Studies on Urban Areas Extraction from Landsat TM Images

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Abstract—In this paper, extracting urban areas from Landsat TM images is studied. We proposed a new method for urban and rural residential areas extraction. A classification example based on barren index (BI) is given in this article. We classified the image with several methods and compared the classification results.

The result indicates this proposed method based on BI has obvious advantages over conventional multi-band spectral data classification. Classification map created by this method suffers less from a lack of spatial coherency and has a high classification accuracy.

Keywords: TM image; urban area; classification; barren index (BI).

I. INTRODUCTION

Classification of remote sensing images has been widely used as a powerful means to extract various kinds of information. Many works have been done on the extraction of no-vegetated areas, especially urban areas, from remote sensing images. However, due to the complexity of city infrastructure, successful examples of urban areas automatic extraction from Landsat Thematic Mapper (TM) images are few at present. Automatic classification of satellite images for urban areas is a difficult task to achieve a high accuracy level. The main reason may be urban area has a high degree of pixel mixture as far as 30-meter resolution is concerned. Therefore, how to construct a feature parameter which reflects a city’s characteristics is the key to solve this problem. Considerable efforts have been done on simplifying the process of automatically mapping land covers. For example, Stuckens et al. (2000) used a hybrid segmentation procedure to integrate contextual information[1],Y.Zha, J.Gao and S.NI used NDBI(Normalized Difference Built-up Index)for automatically mapping urban areas[2].

In this study we propose a simple method for the auto mapping of urban and rural residential areas which is based on barren index(BI). This method has been successfully applied to extract bare lands and urban areas, especially rural residential areas, in Beijing, China. The results indicate that this method can serve as a worthwhile alternative for no-vegetated areas extraction.

II. METHOD AND MATERIAL

A. Study area and data

Our study area is Beijing city, north China, located at 116° 3'E to 117° 4'E, 39° 43' to 40° 28'N. The main land cover types in this area are as follows: urban and rural residential area, vegetated area, bare land(include fallow land and farmland out of crop), water. In order to manifest the features of all the land cover types, we select a TM image of May 19. The image quality was rather good with no cloud cover over the study area. A sub-area of 2790 rows by 2895 columns was cut from the full-scene imagery with six bands 1,2,3,4,5 and 7.

B. Bareness Index

Representative areas are selected from the image for each of these covers and statistics are computed. All samples’ DN values of each type in all six bands are averaged and displayed graphically in figure 1. It can be seen from this profile that DN values of bare land and urban area are low in TM4 and higher in TM3 and TM5, while other types don’t have this character. In order to describe this feature, we present a new parameter named Bareness Index (BI), which presents the bare degree of land. It is defined as follows:

\[ BI = TM3 + TM5 - TM4. \]  

Figure 1. Spectral profiles of four typical land covers in the study area.
We created a new channel use BI, and bare land has the highest value and urban area takes the second place in this channel. Hence, bare land and urban area can be extracted from the image by density slice theoretically speaking. Statistics of band BI, such as standard deviation and mean, derived from all the four types of sample areas are shown in table 1. It can be seen from the mean in table 1 that the four covers’ disparities in BI band are great. These four land cover types are separable on the whole. We also find the standard deviation of vegetation is large but the difference between vegetation and water’s means is not large enough, thereby vegetation and water may be confused in band BI.

### Table 1. Minimum, maximum, mean and standard deviation of DN's of the four covers in the band BI.

<table>
<thead>
<tr>
<th>Cover</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>Stdev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bare land</td>
<td>192</td>
<td>252</td>
<td>221.7</td>
<td>15.5</td>
</tr>
<tr>
<td>Urban</td>
<td>105</td>
<td>182</td>
<td>136.6</td>
<td>12.6</td>
</tr>
<tr>
<td>Vegetation</td>
<td>23</td>
<td>111</td>
<td>77.0</td>
<td>23.0</td>
</tr>
<tr>
<td>Water</td>
<td>52</td>
<td>77</td>
<td>59.1</td>
<td>5.0</td>
</tr>
</tbody>
</table>

We also created new band NDVI (Normalized Difference Vegetation Index), and then created bands Brightness, Greenness and Wetness through tasseled cap transform. Now we have a TM image with eleven bands: band 1,2,3,4,5,7,BI, NDVI, Brightness, Greenness and Wetness.

### C. Classification

We classified the image using several methods and compared their results: density slice in band BI, combination of density slice in band BI and NDVI, maximum likelihood supervised classification.

1) **Classification using BI**

Base on the analysis in section B we presume that the four land covers in our study area are separable, therefore we classified the TM image using the single band BI through density slice firstly. Through many times of trails based on statistics in table 1, we defined density slice ranges as follow: water from 0 to 70, vegetation from 71 to 113, urban area from 114 to 174 and bare land from 175 to 255. The result of density slice image is show in figure 2. The figure shows that water and vegetation pixels have been confused at a large degree. This is consistent with the statistics result in table 1.

2) **Classification using BI and NDVI**

Band BI can’t serve as a powerful index for dividing water from vegetation. In order to improve classification, we decided to combine it with other bands to classify image. We select band BI to apply density slice to extract urban area and bare land, and use band NDVI to divide water from vegetation. First, classify the image to three classes (bare land, urban area, vegetation and water) using band BI density slice. A mask was built over vegetation and water area. And then classify vegetation and water area using NDVI density slice. According to the same ranges as before, band BI density slice is applied. And the NDVI threshold to dived water and vegetation is -0.08. Pixels have value higher than -0.08 in band NDVI are defined as vegetation. Then combine the two classification results to form one image. Classification result is shown in figure 3.

3) **Classification using maximum likelihood supervised classification**

The maximum likelihood classifier is one of the most used classifier and its accuracy is super to other conventional classifiers. Therefore we compared BI and NDVI density slice result with this method.
Separabilities of the four covers’ training areas were computed and the result indicates that combination of band 5, 4, and 3 and combination of BI, NDVI and Brightness have high separabilities among three-band combinations.

Using the same training areas as section B, we classified the imagery using maximum likelihood supervised classification firstly, with the band combination of BI, NDVI and Brightness. Figure 3c is a sub-area cut from the classification result. Then a classification image is generated using a conventional band combination of TM 5, 4 and 3, and the result is shown in figure 3d.

III. RESULTS

We have compared the classification results carefully and found that density slice using BI and NDVI can divide bare land from urban and rural residential area better than the other two classifications using maximum likelihood supervised classification. A close scrutiny of figure 3 reveals that maximum likelihood supervised classification identifies rivers and ponds with towns sometimes, and the method of density slice using band BI and NDVI can division them better. Results of the two maximum likelihood classifications have no obvious difference.

The accuracies of all the four classification are listed in table 2. These results are derived from three times of accuracy assessments.

IV. CONCLUSION

This proposed BI method is able to map built-up areas at an
accuracy level of 95.63%. In comparison with supervised classification, BI enables urban areas to be mapped at a higher degree of accuracy and objectivity. The absence of training samples from the mapping makes subjective intervention from the human analyst redundant. But this accuracy report is based on LULC vector data of Beijing and our verify samples.

As illustrated in this paper, it is achievable to obtain high classification accuracy for a city based on BI. We think that this method can serve as a worthwhile alternative for urban areas automatic extraction. The results indicate that BI is a recommendable index for TM image classification. It is applicable for highly intermixed cities extraction, especially for rural residential areas in Beijing area. But this conclusion is based on our classification experiment in Beijing area, and we have just done some elementary jobs on study of city classification. The universality of this method needs to be tested further in other areas.

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