MODELING AND REPRESENTING SPATIO-TEMPORAL PATTERN OF LAND COVER CHANGE USING MULTI-TEMPORAL SATELLITE IMAGES

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ABSTRACT

This study seeks an efficient and practical methodology to quantify spatial pattern of land cover change that relates to human activities and natural factors. The basic approach is to derive and interpret spatial pattern metrics of multi-epoch trajectories of land cover change. This method integrates multi-temporal and multi-scale remotely sensed data from various sources with a monitoring time frame of 15 years. The history of land cover change for every location in the study area is traced, and nature, area extent and spatial pattern of such changes are also analyzed.

Key words: Remote Sensing, Landuse, Land cover change, Change trajectory, Landscape metric, Spatio-temporal pattern

1. Introduction

Landuse and land cover change (LUCC) is a good indicator that reflects the interaction between human activities and natural environment (Zhou *et al*., 2008). Since satellite imagery can get a wide impression of landscape, remotely sensed data have been widely used for land cover change detection for decades (Lunetta, 1999). Change detection methods can be categorized into two board classes, namely, bi-temporal change detection and change trajectory analysis (Coppin, 2004). With the advancement of remote sensing technology, people are no longer satisfied with merely detecting whether a change has happened, but increasingly demand better knowledge on the process of the change. The field of remote sensing change detection has a tendency of grasping the change dynamics using multi-temporal data.

A typical application of change trajectory analysis is based on numerical indices. For example, a time series of NDVI (Normalized Difference Vegetation Index) values retrieved from multi-temporal images can be used for monitoring the growing track of vegetation and for detecting plant stress factors. The illustration of a trajectory curve in this situation has a shortcoming that cannot represent spatial pattern information. However, changes in landuse and land cover are spatial occurrence and correlated with locational attributes. In order to obtain better understanding of land cover change, it is necessary to analyze the spatial pattern of the change trajectories so that a proper Spatio-temporal model of land cover change can be established.

This study aims to develop an effective method to model spatio-temporal patterns of land cover changes and seeks a good way for representing the change spatial pattern dynamics. Using quantitative spatial pattern indices, it attempts to derive a better understanding on the trend of land cover change by analyzing the impacts of various driving forces.

2. Methodology

The generic approach of this study is based on post-classification comparison method, which is commonly employed in land cover change detection studies. To begin with, multi-temporal land cover types are derived from classifications of multi-temporal remotely sensed satellite images. On the basis of this identified land cover types, land cover change trajectories are then established in GIS and reclassified into several categories according to the nature and driving forces of the change. For the purposes of this study that understanding spatial pattern of the change and easily building a regression model, landscape metrics of the land cover change trajectory classes are computed and their relationships to human activities and environmental factors are analyzed.

2.1. Study area and data

The study area is centered at Yuli County in Xinjiang Uygur Autonomous Region of China (Figure 1). Two rivers, the Tarim River and the Konqi River, flow through this area are the major water resources and create a typical oasis environment at the fringe of Taklimakan Desert. Since vegetation in this region is mainly located along the rivers, this “green corridor” can be considered as one of the most important habitation areas in aridzone of China.

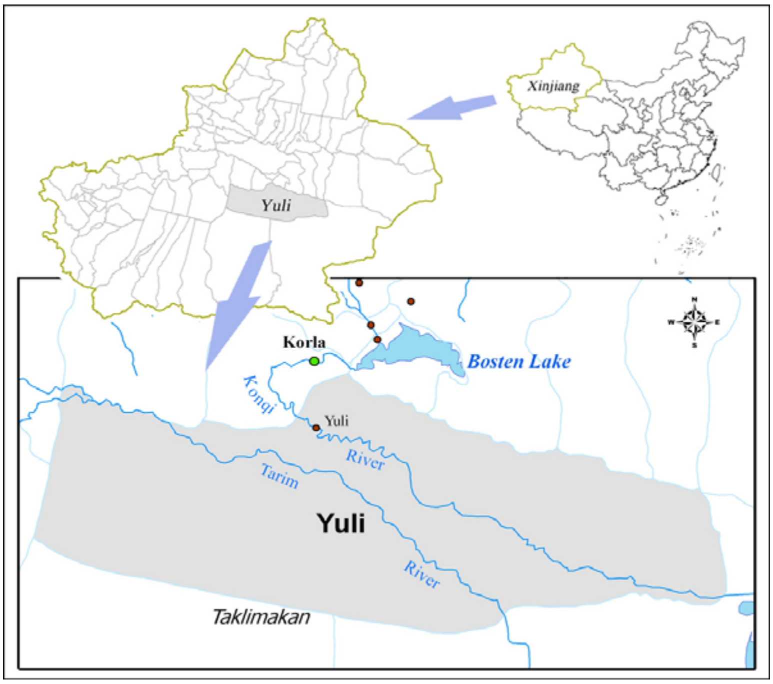

Figure 1. Map of study area

Under the local policies of encouraging economy, irrigated agriculture has been deeply developed in Yuli County since early 1990s, the majority of which is cotton. In order to investigate the land cover change caused by fast agricultural development in a time series, six remotely sensed satellite images acquired from different platforms in different years are used in this study, including multi-spectral images from Landsat-5/TM, Landsat-7/ETM+, CBERS-02 (China-Brazil Environment and Resource Satellite)/CCD and BJ-1(Beijing-1 micro-satellite)/CCD. The acquisition dates are chosen to match the growing season of cotton when there is a large contrast between cotton/vegetations and other land cover types.

2.2. Discrimination of land cover types

Before classification, the 2005 CBERS image need to be registered and geo-referenced based on the topographic map at a scale of 1:50,000. Setting this rectified image as a base image, the other images are then geometrically corrected and registered using image-to-image registration. Efforts are made to control the registration errors within half a pixel of the correspondent image so that the errors of change detection caused by mis-registration are less critical.

In order to minimize seasonal impacts and radiometric calibration problems between different dates and different sensors (Coppin et al., 2004), the post-classification comparison method is employed in this study. All images are classified independently through supervised classification using Maximum Likelihood Classifier (MLC). Five or six classes are distinguished for each image and then merged into two land cover types, namely, “farmland” and “the others”. After classification, a 3×3 majority filter is applied to remove isolated pixels.

Accuracy assessment can be the end stage of the classification scheme. Due to the difficulty of obtaining historical ground truth data as the reference data for all the multi-temporal images, a random sampling test can be employed. As for each image, over 200 samples on the original image are randomly selected and then interpreted manually. Confusion matrix is produced for accuracy assessment.

2.3. Spatio-temporal expression of land cover change

Temporal trajectory analysis based on a time series of imagery has proven to be a good way to understand spatio-temporal pattern of ecosystem dynamics. First of all, the classified images need to be resampled into the same spatial resolution (30m) so that trajectories can be established at a same scale. After this, the change trajectory for each pixel could be meaningful. Considering that our objective land cover type is farmland, only two types are represented at each time point. Land cover change trajectory can be simply defined as the situation of changes between farmland and the others. For example, a trajectory specified as “farmland - others - farmland - others - others - others”, means that the land was once periodically cultivated, but finally abandoned. When using binary number to represent, the trajectory can be replaced like “1-0-1-0-0-0” (“1” for farmland and “0” for the others).

To establish this change trajectory, all classified images are integrated into ArcGIS software with a raster format. After assigning value “1” or “0” to a corresponding bit position in a binary number for each pixel of each classified image, the multi-temporal images were merged together to identify every possible change trajectory with a unique number. For a six-epoch, two-class scenario, the total number of all possible trajectories is 64 (2^6).

2.4. Quantification of spatial change patterns

The landscape metrics are borrowed to this study for quantifying spatial pattern of land cover change. Metric analysis can be employed based on land cover types or land cover trajectory categories in this study. No matter which one to be applied to, class-level metrics are meaningful to explain change patterns. In our experiments, four class-level metric indices are chosen and conducted by FRAGSTATS 3.3 (McGarigal et al., 2002), including Percentage of Landscape (PLAND), Normalized Landscape Shape Index (NLSI), Interspersion and Juxtaposition Index (IJI) and Area-weighted Mean Fractal Dimension Index (FRAC_AM). The definitions or equations are shown as follows.

$$PLAND = P_i = \frac{\sum_{j=1}^{n} a_{ij}}{A} \times 100 \quad (1)$$	$$NLSI = \frac{e_i - \min e_i}{\max e_i - \min e_i} \quad (2)$$
$$IJI = \frac{-\sum_{k=1}^{m}\left[\left(\frac{e_{ik}}{\sum_{k=1}^{m} e_{ik}}\right)\ln\left(\frac{e_{ik}}{\sum_{k=1}^{m} e_{ik}}\right)\right]}{\ln(m-1)} \times 100 \quad (3)$$	$$FRAC\_AM = \sum_{j=1}^{n}\left[\left(\frac{2\ln(0.25 p_{ij})}{\ln(a_{ij})}\right)\left(\frac{a_{ij}}{\sum_{j=1}^{n} a_{ij}}\right)\right] \quad (4)$$

Where:
(1) Pi = proportion of the landscape occupied by class i; aij = area (m2) of patch ij; A = total landscape area (m2);
(2) ei = total length of edge of class i in terms of number of cell surface including all landscape boundary and background edge segments involving class i;
(3) eik = total length (m) of edge in landscape between classes i and k; m = number of classes;
(4) pij = perimeter (m) of patch ij; aij = area (m2) of patch ij.

Table 1. Selected metrics for spatial pattern analysis of land cover change (retrieved from McGarigal et al., 2002 and Leitao et al. 2006)

3. Results and Analyses

3.1. Land cover classification

On the basis of the assessment on only two combined classes, the classifications have shown high accuracy between farmland and the others. As Table 2 shows, the overall accuracy of image classification ranges from 88.9% to 95.2%, with kappa coefficient ranging from 0.762 to 0.896.

Images	1994	2000	2005	2006	2007	2008
Overall accuracy (%)	93.8	95.2	88.9	90.7	92.5	92.3
Kappa coefficient	0.877	0.896	0.762	0.799	0.837	0.835

Table 2. Accuracy assessment results of image classification

3.2. Area change of farmland

Figure 2 illustrates the overall situation of farmland change according to the classification results. The sawn area of farmland has rapidly increased till 2007 with average annual growth rate of 10.3%. Due to the limitation of water supply, the sawn area of farmland in 2008 decreased 15.2% comparing with the former year of 2007.

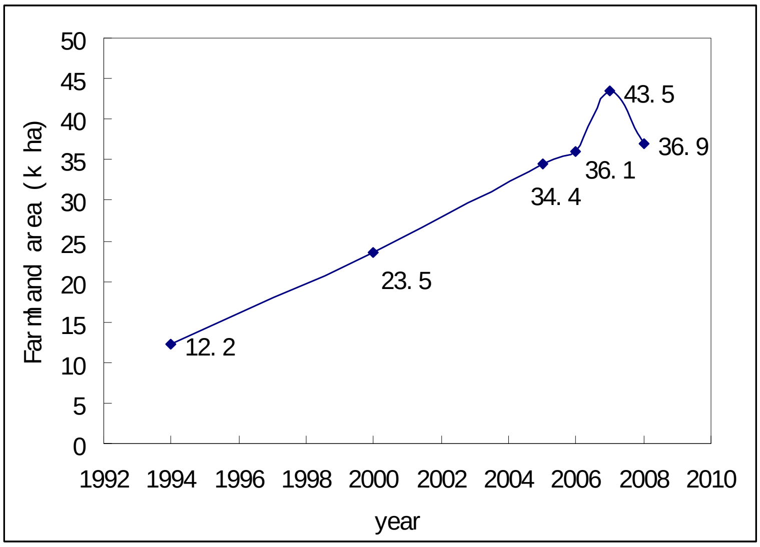

Figure 2. Change trajectory of farmland area during 14 years

3.3. Spatio-temporal representation of land cover change

Figure 3 shows the result of land cover change trajectories in both spatial and temporal. Since land cover change is mainly caused by increased farmland in the past decade with the exception of 2008, the increased farmland trajectories are highlighted, representing the old farmland since 1994 and the expansions since the other study periods. The trajectories are established without residents and main roads.

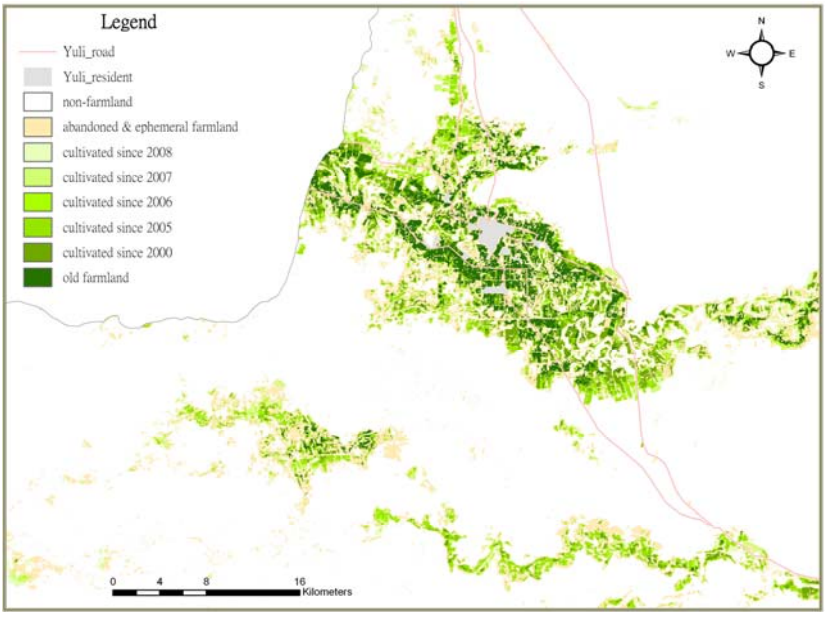

Figure 3. Spaio-temporal change trajectories in Yuli County from 1994 to 2008

3.4. Spatial pattern of the changes

NLSI and FRAC_AM are two indices to describe the shape of a landscape. NLSI is to quantify the overall shape by comparing with a regular shape like rectangle, while FRAC_AM is to measure the edge complexity. Table 3 lists the results of calculated metrics based on land cover types. To put focus on rapid farmland expansion, the decreasing NLSI values of farmland shows that, as the expansion of farmland areas, farmland patches are tend to present an aggregative pattern. However, the edge shape becomes more complex when small patches are combined.

Year	*NLSI*	*FRAC_AM*
1994	0.109	1.204
2000	0.118	1.242
2005	0.101	1.252
2006	0.082	1.254
2007	0.086	1.284
2008	0.067	1.258

Table 3. Metric analyses of cultivated farmland in each year

Contrasted with the metrics in Table 3, metrics in Table 4 are based on the established land cover change trajectories. Since farmland in the study area keeps a high-speed expansion, at the same time, the stabled parts become much less by PLAND. IJI is a measurement of adjacency between a patch type and the others. The bigger the IJI value is, the more adjacent for one trajectory to the other trajectory types.

Trajectory	*Description*	*PLAND*	*IJI*
X-X-X-X-X-X	Old farmland	1.848	48.98
O-X-X-X-X-X	Cultivated since 2000	1.830	67.49
O-O-X-X-X-X	Cultivated since 2005	1.812	71.50
O-O-O-X-X-X	Cultivated since 2006	0.550	75.81
O-O-O-O-X-X	Cultivated since 2007	0.796	75.50
O-O-O-O-O-X	Cultivated since 2008	0.778	67.84
Where: X = farmland, O = others. Ordered from 1994 to 2008			

Table 4. Metric analysis based on land cover change trajectories

4. Discussions

4.1. Accuracy of classification-based change detection

Because images are classified independently in this approach, errors might be accumulated when merge them together. That is to say, the accuracy of change detection using the merged map could be much lower than individual classification results due to error propagation at the scenario that all errors are absolutely not correlated (Congalton and Green, 1999).

Another kind of error may occur when those images don't match well in spatial position. This issue will lead to a position error when detecting land cover change, especially in the boundary between two different land cover types. That is the reason why we omit the part of residents and main roads when creating change trajectory maps.

4.2. Metrics of land cover change trajectories

Traditional metric analyses are focused on land cover types and the structure of landscapes. A change detection using that way can only give a numeric comparison in temporal but reveal the spatial pattern of the change. This study takes the approach that the class-level landscape metrics are applied to the land cover change trajectories, also to land cover types at each given time point. The results reflect not only the pattern of land cover type distributions but also the spatial pattern of the change. The latter can further be analyzed for the reasoning on why a change happened and the trend of how the change will develop.

5. Conclusions

This study has proposed a method to establish the history of land cover change and to represent spatial patterns of the changes by quantified class-level metrics. Different from traditional applications of landscape metrics focused on land cover types, this study has explored the possibility of using metrics for obtaining the spatial pattern of land cover change trajectories. Thus, this method does not only consider the temporal pattern of farmland expansion but also care about the spatial distribution of the change. This spatio-temporal model and the way of representation can give us a better understanding of the process how land cover changes in visualization.

According to the results, farmland has rapidly increased in the study area during the 14-year period. Accompanied with the high speed of farmland expansion, high speed of water consumption seems to come to the end in accordance with the situation of the last year of less water. At the fringe of old farmland, far from water resource, the newly cultivated farmland will be abundant. This will result in land degradation or wind erosion once the shortage of water supply happens.

In order to grasp land cover change dynamics and maintain a sustainable environment, further efforts still need to be made. Developing other spatial pattern indices will help to understand the rule of changes. On the basis of this method, a relationship between changes and driving forces can help to establish a predicting model for land cover change.

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References

Congalton, R.G. & Green, K., 1999. Assessing The Accuracy of Remotely Sensed Data: Principles and Practices. Boca Raton: Lewis Publications.

Coppin, P., Jonckheere, I., Nackaerts, K., Muys, B. and Lambin, 2004. Digital change detection methods in ecosystem monitoring: a review. International Journal of Remote Sensing, 25(9), pp.1565–1596.

Leitao, A.B., Miller, J., Ahern, J. & McGarigal, K., 2006. Measuring Landscapes: A Planner's Handbook. Washington, DC: Island Press.

Lunetta, R.S., 1999. Applicaions, project formulation, and analytical approach. In R.S.Lunetta & C.D.Elvidge, ed. Remote Sensing Change Detection: Environmental Monitoring Methods and Applications. London: Taylor & Francis, pp.1-19.

McGarigal, K., Cushman, S.A., Neel, M.C. & Ene, E., 2002. FRAGSTATS: Spatial Pattern Analysis Program for Categorical Maps. Computer software program produced by the authors at the University of Massachusetts, Amherst. Available at the following web site: www.umass.edu/landeco/research/fragstats/fragstats.html.

Zhou, Q.M., Li, B.L. & Kurban, A., 2008. Trajectory analysis of land cover change in arid environment of China. International Journal of Remote sensing, 29(4), pp.1093-1107.