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基于 TM 影像的景观空间自相关分析
——以北京昌平区为例

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摘要：格局与尺度之间的关系是景观生态学的核心研究内容。景观格局发生在不同的尺度，而尺度又影响格局的研究，因而，在景观生态学研究中应用多种量化研究方法于一系列尺度来确定和特征化空间格局研究，并探求空间格局与生态学功能和生态学过程之间的关系是非常必要的。以北京昌平区为例，从 TM 影像中选取 5 个具有突出自然和社会经济背景差异的景观，即林地景观、农田景观、都市边缘景观、卫星城景观和灌丛景观为研究对象，基于归一化植被指数（*NDVI*），采用常用空间自相关指数，即 Moran 的 *I* 系数和 Geary 的 *c* 系数进行一系列的空间自相关分析，旨在阐明：变化的空间粒度如何影响空间分析？以及空间分析如何响应划区效应？此外，基于 *NDVI* 和数字高程模型（DEM）也探讨了对于不同的数据类型，格局的尺度依赖性如何变化。研究结果表明：空间粒度的变化对于景观分析有着显著的影响，随着空间粒度的增加，空间自相关均呈下降趋势；不同景观类型对于空间粒度的变化有着不同的响应，人为干扰较多的景观具有较低的空间自相关，但对空间粒度的变化表现出较强的敏感性；对于不同的数据类型，格局分析对空间粒度变化的响应是不同的。

关键词：空间自相关分析；粒度；划区效应；景观生态学

Landscape spatial autocorrelation analysis of TM remote sensing data: A case study of Changping District, Beijing, China

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Abstract: A strong motivation for developing landscape ecology is to deal with the relationship between spatial pattern and scales. The patterns of landscape development in time and space result from complex interactions of physical biological and social forces. Numerous studies have shown that the spatial pattern of landscape may have significant influences on ecological processes, such as population dynamics, biogeochemical cycling, and biodiversity. Thus, identifying and characterizing spatial pattern across a range of scales using various quantitative methods in order to appropriately understand the interaction of spatial pattern and ecological process are often necessary in landscape ecological studies. This study, therefore, conduct a series of spatial autocorrelation analyses mainly based on *NDVI* (Normalized Difference Vegetation Index) for five landscapes with contrasting natural and socioeconomic settings in Changping District, Beijing, to demonstrate: how does changing grain size affect the results of spatial analysis? How do the results of spatial analysis differ in changing zoning alternatives? In addition, we also investigate how do such scale-dependent changes vary with different types of landscape data, based on *NDVI* and DEM (Digital Elevation Model). Results show that changing grain size have significant effects on the values of landscape analysis,

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and spatial autocorrelation decline with increasing grain. Different landscapes have different sensitivity response to grain size. Landscapes with stronger human disturbance have lower spatial autocorrelation, and more sensitivity to changing grain size. Landscapes with more disturbances by human, almost have no zoning effect. The effect of changing scale varies in their magnitude and rate of change when different types of landscape data are used.

Key words: spatial autocorrelation analysis; grain; zoning systems; landscape ecology

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A strong motivation for developing landscape ecology is to deal with the relationship between spatial pattern and scales[1]. Pattern occurs on different scales, and scale affects pattern to be observed[2]. Numerous studies have shown that the spatial pattern of landscape may have significant influences on ecological processes, such as population dynamics, biogeochemical cycling, and biodiversity[2]. Therefore, identifying and characterizing spatial pattern across a range of scales using various quantitative methods are necessary in landscape ecological studies[2,3].

Usually the spatial scale encompasses both grain and extent. Grain is the resolution of the data (minimum mapping unit, pixel size). Extent refers to the overall size of the area mapped or studied[4,5]. Additionally, the modifiable areal unit problem (MAUP) becomes key obstacle issue for spatial analysis in landscape ecology. MAUP has two related but distinctive components: the first is the "scale problem", where the same set of areal data is aggregated into several sets of larger areal units, with each combination leading to different data values and inference[6,7]. The second aspect of the MAUP is the "zoning problem", where a given set of areal units is recombined into zones that are of the same size but located differently, again resulting in variation in data values and, consequently, different conclusions[6,7].

Much work has been done in this area either in the term of MAUP or scale effects. Nellis and Briggs used textural analysis at three levels of spatial resolution to assess landscape structure of tall grass prairie subject to different management regimes[8]. Turner *et al.* studied the scale effects in landscape pattern analysis, using indices measuring diversity, dominance, and contagion, and studies showed that there are thresholds in spatial patterns[4]. Qi and Wu studied the effects of changing spatial resolution on the results of landscape pattern analysis using spatial autocorrelation indices, Moran Coefficient, Geary ration, and Cliff-Ord statistic[2]. Dennis and Wu conducted a series of spatial autocorrelation analysis based on *NDVI* to demonstrate how the MAUP may affect the results of landscape analysis. Wu *et al.* adopted scale variance, semi-variance, landscape metrics statistical methods and so on, to investigate the effects of spatial scale on spatial analysis[9~11]. However, it is not always clear whether the effect of changing scale is an artifact due to improper use of analysis methods, an indication of the scale multiplicity of ecological systems, or neither of the two[10]. The questions regarding how changing scale affect the results of spatial analysis remain largely unanswered, and systematic investigations to address such issues are urgently needed[2].

Multi-scale methods used frequently in landscape ecology include tests of non-randomness, semi-variance analysis, wavelet analysis, spectral analysis, fractal analysis, lacunarity analysis, blocking quadrat variance analysis and so on[7]. Cullinan and Thomas evaluated several methods, and asserted that multiple methods should be used for examining landscape pattern and scale[12]. Qi and Wu, Dennis and Wu showed that spatial autocorrelation coefficients are effective techniques[2,6]. Additionally, Wu *et al.* showed that vegetation indices could be correlated with various characteristics of landscapes. Especially *NDVI* (Normalized Difference Vegetation Index) is a sensitive indicator of green biomass[9]. Therefore, in this paper, we conducted a series of spatial autocorrelation analyses using two spatial autocorrelation coefficients-Moran's I and Geary's c, mainly based on *NDVI* of five landscapes in Changping District, Beijing, to demonstrate: (1) How does changing grain size affect the results of analysis? (2) How do the results of analysis differ in changing zoning alternatives? In addition, we also investigated (3) how do such scale-dependent changes vary with different types of landscape data, based on *NDVI* and DEM (Digital Elevation Model).

1 Data and methods

1.1 Landscape data

Studies show that *NDVI* can be correlated with various characteristics of landscapes[13,9]. Therefore, to characterize the structure of the landscape we calculated *NDVI* from five landscapes with contrasting natural and socioeconomic settings representatively selected from Landsat Thematic Mapper (TM) scenes of May 19, 2001, for Changping District, Beijing, to characterize the structure of the landscape. The spatial resolution for five landscapes is 30m × 30m, and the extent is 81km^2 (300 × 300 pixels). These five landscapes are Forest Landscape, Cropland Landscape, Urban Fringe Landscape, City Landscape and Shrub Landscape, respectively (Plate Ⅰ). The first is Forest Landscape, located in north mountainous region of Changping District. The elevation of this study ranges from 250～800m, and vegetation is mainly artificial forest, for instance, *Pinus tabulaeformis*, *Platycladus orientalis* and various orchards in foothill zone. The second is Cropland Landscape, located in the east of Changping District. This region consists of massive cropland landscape, in addition to towns and villages. The third Urban Fringe Landscape has good location, neighboring urban center. Besides some urban agriculture, there are many urbanizing town. The fourth City Landscape refers to government location of Changping District, mainly municipal infrastructure, and partly cropland landscape. Finally, Shrub Landscape lies in the west of Changping, with the highest elevation and least human disturbance in local district. Vegetation is mainly shrubs, and some artificial forest.

To compare the effects of different type landscape data, we adopted *NDVI* calculated from TM scenes of the whole Chang Ping District, and DEM (1 : 250 000, a grid cell size of 260×260 meters). We converted the data resolution of *NDVI* from 30m×30m to 260m×260m to agree with DEM, and both data sets have 153 rows and 219 columns (Plate Ⅱ).

NDVI (Normalized Difference Vegetation Index):

$$NDVI = \frac{NearInfrared - Red}{NearInfrared + Red}$$

Near-infrared part of the spectrum is band 4, ranging from 760～900 nm, and red refers to band 3, brightness value from 520 to 600 nm.

1.2 Methods

1.2.1 Effects of changing grain

We adopt a range of scale grain for *NDVI* data of five landscapes, the number of pixels on a side is 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20.

To contrast the difference of DEM data and *NDVI* data responding to changing grain size, the number of pixels on a side is also: 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20.

1.2.2 Zoning effects

Equal numbers of pixels per zone are the premise of zoning effects study. To investigate spatial autocorrelation analysis responding to the zoning problem, we design two zoning system as following:

(1) Zoning System at Small Scale-Eight alternatives zones at the 24 BSU (basic spatial units) scale had the following dimensions for equal area zones: 1×24, 2×12, 3×8, 4×6, 6×4, 8×3, 12×2, 24×1.

(2) Zoning System at Large Scale-Nine alternatives zones at the 100 BSU scale had the following dimensions for equal area zones: 1×100, 2×50, 4×25, 5×20, 10×10, 20×5, 25×4, 50×2, 100×1.

1.2.3 Spatial autocorrelation analysis

Spatial autocorrelation reflects the degree of spatial clustering, which depends on the degree to which values at one spatial locality are determined in part by values at neighboring spatial locations. Moran's *I* and Geary's *c* coefficients are the two most commonly used for the analysis of spatial autocorrelation in landscape ecology[14, 2, 6, 7].

(1) Moran's *I*

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

(2) Geary's *c*

$$c = \frac{(n-1)\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - x_j)^2}{2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

Where n is the total number of areal units over the entire landscape observed; x_i and x_j are the values of areal units i and j, respectively; $\bar{x}$ is the mean of all areal units; w_{ij} denotes the connectivity between areal units i and j, and it takes a value of 1 if areal units i and j are adjacent and 0 otherwise[2, 15, 7].

Moran's I computes the degree of correlation between the values of a variable as a function of spatial location, and it represents the deviation between the values of the variable and its mean[15]. Moran's I values vary from -1 (negative autocorrelation) to 1 (positive autocorrelation), and has an expected value close to zero in the absence of spatial autocorrelation $-1/(n-1)$. Geary's c, on the other hand, measures the difference among values of a variable at nearby location. Geary's c fall in 0 (perfect positive autocorrelation) and 2 (strong negative autocorrelation), and the expected value is 1 in the absence of spatial autocorrelation[2, 15].

2 Results

2.1 Effects of changing grain size

In general, changing grain size has significant effects on the values of landscape analysis. Fig. 1 shows how the numerical values of these two autocorrelation coefficients respond to increasing grain sizes for different landscapes. The results unanimously indicate that spatial autocorrelation decline with increasing grain.

Fig. 1 also indicates that different landscapes have different spatial autocorrelation degree and different changing rate responding to increasing grain size. Magnitude ranking is Urban Fringe Landscape < Cropland Landscape < City Landscape < Forest Landscape < Shrub Landscape, while their sensitivity responding to changing grain size is Urban Fringe Landscape > Cropland Landscape > City Landscape > Forest Landscape > Shrub Landscape. The cause of this is linked to surface geology, human disturbance and so on, depending on different vegetation condition and vegetation distribution patterns, as indicating in Figure 2a, because the spatial correlation indices are determined by two factors: the value of each areal unit and the spatial relationship among all the areal units[2]. The Shrub Landscape with the highest elevation and the least human disturbances has better vegetation, mainly shrubs and some artificial forest, and large-area higher $NDVI$ values are distributed there. However, Urban Fringe Landscape, with more human disturbance and structures more fragmented, has more and smaller green patches, therefore it is most sensitivity to grain size change.

The effects of changing grain size on the results of spatial analysis show that spatial autocorrelation decline with increasing grain; different landscapes have different spatial autocorrelation; spatial autocorrelation gradually increase and sensitivity to grain size change decrease with decreasing human disturbance.

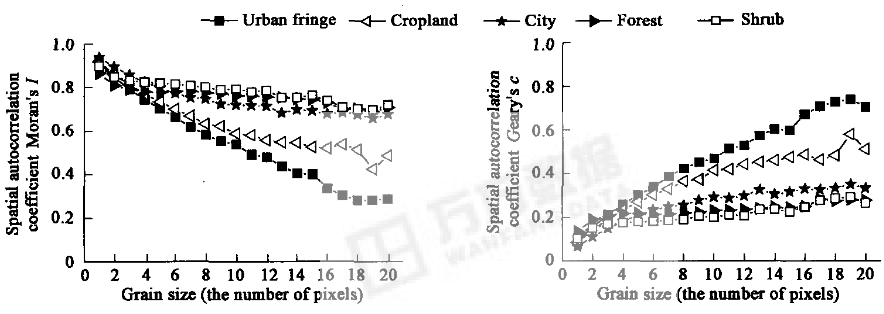

Fig. 1 Effects of changing grain on spatial autocorrelation coefficient (Moran's I, and Geary's c) for a 300×300 matrix of 30×30 m^2 pixels of $NDVI$ for urban fringe landscape, cropland landscape, city landscape, forest landscape and shrub landscape

2.2 Effects of zoning system

Because of great similarity and good agreement for both coefficients, only Moran's I is presented to illustrate the effects of zoning systems (Fig. 2). Based on both large scale 100 BUS and small scale 24 BUS, it unanimously implies no directional patchiness. In a whole, curves basically behave upward "U" or downward "U", showing nearly no zoning effects on spatial autocorrelation. Just because the whole study of Changping District, Beijing has much more disturbances induced by human, thus landscapes fundamentally show more regular.

2.3 Effects of different type of landscape data

The results show that both data sets ($NDVI$ and DEM) of Changping District are positively correlated across a range of scales (grain size from 260 m×260 m to 5.2 km×5.2 km, Fig. 3). It also indicates that spatial autocorrelation declines with

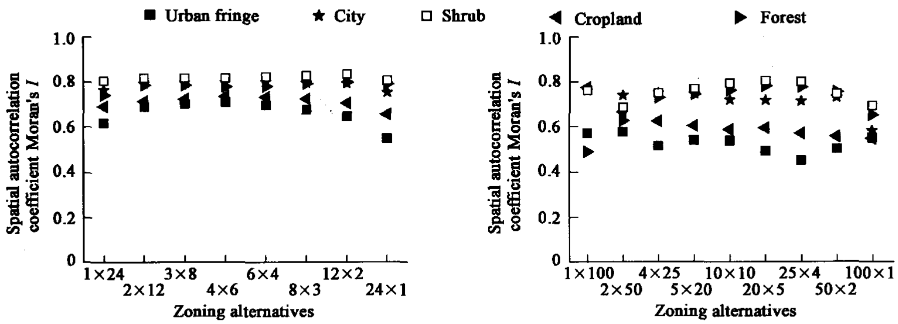

Fig. 2 Effects of selected zone systems on spatial autocorrelation at the 100 BSU scale and 24 BSU scale for a 300×300 matrix of 30×30m^2 pixels of *NDVI* for urban fringe landscape, cropland landscape, city landscape, forest landscape and shrub landscape

increasing grain, but different type data sets have different sensitivity to changing scale. The changing magnitude of spatial autocorrelation for *NDVI* data (0.9605～0.6998 of Moran's *I*, and 0.0445～0.3352 of Geary's *c*) is appreciably less than that of DEM data (0.9506～0.5897 of *I*, and 0.0532～0.4322 of *c*), and the values of DEM data shows a faster changing pace than that of *NDVI*.

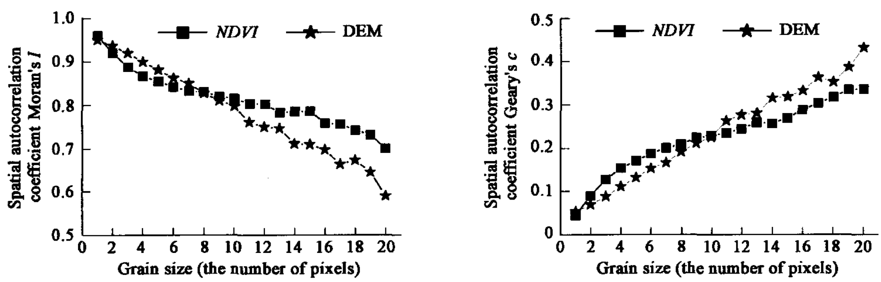

Fig. 3 Comparison of scale effects on spatial autocorrelation based on DEM and *NDVI*

3 Discussion and conclusions

The relationship between pattern and scale is a central issue in landscape ecology. When conducting ecological research at larger spatial scales-landscape or regional scales, different data source have different spatial resolution, for instance, 16×16 meters for SPOT, 30×30 m^2 for TM, 180×180 m^2 for MSS, and 1×1 km^2 for NOAA-AVHRR. Thus, it is very imperative to first understand how changing spatial scale (*e. g.* grain size) affects the results of spatial analysis of landscape patterns.

The effects of zoning alternatives show that landscapes with more human disturbance have no zoning effect or have no directional patchiness, and they present artificial, even and regular landscapes. The cause of orientation in landscape structure may be linked to surface geology, and super imposed on this cause are vegetation and its disturbance history[6]. Based on effects of MAUP on the results of landscape analysis, Jelinski concluded the dramatic difference in spatial autocorrelation between Forest landscape and the Grassland and Crop landscapes at certain scales may reflect highly conspicuous patchiness in Forest landscape, while the other two are relatively homogeneous. However, it is known that landscapes are more heterogeneous with more human disturbance, while landscapes more homogenous with little disturbance. Different landscapes have different natural environmental conditions, and this study agree with the latter, that human disturbances lead to greater heterogeneity, just as comparisons of fives different nature and socioeconomic setting landscapes indicate that landscapes with more socioeconomic factors have lower spatial autocorrelation, while landscapes with fewer human disturbances have higher spatial autocorrelation. Explanations for this are that human disturbances lead to fragmentation. In addition, the results also suggest that different data set, or different landscapes of the same data have different spatial autocorrelation degree and changing rate responding to changing grain size, which concur with Qi and Wu[2].

Similar to Qi and Wu, we comprehensively investigate the question how changing scale (e. g. grain size) affects pattern analysis, but we cannot address the question detecting or identifying "scale breaks" or hierarchical levels in study area. Thus; it is still essential that multiple methods should be developed and used wherever possible for the sake of comparison and verification.

This study is only the first step, and the ultimate goals are to comprehensively investigate the relationships between spatial pattern and ecological process. Only when we learn more about the scale-dependence of spatial pattern, we could make full use of our limited knowledge to learn more about spatial pattern and ecological process. We may detect or identify characteristics scales and hierarchical levels to understand and predict ecological phenomena. At the same time, theories, models, and procedures for extrapolating information across scales may be developed for understanding and managing heterogeneous landscapes in concrete region.

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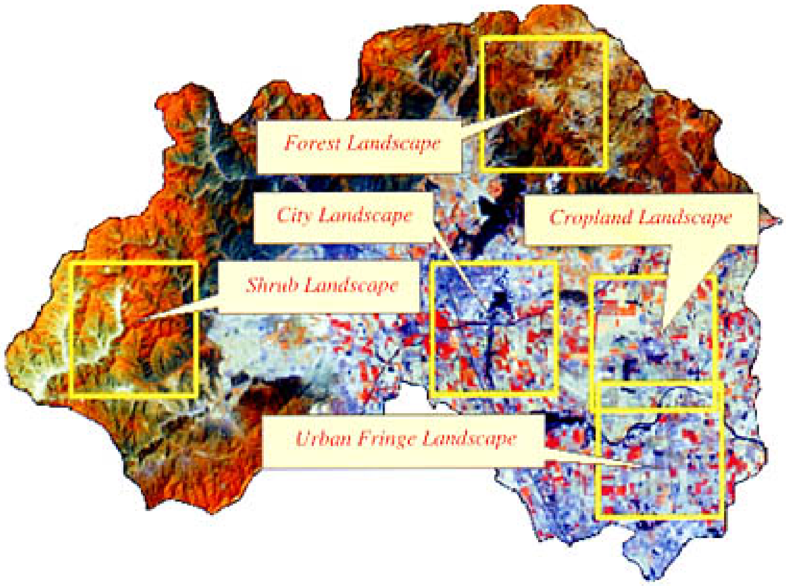

Plate Ⅰ Maps of the five different landscapes on May 19, 2001, of Changping District, Beijing, used for the study: forest landscape;cropland landscape;urban fringe landscape; city landscape;shrub landscape

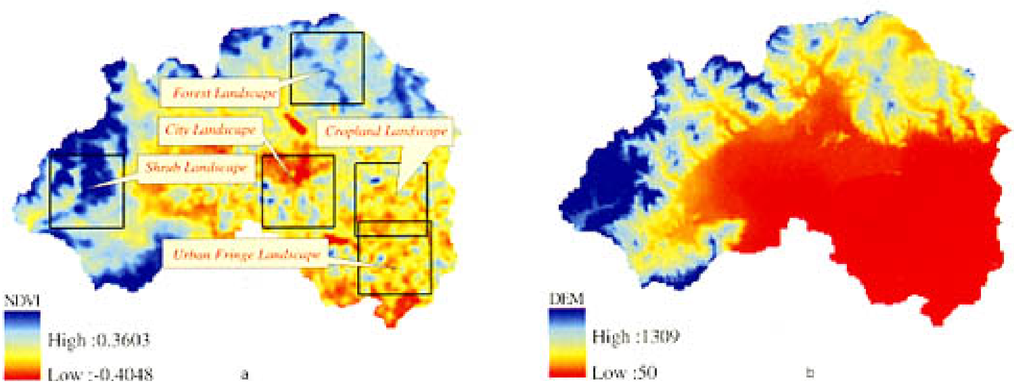

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Plate Ⅱ The landscape data sets of Changping: (a) NDVI on May 19, 2001; (b) DEM (m) of Changping District, Beijing. All the data sets have 153 rows and 219 columns, and have a spatial resolution of 260m × 260 m