A STUDY ON IDENTIFICATION OF URBAN CHARACTERISTIC USING SPATIAL ARRANGEMENT METHOD

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Abstract: In order to rapidly catch up urban region's detailed land-use or land-cover information; this research used the post-classification algorithm (Spatial Reclassification Kernel: SPARK) to create a land-use map of Taichung City. We discussed the urban land-use classification model with the IKONOS images. The conclusions may be distinguished as follows:(a) Using the Maximum-Likelihood algorithm to classify seven broad land-cover categories. The overall accuracy in this stage achieves 92.72% and Kappa coefficient will be obtained 0.91; and (b) Using the SPARK method to classify images for detect the land-use, the overall accuracy achieves higher 89.64% and Kappa coefficient will be 0.86. To conclude, the research process in this study can fully and carefully describe local land-use pattern and assist the demand of land management and resources planning reference.

Keywords: post-classification, urban characteristic

1. Introduction

Urban landscape is composed of diverse construction materials (concrete, asphalt, metal, plastic, glass, shingles, water, grass, shrubs, trees, and soil) arranged by nature human in complex ways to build housing, transportation systems, utilities, commercial buildings, and recreational landscapes (Welch, 1982). Land use pattern in Taiwan has the feature of fragment and sophistication, while land use information is very important to support management and planning activities in urban areas. Traditional land use information identification methods are like ground surveys or aerial photography are costly and time-consuming.

The objective of this study was relating to urban mapping aim to identify high accuracy of image interpretation techniques, which account for the urban complexity in relation to the data spatial resolution. This is because these two factors affect the essential use of remotely sensed data in urban studies (Barnsely and Barr, 1996). This research apply IKONOS images as collection sources for urban land use information, and to perform post-classification algorithms technique for increasing the accuracy of classification.

2. Materials and Method

1) Study area

The study site is situated in the southwest of the Taichung basin, in the central part of Taiwan. Many details such as buildings, roads, trees, grass and other component elements of urban scenes can only be seen clearly with IKONOS. This research select ground control points and homonymy ground object in topographic map (scale 1:1000), using the polynomial distortion method and nearest neighbor assignment to resampling images, finally measure their RMS errors. In contrast to geographic coordinate spatial distance and spatial area in the image with those in the map, the spatial distance error is less than 10 meters.

2) Landuse/Landcover Categories

Basically, the land-cover emphasizes the land's natural attribute that displays the result combine natural overall operation with artificial operation. Besides, land-use focuses on land's social attribute that people use a series of biological and technological methods, in accordance with land's natural characteristic and established economical and social purposes, to precede long-term/periodic management or political transform activities. From the above-mentioned definition, it appears land-use can be displayed by different land-cover categories.

According to the characteristics of urban land-use/land-cover in Taiwan, this research tends to classify land-use/land-cover categories into seven land-cover categories, 'Crop', 'Grass', 'Large Size Facility', 'Small Size Facility', 'Soil', 'Tree', 'Water', and eight land–use categories, 'Arable Crop', 'Industrial', 'Low Density Residential', 'Medium Density Residential', 'Soil', 'Water', 'Grass' and 'Forest'.

3) Pre-classification

The Maximum-Likelihood algorithm（MLAs） is a usual algorithm that assumes a previous supervised knowledge (training areas) of part of the land to classify. In this study MLAs was used in the first stage to obtain the land-cover map. Training samples were extracted manually with the assist from 1:5000-scaled aerial photography imagery. All these information were digitized and divided to two groups for training site data and accuracy examined data.

4) Post-classification

The post-classification algorithm (Spatial Reclassification Kernel: SPARK) is used to create a land-use map. SPARK must taking into account the arrangement of the neighboring pixels, in contrast with a per-pixel classification, which considers the spectral characteristics of only one pixel（Barnsley and Barr, 1996）. With the help of SPARK it is possible to classify heterogeneous land cover types based on their spectral properties as well as their spatial patterns.

At the second stage examining pairs of adjacent pixels within a square kernel operated us. The identified land use category label associated with each pixel defines the nature of the "adjacency event" by a kernel. And each pair of pixels produces a single adjacency event, so that the order of the labels is not significant. Figure 1 illustrates an adjacency-event matrix in a 3- by 3-pixel window.

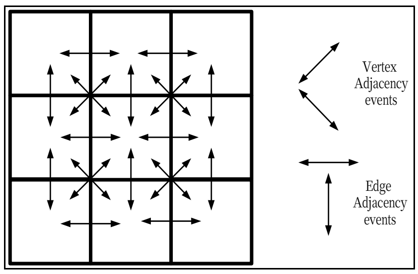

Fig. 1. Adjacency events in a 3*3 pixel window

In this stage, one crucial point for accuracy classification is the threshold to determine appropriate window size for extracting sufficient local information. From computational perspective, the optimum window size is the smallest size that also produces the highest accuracy. In general, for per-pixel classification, the appropriate window size for operating on spectral data ranges from a 3 by 3 to a 9 by 9 matrix of pixels (Jensen, 1996). In this study, the window size experimented from a 3 by 3, 5 by 5,…, 31 by 31 matrix of pixels. And these windows size were also used to generate the template matrices for defining the land-use categories.

During classification in this stage the adjacency-event matrix (M-matrix) that is calculated for each new position of the kernel is compared with each of the template matrices (T_k-matrices). The land use category defined by the template matrix intend to best match the current adjacency-event matrix is assigned to the central pixel of the kernel. The equation of comparison is as following:

$$\Delta_k = 1 - \sqrt{0.5N^2 \sum_{i=1}^{C} \sum (M_{ij} - T_{kij})^2} \tag{1}$$

$$0 \le \Delta_k \le 1 \tag{2}$$

Where M_{ij} is an element of the current adjacent-event matrix, T_{kij} is the corresponding element of the template matrix for land-use category k. N is the total number of adjacency events in the window and C is the number of land-cover classes in the image.

Separability of classes in the training samples can be defined by calculating the Δ_k value between all of the T_k -matrices. If the value of Δ_k is close to 1, that means a perfect match with one of the land-use categories. By contrast, a value of 0 indicates no match.

3. Results

1) Outcome of Pre-classification

The first stage in this study is to produce an initial land-cover map from remotely sensed image. In the meanwhile, we also refer to a number of vector data. In this respect, seven broad land-cover classes have been identified in the study area. And it's worthy of note that the accuracy of classification in this stage will effect both selection of template and accuracy of reclassification in the next stage. We defined separately the training areas and test sites for each of the categories of land-cover by using aerial photography imagery. Figure 2 illustrates the Classification outcome maps resulted from the application of the Supervised MLAs. And the accuracy of the result of this stage is acceptable for the next stage.

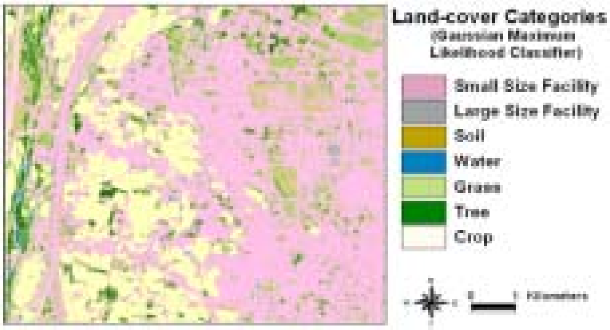

Fig. 2. Classification maps identified from application of Supervised MLAs

2) Outcome of Post-classification

In the second stage, we took some training samples for the Tk -matrices by the land-cover map, and the SPARK method was used to classify the imagine for detect the land-use. In this study, an 11- by 11-pixel kernel was selected to examine the land-use categories for better accuracy. Figure 3 illustrates the Land use map outcome from post-classification with an 11- by 11-pixel kernel.

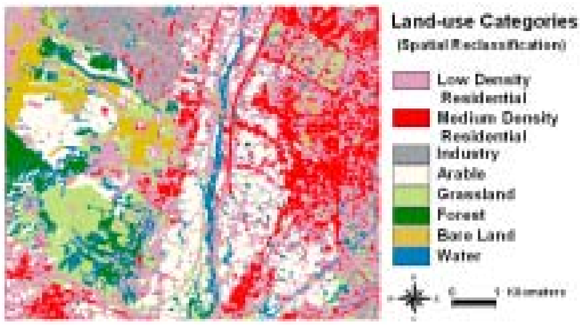

Fig. 3. Land-use map produced using the kernel-based spatial reclassification scheme (SPARK) with an 11 by 11 pixel kernel

4. Conclusion

The spatial post-classification model included two stages. First, labeling the image pixels into single land cover category using MLAs. Secondly, the pixel labels were grouped into discrete land use categories on the basis of frequency of occurrence and spatial arrangement within a kernel. The conclude stages for better land use categories identification from high resolution satellite image can provide this is a useful tool for further urban land use study. The conclusions of this study may be distinguished as follows:(a) Using the MLAs to create the land-cover map, the overall accuracy achieves 92.72% and Kappa coefficient will be obtained 0.91, this result can be used to build training samples for the image post-classification; and (b) Using the SPARK method to classify images for detect the land-use, overall accuracy achieves higher 89.64% and Kappa coefficient will be 0.86. To conclude, the research process in this study can fully and carefully describe local land-use pattern and assist the demand of land management and resources planning reference.

Reference

[1] Barnsley M. J. and Barr S. L., 1996. Inferring Urban Land Use from Satellites Sensor Using Kernel-Based Spatial Reclassification, Photogrammertric Engineering and Remote Sensing, 62(8), pp.949-958.

[2] Jensen J.R., 1996. Introductory Digital Image Processing: A Remote Sensing Perspective, Second Edition, Prentice-Hall, Englewood Cliffs, New Jersey.

[3] Lillesand T. M., and Kiefer R.W., 1996. Remote Sensing and Image Interpretation, John Wiley & Sons, Inc.

[4] Welch R., 1982. Monitoring Urban Population and Energy Utilization Patterns from Satellite Data, Remote Sensing of Environment, 9,pp.1-9.

[5] Wharton S.W., 1982. A Context-Based Land Use Classification Algorithm for High Resolution Remotely Sensed Data, Journal of Applied Photographic Engineering, 8,pp.46-50.