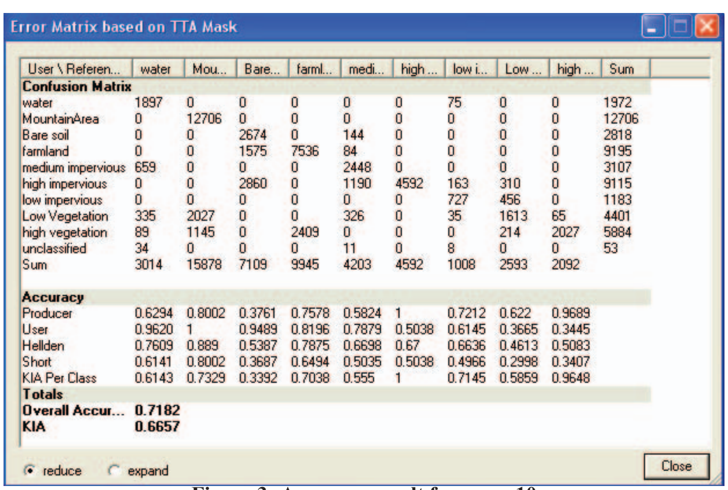


Figure 2: A section of classification result

Moreover, this study discovered that eCognition's polygon-based image analysis method unintentionally provided an effective solution for the void data problem of SRTM data. As we know, SRTM elevation data which produced by radar data acquired by the Shuttle Radar Topography Mission, include data voids (holes) due to localized problems with the radar acquisition process, including layover, shadowing, and lack of signal return from smooth water surfaces. The value of SRTM holes is set to -32768. Since eCognition analyses image based on image objects, the "Max pixel value of the object" feature can prevent the negative effect of data voids as long as the image objects is big enough not to be filled with SRTM holes, i.e. among an image object if only one pixel whose elevation value is greater than -32768, the data voids can be avoided. Therefore, the usual preprocess for patching holes in SRTM data can be overleaped in eCognition, once a suitable scale parameter for segmentation is selected. In this study, the scale parameter of twenty (level3) is fit for Beijing's SRTM data (Figure 4).


Error Matrix based on TTA Mask

User \ Referen...	water	Mou...	Bare...	farml...	medi...	high ...	low i...	Low ...	high ...	Sum
Confusion Matrix										
water	1897	0	0	0	0	0	75	0	0	1972
MountainArea	0	12706	0	0	0	0	0	0	0	12706
Bare soil	0	0	2674	0	144	0	0	0	0	2818
farmland	0	0	1575	7536	84	0	0	0	0	9195
medium impervious	659	0	0	0	2448	0	0	0	0	3107
high impervious	0	0	2860	0	1190	4592	163	310	0	9115
low impervious	0	0	0	0	0	0	727	456	0	1183
Low Vegetation	335	2027	0	0	326	0	35	1613	65	4401
high vegetation	89	1145	0	2409	0	0	0	214	2027	5884
unclassified	34	0	0	0	11	0	8	0	0	53
Sum	3014	15878	7109	9945	4203	4592	1008	2593	2092	
Accuracy										
Producer	0.6294	0.8002	0.3761	0.7578	0.5824	1	0.7212	0.622	0.9689	
User	0.9620	1	0.9489	0.8196	0.7879	0.5038	0.6145	0.3665	0.3445	
Hellden	0.7609	0.889	0.5387	0.7875	0.6698	0.67	0.6636	0.4613	0.5083	
Short	0.6141	0.8002	0.3687	0.6494	0.5035	0.5038	0.4966	0.2998	0.3407	
KIA Per Class	0.6143	0.7329	0.3392	0.7038	0.555	1	0.7145	0.5859	0.9648	
Totals										
Overall Accur...	**0.7182**									
KIA	**0.6657**									

reduce expand Close

Figure 3: Accuracy result for scene 10

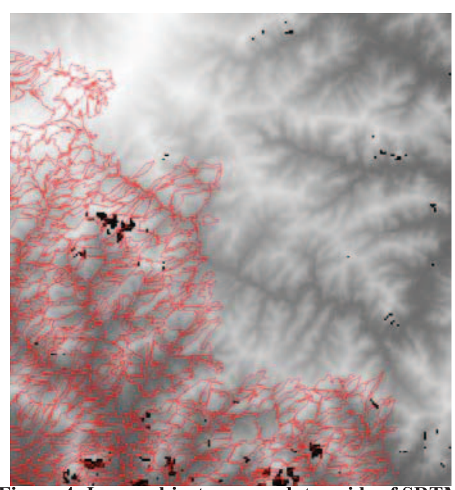


Figure 4: Image objects versus data voids of SRTM

5. CONCLUSION

This paper aims at to developing a timely and cost-effective classification scheme and cartographic workflow for Beijing based on object-oriented image analysis. It's very necessary for metropolis like Beijing, whose land use and land cover is changing dramatically. How to mapping 16,800 square kilometers area quickly and accurately is a challenge for cartographer. The developed workflow in this paper could significantly improve the efficiency of mapping and provide results with an acceptable accuracy. The next step would be to detect the potential:

(1) To apply the workflow to other cities with the similar natural environment

(2) To discriminate between similar classes such as grassland, woodland and orchard.

6. REFERENCES

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