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Analysis of green space in Chongqing and Nanjing, cities of China with ASTER images using object-oriented image classification and landscape metric analysis

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Green space is an important urban land use which can enhance the livability of cities. Chinese cities develop rapidly, and increasingly strong emphasis has been put on the provision of better landscape and more green space. We used an object-oriented approach to classify different land covers in Chongqing and Nanjing, two historical Chinese cities. Suitable segmentation levels were selected by locating break points along the variation of selected object variables. Three segmentation levels were identified for each city. Object variables with good discriminatory power were selected to identify different land covers by making use of their spectral, textural and shape properties. Decision tree classifiers were formulated for classifying images into eight land cover classes. Accuracy of object-oriented classification was the highest in Chongqing and ranked second in Nanjing. The result was compared to those of maximum likelihood classification, fuzzy classification and linear unmixing classification. Land covers were then generalized as green space for landscape metric analysis. The fragmented nature of green space was discussed. It was revealed that there existed a general lack of green space in old urban centres. With an increasing distance from city centres, more large patches were found.

1. Introduction

Provision of green space is vital for the beautification of the urban environment, to help improve air and water quality, to provide recreational space, to promote public health and to enhance the economy of the city (Fabos 1995, Attwell 2000, Jim and Liu 2001, Swanwick et al. 2003). Green space is an important landscape component in cities, and possesses the ability to enhance biodiversity. Urban green space studies cover a wide range of topics including the assessment of amenity value (Tyrvainen and Vaananen 1998); perception and use of green space (Robertson and Walford 2000); the relationship between adjacent neighbourhood and open space (Gobster 2001); ecological studies on the role of green space in supporting target species for conservation (Mortberg and Wallentinusb 2000); and demand for urban green

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space. This field also involves studies on the specific form of green space, e.g. greenways as nature’s corridors (Fabos 1995); the relationship between land cover composition, housing and landscape in urban domestic gardens; and the changing functions of green belts (Amati and Yokohari 2006).

Echoing its diverse functions, green space takes a diversity of forms including lawns, neighbourhood parks, community gardens, landscaped components within public and private institutes, green belts, greenways, country parks and natural reserves. In the broadest sense, it comprises land surface that is covered by vegetation. Jim (2002) regarded urban green space as ‘plantable spaces’ in the context of town planning. Based on the spatial configuration and pattern of green spaces, Yu (1998) described four models of green space, namely concentric ring, embedment, nuclei and ribbon. Gobster (2001) also categorized urban space into four major types: interspaces within the neighbourhood, public parks shared by different neighbourhoods, regional greenways that span across counties, and metropolitan bioreerves.

Spatial distribution, species composition and density, landscape characteristics such as size, shape, density, and contagion and connectivity of green space vary significantly within a metropolis and among cities. An inventory of green space within the city concerned provides the basic information. This involves either a detailed field survey of the nature and characteristics of tree habitats (Jim 1989a, b); the use of aerial photographs for mapping and inventory of green space (Teh 1994) or the application of satellite images (Fung and Siu 2000, 2001, Small 2001). Undoubtedly, remote sensing plays a key role in exploring the spatial distribution and configuration of green space in cities. Image classification helps identify the location of green space from which landscape metric analysis can be applied to shed light on their landscape characteristics. Landscape metric analysis can be utilized at patch, class and landscape levels to unravel the composition, pattern and configuration of landscape components as well as the ecological processes involved (Turner et al. 2001). Leitão and Ahern (2002) proposed the use of nine basic metrics amongst hundreds of them. In a study of urban green spaces in Jinan City of China, Kong and Nakagoshi (2006) investigated the spatial-temporal gradient of green space based on a temporal series of SPOT images. Local area green space was quantified and gradient analysis of landscape metrics was performed with respect to the city centre. Their analysis revealed the impact of urbanization and government policy on the altered green space. Kong et al. (2007) further examined the amenity value of green space in hedonic price modelling.

Conventional remote sensing applications rely principally on per-pixel based image processing techniques which in most circumstances adopt a single scale classification methodology. Per-pixel classification techniques have been effective to map land use and land cover at Level I or II classifications using medium resolution satellite data such as Landsat TM/ETM+ and SPOT HRV/HRVIR. But they are heavily confined to the use of spectral data. Their ability to make effective use of other image characteristics, such as neighbourhood, size, shape, compactness, texture and contexture, is also limited.

There have been increasing studies making use of object-oriented image analysis techniques in remote sensing for several reasons. First, object-oriented techniques encapsulate each image object not only with basic spectral information, but also with additional image data including object size, object complexity, texture, number of sub-objects and spectral difference to neighbouring objects (Baatz and Schape
2000, Lang and Blaschke 2003, Benz et al. 2004). This multitude of object features is a definite advantage in using the object-oriented approach (Chubey et al. 2006). Second, the object-oriented approach points directly to the objects of interest and can produce more meaningful and useful results. Using it to extract a patch of woodland, an agricultural field or a building block in the form of objects produces more meaningful results than working with pixels. Objects can be used to represent homogeneous landscape components (Chubey et al. 2006). They can also be used to eliminate area of no interest (Barlow et al. 2006). Third, the object-oriented approach has shown great potential in image classification particularly for very high resolution images such as IKONOS (Herold et al. 2002, Rego and Koch 2003, Hájek 2005), Quickbird (Frauman and Wolff 2005) and airborne scanned data. It has been noted that spectrally homogeneous areas in low resolution imagery may become areas of high spectral variation in these high resolution data (Huang et al. 2003, Zhang and Feng 2005). Per-pixel based classification approaches simply cannot generate good results. The use of segmentation in aggregating pixels into objects helps reduce the variability. It also overcomes salt-and-pepper effects commonly found in pixel-based classification (Yu et al. 2006). Finally, benchmarking the classification accuracy of the object-oriented approach with reference to conventional per-pixel based classification (e.g. maximum likelihood classification) reveals a significant improvement (Herold et al. 2002, Wang et al. 2004a, b, Zhang and Feng 2005). Huang et al. (2003) found that the object-oriented approach is better not only in thematic accuracy, but also in area and shape consistencies.

Undoubtedly, the object-oriented approach has great potential in land use and land cover mapping. With regard to urban green space, it may vary from scattered road side trees and fragmented small urban parks to large patches of preserved woodland. The great variety in terms of form, size and shape poses a great challenge. Will the object-oriented approach be able to extract various forms of green space? An important decision will be the scales at which various forms of green space, together with other land covers, are extracted. Will the use of additional object features be effective in identifying different land covers, and how can these features be used to improve classification results? It is important to investigate how to make good use of this multitude of object features and select suitable ones which possess good discriminatory power for formulating a decision tree classifier that is effective and efficient. Certainly, the accuracy using an object-oriented approach has to be assessed based on comparison with conventional per-pixel based classification methods.

In this paper, we investigate the ability of object-oriented image classification to identify green space amongst different land use and land covers in two cities in China, Chongqing and Nanjing. Both are important historical cities in China experiencing rapid urban expansion and calling for better landscaping in the process of urban development. They are similar in terms of population, industrial output and urban area (table 1), but they also form sharp contrast as Nanjing is located close to the coast whereas Chongqing is an inland city. Similarities and differences of landscape characteristics of green space form an interesting research topic to understand these rapidly changing Chinese cities. Specifically, the objectives of this paper include:

1. to extract spectral, shape and textural features of different land covers by means of multiresolution segmentation so as to track their variability along different segmentation scales;
2. to investigate the suitable scales at which image objects should be extracted;
3. to compare the classification results using object-oriented techniques with three other classification methods, namely maximum likelihood classification, classification using linear unmixing techniques and fuzzy classification in two study sites, Chongqing and Nanjing; and
4. to assess the landscape characteristics of green space between the two cities with selected landscape metrics.

2. Study sites and data

Both Chongqing and Nanjing are located at around 28°–33°N in latitude. Nanjing is located near to the delta of Changjiang and is considered one of the major coastal cities in China. It was the capital of ancient Chinese monarchies for several centuries and has long been the political, economic and cultural centre in China. Currently, it is the capital of Jiangsu Province and ranks eighth in terms of urban population among large cities in China (National Statistical Bureau 2003). In contrast, Chongqing is situated inland in the mountainous middle course of Changjiang. Among the four municipalities under the Central Government (including Beijing, Tianjin, Shanghai and Chongqing), it is the only one located inland (Luo and Chen 1999). Both cities have experienced rapid economic growth in the past decade. Their urban built-up areas were reported at around 440 km² in 2003 (table 1). While both cities possess an old urban core of high density construction, Nanjing enjoys more space for development in the flood plain as compared to the mountainous setting of Chongqing. The difference in location provides a sharp contrast in the landscape characteristics of green space between these cities. Two ASTER images acquired on 21 July 2000 and 6 November 2001 for Chongqing and Nanjing, respectively, were used in this study (figure 1).

3. Methodology

3.1 Data preprocessing

The two ASTER images were acquired as Level 1B data stored in Hierarchical Data Format (HDF). They were transferred into Pix format using OrthoEngine in PCI Geomatica V.9.1.0 ©. Rectangular areas covering the city centres of both cities were clipped out from the whole image for the study. ASTER collects data at 14 spectral bands ranging from visible to the thermal infrared region. In this study, three visible
and near infrared (VNIR) channels were used in the object-oriented classification approach. Additionally, we adopted the Smoothing Filter-based Intensity Modulation (SFIM) image fusion algorithm (Liu 2000) to upgrade the six shortwave infrared (SWIR) images to 15 m spatial resolution. A comparison between the raw SWIR image and SFIM SWIR image is shown in figure 2. It is noted that edge details of different spatial objects have been enhanced significantly after SFIM was applied. These six SWIR channels were merged with the original three VNIR channels such that nine channels were used in the pixel-based classification approaches.

3.2 Designing classification schemes

Hierarchical land cover classification schemes were designed separately for the two cities. Based on interpretation of the images, land use plans and existing literature, land cover classes were defined from the general Level 1 to the more detailed classes at Level 2 and Level 3 respectively. Due to specific land use conditions and seasonal differences of the two images, classes at Level 3 are not identical for the two cities.

The hierarchical land cover classification scheme of Chongqing is shown in table 2(a). Eight land cover classes are targeted. The eight land cover classes were set...
up based on secondary data such as Chongqing City Proper 1996–2010 Urban Master Plan, and visual interpretation of the satellite image. A similar process was carried out for Nanjing (table 2(b)).

Figure 2. A SWIR image of Chongqing (a) before and (b) after data fusion with smoothing filter-based intensity modulation.

Table 2. Hierarchical land cover classification schemes for

(a) Chongqing

<table>
<thead>
<tr>
<th>Level 1</th>
<th>Level 2</th>
<th>Level 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>Lake</td>
<td>Bare land</td>
</tr>
<tr>
<td></td>
<td>River</td>
<td>Low density urban land</td>
</tr>
<tr>
<td>Vegetation</td>
<td>Woodland</td>
<td>High density urban land</td>
</tr>
<tr>
<td></td>
<td>Cropland and grass</td>
<td>Industrial sites</td>
</tr>
<tr>
<td>Non-vegetation</td>
<td>Bare soil</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Impervious cover</td>
<td></td>
</tr>
</tbody>
</table>

(b) Nanjing

<table>
<thead>
<tr>
<th>Level 1</th>
<th>Level 2</th>
<th>Level 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>Lake</td>
<td>Cropland 1 (with higher IR reflectance)</td>
</tr>
<tr>
<td></td>
<td>River</td>
<td>Cropland 2 (with lower IR reflectance)</td>
</tr>
<tr>
<td>Vegetation</td>
<td>Vegetation with high reflectance</td>
<td>Aquatic crops</td>
</tr>
<tr>
<td></td>
<td>Vegetation with low reflectance</td>
<td>Woodland</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Grass</td>
</tr>
<tr>
<td>Non-vegetation</td>
<td>Bare soil</td>
<td>Fallowed cropland</td>
</tr>
<tr>
<td></td>
<td>Impervious cover</td>
<td>Bare land</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Low density urban land</td>
</tr>
<tr>
<td></td>
<td></td>
<td>High density urban land</td>
</tr>
</tbody>
</table>
3.3 Multi-scale segmentation

eCognition version 3 was adopted in this study for object-oriented image analysis (Definiens Imaging 2003). Multi-scale segmentation was first used as a region-growing algorithm. Starting with individual pixels, neighbouring pixels were merged into image objects which minimize spectral heterogeneity and maintain shape compactness (or smoothness) at a predetermined scale parameter. Average sizes of resulting objects were controlled through this scale parameter. It is essential to decide the spectral versus shape ratio, the number of levels required and at what segmentation level (scale) the spatial objects should be extracted.

3.3.1 Selection of spectral-shape ratio. An experiment was carried out to examine spatial objects derived at different spectral–shape ratios. The object signature, in terms of spectral, shape and texture variables, was examined to explore the variation in scale. The spectral–shape ratio was set such that a high ratio will preserve spectral similarity within the object during segmentation whilst a low ratio will incline towards maintaining the shape of objects as close to square/circle as possible (Definiens-Imaging 2003). The choice of spectral–shape ratios used in the experiment included:

- 10:0 the weight of shape in the spectral–shape ratio is 0%;
- 9:1 the weight of shape is 10%;
- 7:3 the weight of shape is 30%;
- 5:5 the weight of shape is 50%;
- 3:7 the weight of shape is 70%; and
- 1:9 the weight of shape is 90%.

The objects derived were examined in terms of the total number of image objects created, standard deviation of spectral means of objects and differences in image appearance.

It is obvious that as the segmentation level increases, the number of image objects yielded decreases exponentially. Both datasets exhibit this phenomenon. The following observations were made in the analysis:

- At each segmentation level, a decrease in spectral–shape ratio (increasing the weight of shape) yielded a smaller number of image objects but a larger size of image objects. This effect is illustrated in figure 3(a) based on the Chongqing data. For the Nanjing data (figure 3(b)), a similar feature appears, but the difference at ratios of 10:0 and 9:1 is not significant based on a detailed visual inspection of objects produced in both results.
- With larger image objects, the standard deviation of their spectral values also surges under a smaller spectral–shape ratio (figure 4). For the Nanjing data, it is noted that the difference in SD among the spectral–shape ratios of 10:0, 9:1 and 7:3 reduces when the segmentation level increases from three (scale factor of six) onward.
- At the same segmentation level, a high ratio tends to produce objects that are too fractal whilst a low ratio generates objects with regular shapes. It was decided that a spectral–shape ratio of 9:1 should be adopted for multi-resolution segmentation for Chongqing data. For the Nanjing data, ratios of 10:0 and 9:1 tend to produce objects fractal in shape at high segmentation level. It was thus decided to use a 7:3 spectral–shape ratio.
3.3.2 Selection of segmentation levels. The next procedure was to determine which segmentation levels should be used. It was hypothesized that break points identified along selected object variables at different segmentation levels should be the critical segmentation levels. Object signatures derived from the three VNIR bands, standard deviation (SD), grey level co-occurrence matrix (GLCM) homogeneity (HOM), GLCM contrast (CON), GLCM entropy (ENT) and GLCM angular second moment (ASM) derived at different levels were examined for exploring whether critical levels could be depicted. Three land cover classes—lake, cropland and grass—and high density urban land were used in the analysis of the Chongqing data. For the Nanjing data, lake, cropland and bare land were used for a similar analysis. The selection of final break points was also based on whether different land cover classes could be discerned at that particular level.
The lowest segmentation level at scale factor 1 was compared with the raw pixel-based image. Visually speaking, the two images exhibit close similarity. Considering that many green spaces are patchy and scattered in the urban land, pixel level was selected as the lowest level for the Chongqing data. In the case of Nanjing, the level 1 image and the raw pixel image look very similar. The level 1 images have very low standard deviation (SD) values for selected land cover objects. To allow a contrast between the two cases, level 1 was selected for the Nanjing data.

A series of graphs was produced to explore the existence of critical levels at higher segmentation levels for different land cover classes (examples are illustrated in figure 5). In the case of Chongqing, it was found that for most object variables, SD values increased gently with an increasing segmentation level. But from the textural features, particularly ASM, there existed an obvious break point at segmentation level 5 when the scale parameter was set at 10. Beyond segmentation level 5, some land cover classes exhibited different break points at levels 8, 9 and 10. As more classes found their break points at level 9, it was thus selected as another segmentation level. The three levels used in subsequent analysis were pixel level, levels 5 and 9 for the Chongqing data.

In the case of Nanjing, two common breaks could be detected from the variables. The first break point existed between segmentation levels 4 and 5. Level 4 tended to maintain more detailed information and contrast among different types of

Figure 4. Variation of standard deviation (SD) of VNIR3 (infrared band) of selected land cover classes along segmentation levels in (a) Chongqing and (b) Nanjing. The colour legend represents different spectral-shape ratios (e.g. 10%–10% weight of spectral-shape ratio).
vegetation classes. It was thus selected. The second break point existed between segmentation levels 8 and 10; this was very similar to the Chongqing data. The final decision was made at level 8 since more land covers could be differentiated based on the variables at this level. The three levels used in subsequent analysis were levels 1, 4 and 8 for the Nanjing data.

Figure 5. Variation of (a) standard deviation (SD) and (b) angular second moment (ASM) of VNIR3 for the classes lake, high density urban, and cropland and grass in the Chongqing data.
3.4 Formulation of class hierarchy with membership function rules

Extraction of object features for land cover classes was made possible after image segmentation through feature view, which provides visualization of object feature variables for different features (including spectral, shape and textural). Features which can be used to separate classes are selected to set up membership rules for each class in class hierarchy (Zhang and Feng 2005). This process involves a trial and error experiment testing the applicability of each rule as well as the use of Boolean operator AND in combining several rules together. Classifying rules were set using fuzzy logic under which the feature values interval was transformed into a set of membership values within the interval [0, 1] (Leung 1988). The output of the classification includes a crisp classification in which each object has exactly one class assignment.

3.4.1 Chongqing. The decision tree (figure 6(a)) started differentiating water from non-water objects, making use of four variables at object level 2: mean difference from neighbouring objects VNIR3, VNIR3 × VNIR2, VNIR3/VNIR2 and size of objects. To identify green space, non-water objects were subdivided into vegetation and non-vegetation, in which vegetation was identified using a simple ratioed vegetation index, i.e. VNIR3/VNIR2 at object level 2, which was found more effective than NDVI. It was further divided into woodland and cropland and grass using the object mean values of the three bands at level 1. Woodland tended to have lower spectral mean values than cropland and grass. For non-vegetation classes, they were further classified as low density urban land, high density urban land and bare soil. Textural variables such as GLCM contrast from VNIR1 and VNIR2 were useful to identify low density urban land. The classification of high density urban and bare soil relied upon their difference in spectral mean values.

3.4.2 Nanjing. Like the Chongqing data, the decision tree for Nanjing (figure 6(b)) also started differentiating water from non-water objects. Size in this case was not helpful. Rules were set making use of spectral means and their standard deviation values. The identification of green space basically followed the Chongqing case. A simple ratioed vegetation index, VNIR3/VNIR2 was used to differentiate vegetation from non-vegetation objects. Vegetation was divided into woodland and non-woodland, making use of the lower spectral values of the former. However, there existed a greater variety of crops growing in the urban fringe with distinctive spectral information. They were originally identified as four classes. Owing to confusion in different trials of classification results, they were finally grouped into two major types and are identified as cropland and grass 1 (vegetables and including aquatic crops, e.g. lotus) and cropland and grass 2. The high NDVI values and lower VNIR1 reflectance constituted the major rules to separate them. Again, the use of textural features helped differentiate different urban land cover classes.

3.5 Pixel-based classification

In order to compare the classification accuracy of the object-oriented approach, three pixel-based classification methods were tested: (a) maximum likelihood classification (MLC); (b) supervised fuzzy classification (SFC); and (c) linear spectral unmixing (LSU). They were chosen because they are the most commonly used pixel-based classification algorithms. In particular MLC has been used as a benchmark to compare target classification algorithms in the literature (e.g. Gomes...
and Marçal 2003, Rego and Koch 2003, Wang et al. 2004a). Methods of producing MLC and SFC are very similar. Training samples for each class were selected from the image to model the feature space for classification. While MLC assumes Gaussian distribution for each class, SFC utilizes multispectral data to model membership functions for classification without restrictive assumptions. SFC was adopted because a similar fuzzy sets approach was also used in object-oriented classification. It served as a reference for comparing the object-based approach versus the pixel-based approach. LSU adopts a different methodology in which

Figure 6. Classification decision trees for (a) Chongqing and (b) Nanjing. Classification rules are printed in italic under the associated land cover class.
endmembers, i.e. multispectral values of pure classes, were required. Linear equations were then generated, under which class assignment of each pixel was based on the relative composition of the pure classes in that particular pixel (Roberts et al. 1998). For MLC, we used the PCI Geomatica image analysis system, whereas IDRISI was used for SFC and LSU. All three pixel-based classifications were performed using the merged VNIR and SWIR bands. With nine input variables, the number of classes used in LSU for the Nanjing case was reduced to nine. River and lake were merged as water whilst fallowed cropland and bare land were merged into bare soil.

3.6 Accuracy assessment

Accuracy assessment was used to compare the results of four classification methods. A stratified random sampling method was used such that 50 independent samples were selected for each class. Reference information was obtained mainly from visual interpretation of the ASTER images aided by ancillary data including land use plans (Nanjing Urban Planning Bureau 2003, Chongqing Urban Planning Bureau 2004) and earlier Landsat TM images. A total of 399 and 472 samples were selected for the Chongqing and Nanjing data, respectively. Producer’s accuracy and user’s accuracy were used to assess the accuracy of individual classes whilst overall accuracy and Kappa coefficient of agreement were used to determine the overall accuracy of the classifying algorithms.

3.7 Landscape metric analysis

After classification, vegetation classes produced from object-oriented classification were grouped together as one single class. This was used to represent green space and ascertain its distribution and composition within two cities using landscape metric analysis. With the aid of buffer analysis, the distribution of green space with an increasing buffer ring of 1 km each was mapped. This facilitated the computation of landscape metrics at patch level using Fragstats version 3.1 (McGarigal 2001). Earlier studies have found that landscape metrics are highly correlated with each other (Leitao and Ahern 2002, Cifaldi et al. 2004). We focused on the composition, fragmentation and availability of space for developing green space in this paper by examining the variation of selected metrics including proportion of landscape (PLAND), number of patches (PN) and mean patch size (MPS) using area weighted means of patch.

4. Results and discussion

4.1 Classification results

Classification accuracy using different classifiers in Chongqing and Nanjing is illustrated in tables 3(a) and 3(b), respectively. The resultant classified images and error matrices of object-oriented classification are shown in figure 7 and table 4, respectively.

4.1.1 Chongqing. Classified images of Chongqing using the object-oriented classification approach were compared with classified images using the pixel-based classification algorithms mentioned above. The object-oriented classification approach attained the highest overall accuracy of 64.16%, followed by MLC (62.66%), SFC (52.88%) and LSU (42%) (table 3(a)). However, the difference between the object-oriented approach and MLC was not significant.
The confusion matrix of object-oriented classification (table 4(a)) revealed that cropland and grass had a high producer’s accuracy of 93.9% but a relatively lower user’s accuracy of 57.5%. For woodland, the two accuracies were 64.4% and 76.7% respectively. In general, vegetation classes could be identified but confusion still existed between the two classes. Confusion also appeared between cropland and grass, and among other non-vegetation classes, including bare land, low density urban and high density urban land.

4.1.2 Nanjing. Overall accuracies of four classifications in Nanjing (table 3(b)) showed different results to those in Chongqing. LSU attained the highest overall accuracy (65.15%), but this might be due to the fact that river and lake were aggregated together as one single class: water. Object-oriented classification attained the second best result in terms of overall accuracy (62.61%; Kappa = 0.544). However, its difference from MLC (59.96%) was not significant. SFC yielded the least accurate result with an overall accuracy of only 50.81%. It was also observed that both woodland and cropland and grass 1 had high user’s accuracy (95.7% and 84.6% respectively) but much lower producer’s accuracy (50% and 37.9% respectively) (table 4(b)). A reverse pattern was found in cropland and grass 2 where the producer’s accuracy was higher than the user’s accuracy. Confusion between cropland and grass 2 with the other vegetation classes was common. Among other land covers, river and low density urban land had the highest and most balanced producer’s and user’s accuracies.

Results from both cases help to assert the potential of object-oriented image classification, though the classification accuracy is not consistently higher (Rego and Koch 2003). It should be noted that classification rules are mainly derived from the three VNIR bands, whilst the pixel-based classifications make use of nine bands, both the VNIR and SWIR bands. Certainly, object-oriented classification does not solve the problem of class confusion which occurs commonly in pixel-based classifications. Confusion between some land cover classes is even worse in the case of Nanjing, which is similar to earlier findings by Gomes and Marçal (2003). Class confusion reveals the mismatch between the sizes of target objects and the scales used to extract them. When segmentation is applied to high resolution data, spectral variation within a land cover is reduced, thus class confusion problem should be
improved (Zhang and Feng 2005). In this study, the medium resolution ASTER data inherently have many mixed pixels. Applying segmentation may aggravate the problem. Therefore, the critical task is to identify which land covers need segmentation to reduce complexities, at what level segmentation should be performed, and which land cover is more suitable at pixel level.

From the two cases, it is also found that although segmentation parameters are different in each case, many classifying rules are actually transferable. For example, standard deviation can be used to distinguish water in both cases. Textural information is critical to classify urban land covers in both cities. Shape feature density, which is used to differentiate river from lakes in Chongqing, can also be

Figure 7. Object oriented classified images of (a) Chongqing and (b) Nanjing.
Table 4. Confusion matrix of OO classification in

(a) Chongqing

<table>
<thead>
<tr>
<th>Classified Data</th>
<th>Lake</th>
<th>River</th>
<th>Cropland and grass</th>
<th>Woodland</th>
<th>Bare land</th>
<th>Industrial</th>
<th>High density urban</th>
<th>Low density urban</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lake</td>
<td>3</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>River</td>
<td>0</td>
<td>25</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>25</td>
</tr>
<tr>
<td>Cropland and grass</td>
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Producer's accuracy (%)          | 37.5 | 89.3  | 93.9               | 64.4     | 24.4      | 100.0      | 48.5               | 39.4             |
User's accuracy (%)               | 50.0 | 100.0 | 57.5               | 76.7     | 54.3      | 25.0       | 69.6               | 68.4             |
Overall accuracy (%)              | 64.16 | 52.23 |
Kappa coefficient (%)             |      |       |                    |          |           |            |                    |                  |

(b) Nanjing

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Producer's accuracy (%)          | 26.1 | 84.8  | 50.0     | 37.9                 | 76.1                 | 78.1      | 70.6              | 38.5             |
User's accuracy (%)               | 60.0 | 84.8  | 95.7     | 84.6                 | 59.0                 | 43.9      | 76.6              | 62.5             |
Overall accuracy (%)              | 62.61 | 54.39 |
Kappa coefficient (%)             |      |       |          |                      |                      |           |                    |                  |
applied in the case of Nanjing. The use of spatial objects simply makes available a large pool of textural, shape and contextual variables for selection in classification which alleviates drawback in the pixel-based approach.

4.2 Landscape metric analysis

The proportion of landscape (PLAND) occupied by green space showed the relative abundance of green areas. Both cities exhibited a similar pattern of PLAND (figure 8). They started with a small value at the city centres and increased with an increasing distance from the city centres.

Figure 8. Proportion of Landscape (PLAND) in Chongqing and Nanjing.

Figure 9. Number of patches (PN) in Chongqing and Nanjing.
In the case of Chongqing, PLAND was less than 10% within the first 2 km, revealing the lack of green space in the old urban centre. It increased to 50% within the 5 km rings. Beyond that PLAND increased to around 70%.

For Nanjing, PLAND increased from 15% to 25% at 3 km from the city centre. At the periphery of the old city centre small landscaping parks appeared, such as Chingliang Shan Gongyuan. Another sharp rise in PLAND started to occur after 5 km from the city centre, where PLAND increased from about 30% to about 55%. Here large-scale green areas occurred, such as Mufu Shan, Zijin Shan and Yuhuatai Lieshi Lingyuan.

Fragmentation is a description of the process and tendency of a landscape component to break into small patches (Frohn 1998). This is illustrated by means of cross examining the PN (number of patches) (figure 9) versus the mean patch size (area weighted means of patch) (figure 10).

In Chongqing there was a sharp increase in PN from below 200 patches to over 400 at the 3 km buffer ring (figure 9). Accompanying the fact that PLAND increased from 10% to over 20% at the same buffer ring, a sharp increase in PN might imply that more space was available for landscaping with increasing distance from the city centre. At the old urban centre, the green spaces were small and scattered, which could be revealed by small mean patch size in the same buffer ring (figure 10). These were mainly small urban parks (such as Pipa Shan Park in the old city centre) and small-scale green areas in residential and industrial land uses. A sharp rise in mean patch size was observed at the 6 km ring, implying that some large patches of green space began to emerge at around 6 km from the city centre. These were mainly woodlands on the mountains in Nan’an, Jiangbei and Yubei Districts. Combining this fact with the constant increase in PLAND, it was apparent that fragmentation of green space was related to the small green patches at 3 km from the city centre; while mountains (such as Nan Shan) provided extensive space for greening at 6 km from the city centre.

The fragmentation pattern of green space in Nanjing resembled that of Chongqing. PN increased consistently from about 200 at the 1 km ring to nearly 1200 at 4 km (figure 9). The greatest increase happened at 4 km from the city centre, in which many small patches of green space and parks were observed, including tourist spots and along the old city wall. After 4 km, however, the rise of PN became much slower and less consistent, even though a general ascending trend was still noticeable. Like in Chongqing, a sharp increase in mean patch size also happened at 5 km from the city centre of Nanjing, where a large piece of woodland was found at the south-western tip of Zijin Shan, and at the 7 km buffer ring (figure 10).

Both cities possess similar landscape characteristics in terms of:

- a congested urban centre without much green space;
- increasing proportion of green space with increasing distance from the city centre by the provision of urban parks;
- making use of natural terrain, where woodlands on mountains are used as urban parks; and
- green space at the urban fringe increases as cropland intertwines with newly developed properties where better landscaping is offered.
5. Conclusion

Green space constitutes an important land use and land cover for urban dwellers. Its functions and forms vary within cities and the provision of green space has been an increasing concern for enhancing the livability of cities. This study has investigated the use of object-oriented image classification in mapping land cover in two Chinese cities, Chongqing and Nanjing. The object-oriented approach allows the use of a much larger pool of variables compared to the pixel-based approach. As more non-spectral variables become available, rules adopted in this or other studies will assist in future works using the object-oriented approach. Accuracy assessment reveals that object-oriented classifications are effective, though they may not be consistently better than pixel-based classifications. The advantage of using an object-oriented approach with the use of medium resolution ASTER data at 15 m is perhaps less apparent when compared with other studies using high resolution IKONOS data. This may reveal the limitation in using medium resolution data with the object-oriented approach. Better results can be expected if high resolution data is available for similar studies. In terms of efficiency, object-oriented classification involves much more time in both the selection of segmentation levels and formulation of classification rules. Expert knowledge is substantially important at each step, in particular the trial-and-error testing of classification rules. Landscape metric analysis reveals that both cities display a lack of green space around city centres. Green space in cities is basically fragmented but their mean patch size does increase with an increasing distance from city centres. Further away from the urban centres, more land is available for the development of green space. The emphasis of landscaping in new urban development is however less easily found. It is important that landscape analysis can be performed along a temporal profile, to monitor how green space and its landscape characteristics vary in both time and space. This will not only bring a better understanding on the processes involved in developing green space...
space, but also will reflect the impact of government policy on such development (Kong and Nakagoshi 2006).

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References
Analysis of green space with ASTER images


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