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Research Article

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Analysis of landscape pattern based on the point pattern method

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ABSTRACT

Landscape pattern is the principal component of landscape ecology. Remotely sensed data can provide a unique view on spatial and temporal landscape change patterns. Whether the point pattern method can be used to analyze urban landscape pattern change, there is less relative research about it. Based on the remote sensing images of TM, CBERS and SSMFDE, this study analyzed the landscape characteristics and spatial pattern of Xi'an City and proposed streamlining steps for a point pattern analysis. These analyses were facilitated by the ENVI, ARCGIS, and IDRISI software. The results showed that the study area had a composite landscape matrix consisted of woodland and farmland. During the study period, the level of landscape fragmentation decreased, accompanied by an increase and a reduction in the woodland and farmland landscape connectivity respectively. The different landscape types unanimously showed a prominent spatial pattern of aggregation. Specifically, the differences in the critical threshold values for the aggregate, random and discrete patterns were relatively significant between individual years and landscape types.

Key words: Landscape pattern analysis; point pattern method; Xi'an China

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INTRODUCTION

Urban landscape patterns are characterized by dramatic changes, particularly when urbanization undergoes a rapid advancement, and artificial landscapes in the cities gradually penetrate into peripheral natural and semi-natural landscapes, which is a notable feature of landscape dynamics during rapid urbanization [1]. The research of urban landscape change has been incorporated into a variety of programmes within the framework of global change research. Monitoring change brought on by urbanization has already received considerable attention [2] and been a critical concern both to those who study urban dynamics and those who must manage resources and provide services in these rapidly changing environments [3].

Remote sensing has advantages in characterizing the spatial temporal trends of urban growth using multi-stage images [4-5] and is an important tool for providing information on urban land-cover characteristics and their changes over time at various spatial and temporal scales [6]. The remotely sensed imageries such as Landsat multispectral scanner (MSS), thematic mapper (TM), and enhanced thematic mapper plus(ETM+) sensor images are frequently used for detecting urban change, characterizing urban areas, and analyzing urban spatial growth [7-8]. However, other remote sensing imagery such as the China-Brazil Earth Resources Satellite (CBERS) and Small Satellites for Monitoring/Forecasting Disasters and Environments(SSMFDE)with the same spatial resolution as TM and ETM+ sensor images have rarely been used in examining urban and landscape changes. So the TM, CBERS, and the small satellites remote sensing data will be used and compared in the paper.

Landscape metrics are often used in analyzing landscape dynamics and urban growth processes [9-10]. But landscape pattern metrics have some shortcomings in analyzing pattern changes because of their inherent relationship [11]. Most systems in the natural world are not spatially homogeneous but display some kind of spatial structure. Because of the inherent difficulty in distinguishing such small clusters from a random distribution, mathematical tools have become increasingly utilized to extract information such as domain size and area fraction [12]. Point pattern analysis comprises a set of tools for looking at the distribution of discrete points and has a long history in statistics and the vast majority of point pattern methods rely on a single distance measurement [13]. Ripley's K function can be used to summarize a point pattern, test hypotheses about the pattern, estimate parameters and fit models [14].The present quantitative work intends to apply a local form of Ripley's *K* function, which is widely used in spatial studies, through point pattern analysis as in Ecology [15]. But point pattern analysis is not used in landscape ecology. In the paper, we will use the point pattern method to analyze urban landscape pattern change from the past to the future.

Based on previous research and the recent trend towards landscape change, this paper analyzed the landscape pattern changes for Xi'an city which were based on the quantity of landscape change characteristics of the structure and spatial pattern as the primary research content. The point pattern method will be used to analyze the landscape pattern change of Xi'an. The remote sensing images of the TM, CBERS-2 and small satellites for monitoring/forecasting disasters and environments were employed as the data sources and appraised using Kappa index, which under the support of GIS was used to analyze the multi-scale changes of the local landscape patterns in recent years combining the landscape indices and point pattern method.

EXPERIMENTAL SECTION

SITE DESCRIPTION

Xi'an City (E 107°40'-109°49' and N 33°39'-34°45') is located in the central Guanzhong Plain of Shaanxi Province, which is in the heartland of China. Xi'an City has jurisdiction spanning nine districts (Xincheng, Beilin, Lianhu, Yanta, Baqiao, Weiyang, Yanliang, Lintong and Chang'an) and four counties (Lantian, Zhouzhe, Huxian and Gaoling). With an average elevation of 400–450 m, the city boasts a variety of geomorphologic types and features a terrain that is south-high and north-low. The southern part of Xi'an, residing mostly within the northern slope of the middle segment of the Qinling Mountains, is dominated by woodlands, grasslands and unused land and accounts for 54.6% of the city's total area. The northern part of Xi'an is mostly divided into farmlands, parks and urban construction land as well as protected areas containing cultural heritage sites and accounts for 45.4% of the city's total area. The total water resources (including the river runoff and groundwater resources) are 3.146 billion m^3. Featuring a climate of the warm-temperate continental monsoon of East Asia, Xi'an City has a 10°C-based accumulated temperature of 4,400°C, an annual average temperature of 6.4–14.9°C, an average annual precipitation of 537.5–1,028.4 mm, an annual average relative humidity of 70–73% and an annual sunshine duration of 1,983.4–2,267.3 h. By the end of 2010, the city had a total residential population of 8.46 million.

RESEARCH METHODS

Data Source and processing: Landscape patterns for 2000, 2004, and 2011 were mapped by using Landsat TM in May 2000, CBERS in May 2004 and small satellites for disaster monitoring/forecasting in May 2011. The TM data were obtained form the University of Maryland, while the latter two data sets were provided by the China Center for Resources Satellite Data and Application. All the data were georectified and resampled to a ground resolution of 30 $\times$30 m and projected to UTM projection in the WGS84 coordinate system with a RMSE of less than 0.5 pixels. Taking into account both the local characteristics and the classification system of China's land uses, the landscapes of the study area were divided into six types: grassland, farmland, woodland, waters, construction land and unused land.

Data processing was supported by the ENVI system (4.7) and the ArcGIS platform (9.3). During this data processing, the 1:100,000 topographic map, which is registered to the same projection system, as well as the field survey data from the ground truthing, were used as important references. The classifications were done using a hybrid approach combining both a supervised (maximum likelihood method) and unsupervised classification using Iterative Self-Organizing Data Analysis Techniques (ISODATA) clustering method. After the interpretation of the three period images, a field inventory, during the summer of 2011, was conducted to check the patch classes and to verify the accuracy of the GIS data: 260 samples were collected. More importantly, errors, especially those produced along the polygon boundaries due to GIS overlay procedures, are eliminated. Afterwards, the "clump" function was used to filter out some small fragments before some patches that were visibly wrong were corrected in a human-computer interactive manner. At this point, the images were ready for the accuracy assessment, which mainly involved Kappa indices to evaluate the precision of the classification results. Although we acknowledge Kappa's limited ability as a measure of accuracy, it is a commonly used method in land use land cover analysis [16-17]. Our assessment results showed that the overall classification accuracy of the three phases, assessed on the basis of the training sample points collected during field visits of 2011, was 81–83%, and the corresponding Kappa index was 0.809–0.829. Imagery was also evaluated by in country experts and field interviews and deemed acceptable for use in this study. These data met the requirements of our subsequent analyses. The classification had a low rate of omission and commission errors.

Point Patterns Analysis: Point patterns can be studied by the order analysis [13]. One of the most commonly used order methods is Ripley's K function, which is a tool for analyzing completely mapped spatial point process data, i.e. data on the locations of events and comparing a given point distribution with a random distribution; i.e., the point distribution under investigation is tested against the null hypothesis that the points are distributed randomly and independently [12]. Ripley's K method is based on the number of points tallied within a given distance or distance class. As every point in the sample is taken once as the center of a plot circle, Ripley's K function provides an inference at the global level of the studied element [15].

Ripley's K function is as follows:

$$L(d) = \sqrt{\frac{A\sum_{i=1}^{n}\sum_{j=1, j\neq i} k(i,j)}{\pi n(n-1)}} \quad (i, j = 1,\ldots, n) \qquad (1)$$

in which A is the study area, *n* is the number of points, *d* is the expected value and $k_{i,j}$ is the weight. $L(d) > d$, $L(d) < d$ or $L(d) = d$ refer to a landscape type that has an aggregate, uniform or random distribution, respectively.

Based on the size and minimal classification removal unit of the study area, the ArcGIS software was used to randomly generate 7000 points in the study area before the corresponding layer was superimposed with the vector graph (of the three phases) in the SHP format, thereby determining the affiliated landscape type of each sampling point. Without regard to whether points are located within or outside domains, Ripley's K-statistic is computed for all points on the lattice. While generating point patterns that simulate K, we require that domains are completely contained within the lattice so that there are no broken or overlapping domains when the lattice pattern is tiled. Subsequently, the point pattern tools, which are found in the toolbox for spatial statistics analyses in the ARCGIS software, were used to perform the analysis of Ripley's K function and the significance tests for the different phases and different landscapes. The starting distance was determined by the geographical scope of the study area and the step numbers of the 20-class distance, and the distance step was set to be 2000 m. The boundary delineation was based on the method of simulating the outer boundary values. A confidence level of 99% was used to denote the deviation of an index from randomness. The spatial statistic result was produced in the excel file format in the ARCGIS software.

LANDSCAPE PATTERN ANALYSIS

Changes in the landscape patterns: During the twelve years between 2000 and 2011, the scale for the maximal spatial aggregation of the farmland in the study area was 18 km in 2000, which was gradually reduced, as was the aggregation intensity. However, no development of diffusion appeared within the maximal aggregation distance. In addition, the observed values were significantly higher than the upper limit of the confidence interval, indicating that the spatial aggregation of the distance was statistically significant. In 2004, the maximal aggregation spatial scale was 16 km, which is slightly lower than that in 2000. The aggregation intensity weakened as the analytical scale increased, so that a random distribution emerged at the scale of 36 km and a discrete distribution appeared at the scale of 38 km. In 2011, the maximal aggregation spatial scale was 16 km. Likewise, a random distribution appeared when the scale reached 36 km, and a discrete distribution arose when the scale reached 40 km. These results indicated that during the study period, the farmland landscape experienced a reduction in its spatial distribution and in its uniformity, corroborating the results of the landscape index method.

The scales for the maximal spatial aggregation of woodlands were 20, 18 and 24 km in 2000, 2004 and 2011, respectively. The path displayed a pattern of initially dropping and later rising and showed that the distribution of woodland displayed less prominent changes. This pattern was echoed by the observations that the uniformity of its spatial distribution showed little alteration and that the aggregation registered little reduction. Furthermore, the aggregation spatial scale was apparently higher than the upper limit of the confidence interval, indicating that the spatial aggregation at the corresponding aggregation characteristic scale during the three phases was statistically significant.

The scales of the characteristic spatial aggregation of the grassland were 16, 22 and 18 km in 2000, 2004 and 2011, respectively, indicating that the spatial aggregation intensity of the grassland displayed a trend of initially decreasing and subsequently rising. This type of landscape showed a reduction in both the spatial distribution and uniformity and exhibited a discrete trend. This trend was the most pronounced in 2011, when random and discrete distributions appeared as the analytical scale reached 34 km and 38 km, respectively. Hence, the grassland landscape developed a statistically significant spatial aggregation and discrete distances during the study period.

The scales of the characteristic spatial aggregation of the construction land were 16, 22 and 28 km in 2000, 2004 and 2011, respectively, and these scales experienced apparent enhancement and were significantly higher than the upper limit of the confidence interval. These results indicated that the characteristic scales of the construction land during the three phases were in a spatial aggregation state, which was statistically significant. The expansion of the construction land was correlated with a reduction in the aggregation intensity and an enhancement in uniformity.

The scales of the characteristic spatial aggregation of the waters were 8, 12 and 2 km in 2000, 2004 and 2011, respectively. The path was similar to that of the grassland. Specifically, the landscape also showed a reduction in its spatial distribution and uniformity and developed a discrete trend, with the threshold discrete scale appearing at 6 km. In contrast, in comparison with the grassland, the water landscape developed a spatial aggregation and discrete distances that were statistically less significant than those of the grassland during the study period.

The unused land had the highest aggregation intensity among all of the landscape types. It had characteristic aggregation scales of 4 and 2 km in 2000 and 2004, respectively. In addition, threshold discrete distances of 18 and 20 km, respectively, appeared within the range of the maximal studied aggregation values.

Overall, the farmland, woodland, grassland, waters, construction land and unused land in the study area all exhibited prominent spatial patterns of aggregation at the established study scales. The farmland showed aggregation spatial patterns at small scales and gradually shifted to a random distribution pattern as the scale increased. The farmland, woodland, grassland and urban-rural construction land all had spatial aggregation intensities significantly below those of the waters and unused land. The spatial distribution of the farmland and grassland had the characteristic scale with the maximal heterogeneity; at this scale, the two landscape types manifested a certain level of macroscopic heterogeneity because both their distributions skewed towards a discrete pattern.

CONCLUSION

The study area exhibited a reduction in landscape fragmentation and generated a high number of large patches, increased connectivity between the woodland and reduced connectivity between the farmland. The spatial distribution of the farmland and grassland had a characteristic scale with a maximal heterogeneity, below which some macroscopic heterogeneity developed and above which discrete distributions were more likely. Hence, at the pre-determined maximal expected distance, both of the landscape types showed aggregate, random and discrete distributions, with the phenomenon being the most pronounced in 2011.The methods of landscape indices and point pattern analysis can be integrated to produce better outcomes.

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