Front. Earth Sci. 2021, 15(1): 94–105
https://doi.org/10.1007/s11707-020-0830-4

RESEARCH ARTICLE

Extraction of lacunarity variation index for revealing the slope pattern in the Loess Plateau of China

Ziyang DAI[1,2,3], Fayuan LI (✉)[1,2,3], Mingwei ZHAO[4], Lanhua LUO[1,2,3], Haoyang JIAO[1,2,3]

1 School of Geography, Nanjing Normal University, Nanjing 210023, China
2 Jiangsu Center for Collaborative Innovation in Geographical Information Resource Development and Application, Nanjing 210023, China
3 Key Laboratory of Virtual Geographic Environment (Ministry of Education), Nanjing Normal University, Nanjing 210023, China
4 Department of Land Information Engineering, Chuzhou University, Chuzhou 239000, China

Abstract Lacunarity analysis is frequently used in multiscale and spatial pattern studies. However, the explanation for the lacunarity analysis results is limited mainly at a qualitative description level. In other words, this approach can be used to judge whether the spatial pattern of the objective is regular, random or aggregated in space. The lacunarity analysis, however, cannot afford many quantitative information. Therefore, this study proposed the lacunarity variation index (LVI) to reflect the rates of variation of lacunarity with the resolution. In comparison with lacunarity analysis, the simulated experiments show that the LVI analysis can distinguish the basic spatial pattern of the geography objects more clearly and detect the scale of aggregated data. The experiment showed that different slope types in the Loess Plateau display aggregated patterns, and the characteristic scales of these patterns were detected using the slope pattern in the Loess Plateau as the research data. This study can improve the spatial pattern analysis and scale detecting methods, as well as provide a new method for landscape and vegetation community pattern analyses. Lacunarity analysis is frequently used in multiscale and spatial pattern studies. However, the explanation for the lacunarity analysis results is limited mainly at a qualitative description level. In other words, this approach can be used to judge whether the spatial pattern of the objective is regular, random or aggregated in space. The lacunarity analysis, however, cannot afford many quantitative information. Therefore, this study proposed the lacunarity variation index (LVI) to reflect the rates of variation of lacunarity with the resolution. In comparison with lacunarity analysis, the simulated experiments show that the LVI analysis can distinguish the basic spatial pattern of the geography objects more clearly and detect the scale of aggregated data. The experiment showed that different slope types in the Loess Plateau display aggregated patterns, and the characteristic scales of these patterns were detected using the slope pattern in the Loess Plateau as the research data. This study can improve the spatial pattern analysis and scale detecting methods, as well as provide a new method for landscape and vegetation community pattern analyses.

Keywords lacunarity variation index (LVI), slope pattern, characteristic scale, the Loess Plateau, digital elevation model (DEM)

1 Introduction

Spatial pattern appears to be ubiquitous. The definition of spatial pattern is complex, and the original one refers to an ecological concept that relates to the distribution of individuals in space and is an important feature of the population of settled organisms (Anderson and Rosenberg, 2016). Oliver and Webster (1986) considered spatial pattern as a special form that can be detected and described. Dale and Gibson (2002) defined spatial pattern as the organized form of objects expressed at a certain time point or period. Generally speaking, spatial pattern recognition is extremely important, and the study of spatial pattern type and intensity change plays an essential role in the disciplines that involve quantitative and statistical studies (Greig-Smith, 1979). For the statistical analysis of ecological and geographical data, although different ecological or geomorphic evolution processes have similar spatial patterns, the quantification of such patterns can still provide important clues for the identification of the process. Moreover, researchers can design hypothesis

Received March 23, 2020; accepted July 30, 2020

E-mail: lifayuan@njnu.edu.cn

testing or modeling according to the corresponding characteristics for further investigations.

According to different research objects, there are many kinds of spatial patterns, such as land use pattern, vegetation pattern, species diversity pattern, etc. In the field of geomorphology, landform is the main manifestation of spatial pattern, and slope is a basic element of geomorphology, so the spatial pattern of slope, namely, the slope pattern, has gradually become the focus of many researchers. The quantificational analysis of loess terrains is a key subject in the research on the Loess Plateau. Tang et al. (2008) proposed the slope spectrum to describe the loess landform quantitatively based on the slope point of view. Zhou et al. (2010) discussed the loess landform based on loess' positive and negative terrains. However, these studies did not describe the spatial pattern of the loess slope properly. Describing the loess landform by studying the slope pattern is a new and effective method considering that different slope combinations can reflect various landform types.

Spatial pattern analysis has always been the main tool of geographical and ecological analyses, and also the basis of slope pattern research. Corresponding spatial pattern analysis is developing rapidly with the widespread use of computing resources. Methods for analyzing spatial patterns in various disciplines have been developed. Dale et al. (2002) and Perry et al. (2002) summarized and compared the common methods used in spatial pattern analysis. Visual analysis is an elementary spatial pattern analysis method. However, this approach identifies and explains spatial patterns insufficiently. Variance is one of the simplest and oldest measures of spatial pattern. In many instances, this analysis mainly aims to distinguish among the three categories of spatial patterns, namely, regular, random and aggregated. In quadrat analysis, the spatial locations of the sample units are included in the investigation; such analysis requires the data to be collected as a complete census in strings or grids of contiguous quadrats. In addition, this analysis is often used to check the spatial distribution of accessibility (Sadahiro, 2005) and measure forest and plant distributions (Falcon-Lang, 2003; Plante et al., 2004). However, the results of quadrat analysis are inaccurate when an inappropriate quadrat size is used. Nearest neighbor analysis has been applied to measure the pattern of animal (Heupel and Simpfendorfer, 2005), plant (Shaw et al., 2005) and landform distribution (Gao et al., 2005). Nearest neighbor analysis is more robust than the quadrat analysis, but both methods are criticized for their inability to measure the correlation of the attributes (Williams and Wentz, 2008). The application of spatial tessellations and Voronoi diagrams in the analysis of the spatial patterns of points is widely used in agriculture, microbiology and astronomy (Kristensen et al., 2006). Fractal analysis is commonly used to generate artificial but real landscapes, as well as to quantify the irregularity of the landscapes. De Keersmaecker, Frankhauser and Thomas (2003) used fractal analysis to describe the irregular urban land use in Brussels, Belgium. Each method has advantages and disadvantages for certain types of problems and data.

Lacunarity analysis is one of the common methods in quadrat analysis and was initially used to describe the geometric structure and distribution in solid materials quantitatively. This analysis was later developed as a multiscale pattern analysis method. Lacunarity, which has been introduced by Mandelbrot and Wheeler (1983), is a specialized term in geometry that refers to a measure of how patterns, especially fractals, fill space. Patterns that exhibit many or large gaps have high lacunarity or a high degree of 'gappiness'. Gefen et al. (1983) considered lacunarity a scale dependent measure of heterogeneity or texture. Lacunarity can be used to distinguish objects with the same or similar fractal dimensions. With the advantage of multiscale information, it can also be used to detect the spatial pattern of a study object (e.g. rank construction, self-similarity, randomicity and aggregated) (Wu et al., 2006).

Lacunarity analysis is now widely used in many fields. Plotnick (1996) introduced lacunarity analysis into landscape ecology, which demonstrated a great application potential (Larsen and Bliss, 1998; With and King, 1999; McIntyre and Wiens, 2000). Lacunarity analysis has also been used successfully in medicine research, such as in vertebral trabecular bone for assessing osteoporosis (Dougherty and Henebry, 2002) and in the automated assessment of melanocytic naevi and melanoma.

However, lacunarity analysis also possesses several shortcomings. Dale (2000) stated that lacunarity analysis can easily distinguish whether the spatial pattern of the study object is systematic regular, randomly distributed or aggregated. However, many geographical objects present aggregated pattern in nature. For aggregated patterns, the analysis fails to detect the characteristic scale, which is a critical factor in spatial pattern analysis. Therefore, Dale (2000) proposed a new index called standard lacunarity. Although the interpretation of the results of standard lacunarity analysis is easier than that of the traditional one, the standard lacunarity still fails to detect the characteristic scale.

Characteristic scale is the scale at which the dominant pattern emerges. Many have argued that ecological and geographical phenomena tend to have characteristic spatial and temporal scales, or spatiotemporal domains (Urban et al., 1987). Different characteristic scales indicate that different mechanisms are involved in determining their pattern. If the characteristic spatial scale of a system of interest is known, researchers could use it to isolate particular phenomena of interest. To better understand the structure of the system, it is a major focus of slope pattern analysis which is to find the characteristic scale of pattern in the system, often as a precursor to experimental studies of pattern-process relationships (McGarigal, 2016). For example, the space-for-time substitution method in the field of geomorphology requires the detection of characteristic scale, because different landform forming process have their own characteristic scale. In the Loess Plateau, the slope characteristic scale can correspond to the development process of gully, and the regional characteristic scale can correspond to the development process of small loess watershed in different spatial locations under the same development mode (Huang et al., 2017).

This study proposes a new index called lacunarity variation index (LVI), and the calculation of LVI is based on the common lacunarity. A simulation experiment verified that the new method can distinguish the basic spatial pattern type and detect the characteristic scales of the aggregated slope pattern easily. In the present study, three sample areas located in the Loess Plateau were selected for the analysis of the slope pattern using LVI.

2 Materials and methods

2.1 Research area and data

The Loess Plateau, one of the four main plateaus of China, was selected as the research area of this study. It is about 640000 km^2 plateau, extending between 34° N and 40° N/100° E and 115° E, which is the central northern part of China (Reiji and Naru, 2014).

Three areas located in the Loess Plateau were selected as the sample areas (Fig. 1). Table 1 shows the detail information of the sample areas. The basic data source of this paper is 5 m resolution digital elevation models (DEMs), which are produced in accordance to the national standard of China.

A series of simulation data sets that represents the three types of spatial patterns are conducted according to the

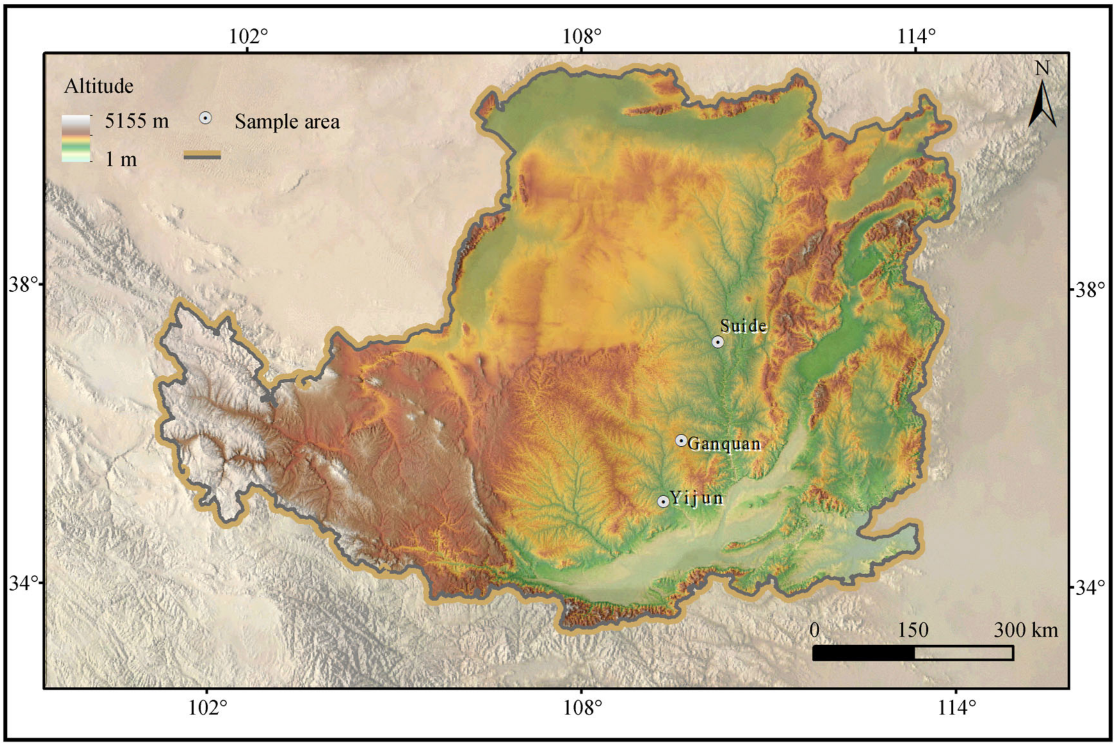


Fig. 1 Spatial distribution of the sample areas.

Table 1 Basic overview of the sample area

Sample area	Geographical coordinates	Landform type	Basic information
Suide	110°15′00″—110°22′30″E; 37°32′30″—37°37′30″N	Loess hill	Suide is a key watershed of soil and water conservation. The highest and lowest elevations in this area are 1115 m and 892 m, the average annual precipitation and temperature is 486 mm and 9.7°C, respectively.
Ganquan	109°30′00″—109°37′30″E; 36°10′00″—36°15′00″N	Loess ridge	The highest and lowest elevations in this area are 1459 m and 1147 m, the average annual precipitation is 670 mm, and the average temperature ranges within 10.4°C–13.6°C.
Yijun	109°18′45″—109°26′15″E; 35°25′00″—35°30′00″N	Loess tableland	The highest elevation above sea is 1158 m, whereas the lowest one is 768 m, the average annual precipitation is 709 mm, and the average temperature is 8.9°C.

basic spatial pattern types (i.e. regular, random and aggregated). Given that the aggregated pattern is more complex and prevalent in real world than the other two pattern types, this study focused on the aggregated pattern. Four types of aggregated pattern are selected, and six simulation data sets are generated (Fig. 2). The attributes of the data sets are listed in Table 2, where density is the proportion of the studied objects covered, and aggregated unit size refers to the number of studied objects that aggregated together as a unit.

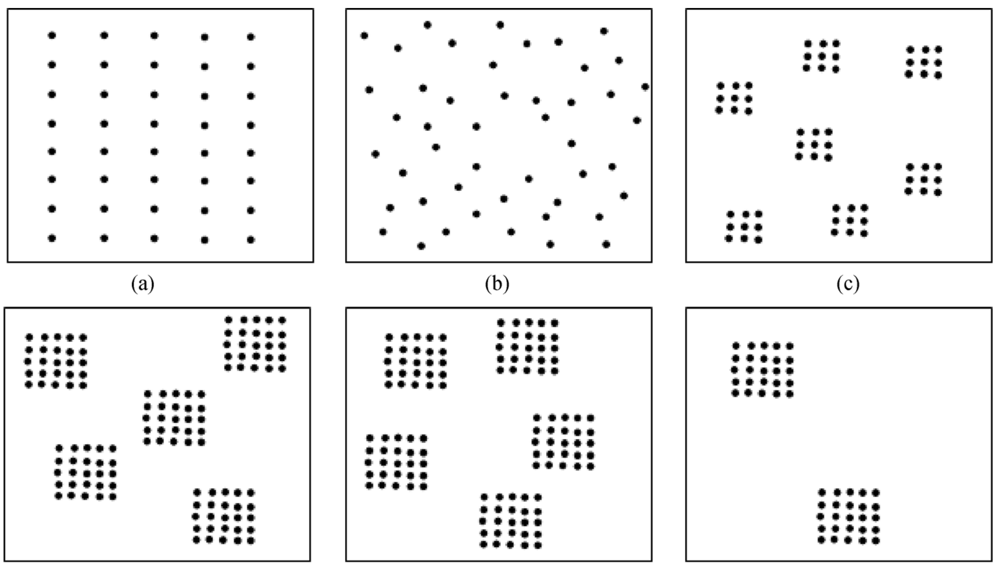
Except for the data set (a), which was created manually, all data sets are generated using the ArcGIS Pro software. First, a random data set is obtained through the Create Random Raster Tool. Secondly, the objects of the random data are broken down to generate small objects by changing the output cell size using the Resample tool. Lastly, the raster data sets are converted into a TXT file to satisfy the requirement of the experiment.

2.2 Methodology

2.2.1 Spatial pattern and characteristic scale

As previously established, the definition of spatial pattern is complex (Anderson and Rosenberg, 2016). In this study, spatial pattern is considered the organized form of the objects expressed at a certain time point or period. Despite the lack of a unified definition, the basal types of spatial patterns, namely, regular, random and aggregated (Heltshe and Ritchey, 1984) are explicit (Fig. 3). Investigating spatial patterns can reveal the regularity of spatial objects through appropriate observation and analysis of scale.

The concept of scale is diversified into different classification systems according to different focuses. Wu et al. (2006) proposed a three-tiered conceptualisation of scale that organized the scale definitions into a conceptual hierarchy that consisted of dimensions, kinds and scale



(a) (b) (c)

(d) (e) (f)

Fig. 2 Simulated data sets.

Table 2 Information of the simulated data sets for the simulation experiment

Data set	Spatial pattern type	Density	Map size	Aggregated unit size
(a)	regular	0.2	250 × 250	\
(b)	random	0.5	250 × 250	\
(c)	aggregated	0.5	250 × 250	9
(d)	aggregated	0.5	250 × 250	25
(e)	aggregated	0.5	150 × 150	25
(f)	aggregated	0.2	250 × 250	25

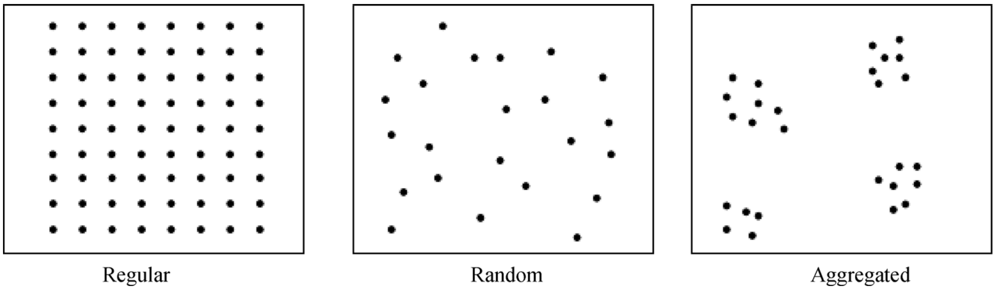


Fig. 3 Types of spatial pattern.

components. The scale can be divided into phenomenon, observation, analysis and modeling scales (Wu and Li, 2009). The investigation on spatial objects is conducted at certain scales (i.e. characteristic scales), and the regularity of the spatial objects can be assessed and easily interpreted by selecting the proper observation, analysis or simulation scales. In fact, the spatial pattern and process can be described only when the observation and analysis scales consist of the characteristic scale.

2.2.2 Lacunarity and LVI

Several methods for calculating lacunarity have been developed. Gefen et al. (1984) proposed different methods for calculating lacunarity, which were improved subsequently by Lin and Yang (1986). Allain and Cloitre (1991) introduced a gliding box algorithm for calculating lacunarity, which was the most widely used method. This algorithm sets an $r \times r$ box at the upper left corner, calculates the mean and variance of the data in the box, moves the box from left to right and then calculates the mean and variance of the data in the new box position. The process is repeated until the entire map is covered. The lacunarity algorithm can be defined as

$$\Lambda(r) = \frac{S_s^2(r)}{\overline{S}^2(r)} + 1, \tag{1}$$

where $\Lambda(r)$ is the lacunarity value when the moving box's size is r; $\overline{S}(r)$ and $S_s^2(r)$ are the mean and variance of the number of sites per box, respectively.

The lacunarity value will change with the moving box's size. However, a single lacunarity value is meaningless and incomparable, whereas the lacunarity values of a series of boxes can offer abundant information. In lacunarity analysis, $\ln(r)$ and $\ln(\Lambda(r))$ are selected as the abscissa and ordinate, respectively. Subsequently, the graph of $\ln(\Lambda(r)) - \ln(r)$. is plotted. The pattern type of the analysis objects can be assessed on the basis of the form of the curve.

As previously mentioned, lacunarity analysis has many disadvantages; hence, the proposal of LVI. LVI can be defined as

$$D_{\Lambda(r)} = \frac{\ln\Lambda(r) - \ln\Lambda(r+1)}{\ln\Lambda(r)}, \tag{2}$$

where $D_{\Lambda(r)}$ is the change rate of the lacunarity value when the moving box's size changes from r to $r+1$. Similar to the lacunarity analysis, LVI analysis sets the abscissa (r) and the ordinate ($D_{\Lambda(r)}$) before plotting the graph of the difference between the two (i.e. $D_{\Lambda(r)} - \ln(r)$) to obtain adequate information.

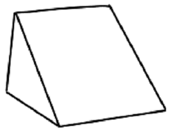
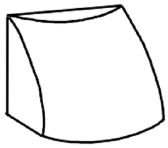
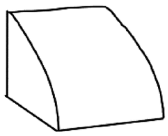
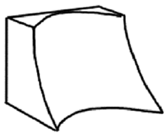
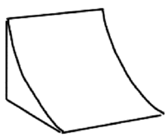
The software package Pattern Analysis, Spatial Statistics and Geographic Exegesis (PASSAGE) is used to calculate the lacunarity values of the different simulated data sets, and MATLAB is utilized to calculate the lacunarity value using Eq. (2).

2.2.3 Classification of slopes

Slope classification has been investigated since the 1950s. Hammond (2005) developed a manual way through contoured maps. With the increasing availability of commercial geographic information system (GIS) software, Dikau et al. (1991) developed a GIS technology to classify slopes automatically according to Hammond's method. In this study, the object-oriented method proposed by Dragut and Blaschke (2006) was applied for loess slope segmentation. First, several data layers, including profile curvature and plan curvature, are extracted from DEMs. Secondly, every data layer is taken as a single-band image, and then three single-band images are combined into a multiband image. Thirdly, on the basis of the multiband image, the previous rules in combining the geometric features of the slope types are adopted for image segmentation and classification. Lastly, five kinds of slope morphological units are segmented (Li, 2010; Zhao et al., 2012). Table 3 shows the geometric feature of the five identified slope types.

CL slope is often related to the negative terrain (Zhou et al., 2010). In the Loess Plateau, CL slope is the one of most widely distributed slope type which is formed by the soil erosion, it can reflect the specific phase of gully development (Cao, 1983). CL slope is one of the most representative slope forms of the natural erosion in the Loess Plateau. Straight slope is rare to see in the nature. LL

Table 3 Geometric feature of the five slope types (ND means no definition)

Slope type	Slope form	Schematic diagram	Geometric feature	
			Plan curvature	Profile curvature
Straight slope	LL slope		±0	±0
Convex slope	VV slope		> 0	> 0
	VL slope		±0	> 0
Concave slope	CC slope		< 0	< 0
	CL slope		±0	< 0

slope is often associated with human activities, because human habitats and agricultural activities require relatively flat surfaces (Tarolli and Sofia, 2016). Terraces, check-dams and other human-made structures which are widely distributed in the Loess Plateau are divided as LL slope in the process of slope classification (Li et al., 2020). In fact, the study of LL slope can reflect the aggregation and distribution of human activities to a certain extent. Due to the different formation mechanisms, the slope patterns and characteristic scales of CL and LL slopes may be different. Therefore, CL and LL slope were selected as research objects in this study, and their slope patterns and characteristic scales were detected by using lacunarity and LVI analysis.

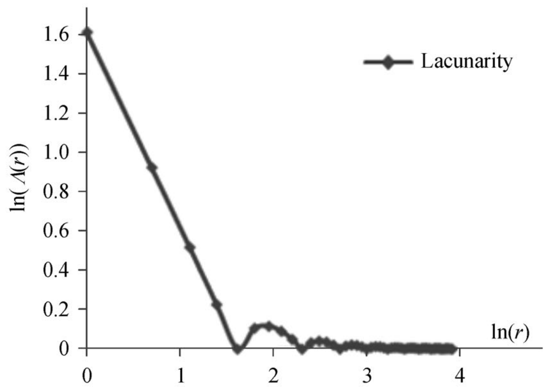
3 Results

3.1 Simulation experiment

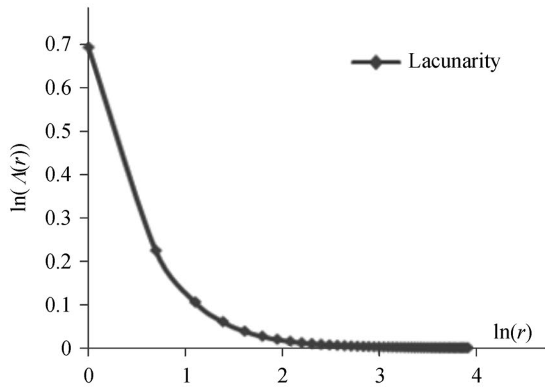
The experiment combined different data sets (Fig. 2) to validate the function of LVI in the spatial pattern analysis. Data sets (a), (b) and (c) were combined to validate the function of LVI in distinguishing the basic pattern types; data sets (c) and (d), which possess similar distribution patterns but different characteristic scales, are used to validate if the LVI can detect the characteristic scales of each pattern; data sets (d) and (e) are used to verify if the map size influences the LVI in detecting the characteristic; and data sets (d) and (f) are combined to determine if the density of the studied objects will affect the performance of LVI in detecting the characteristic scale.

Unlike that of the regular patterns, where the LVI value can be set as 0, the denominator of the lacunarity value cannot be 0. The calculated lacunarity value (logarithm) and LVI are used as the ordinate coordinates, whereas the window size (logarithm) is used as the abscissa coordinates. The change trend of the lacunarity value and LVI with respect to the change in the analysis window is illustrated in Fig. 4.

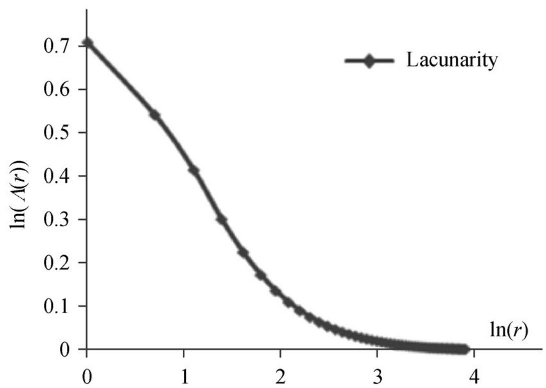
Figures 4(a)–4(f) are the lacunarity analysis results of the six simulated data sets, Figs. 4(g)–4(l) are the LVI analysis results. The difference in the results of the two methods for the six simulated data sets are distinct. Figures



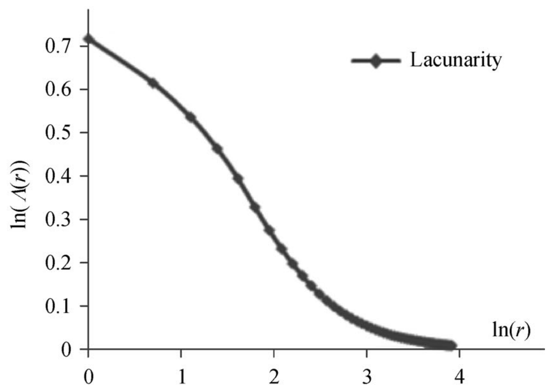
(a) Data set (a)



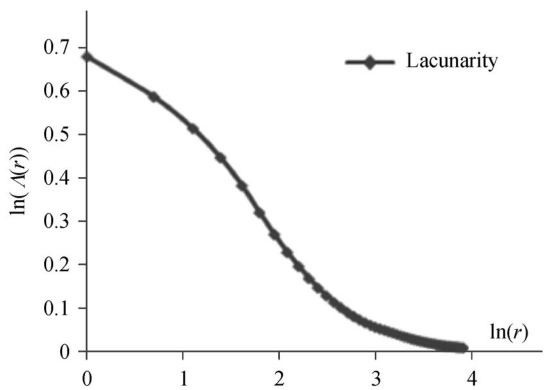
(b) Data set (b)



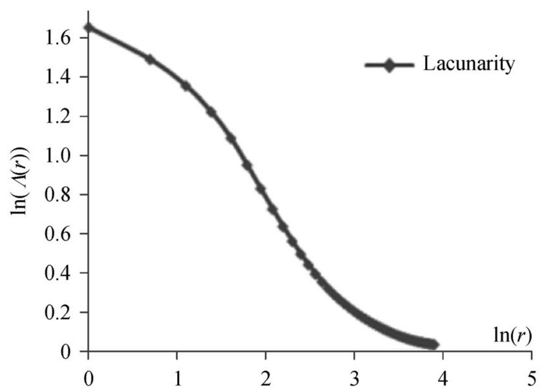
(c) Data set (c)



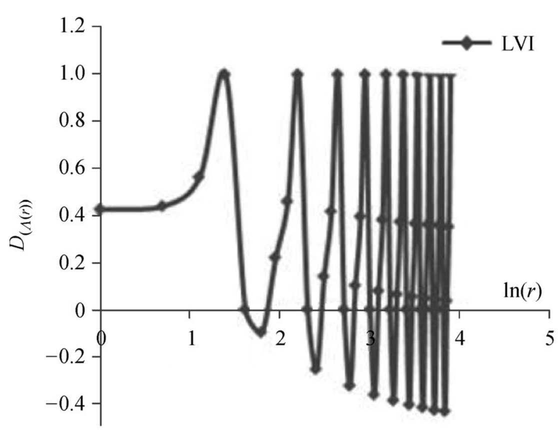
(d) Data set (d)



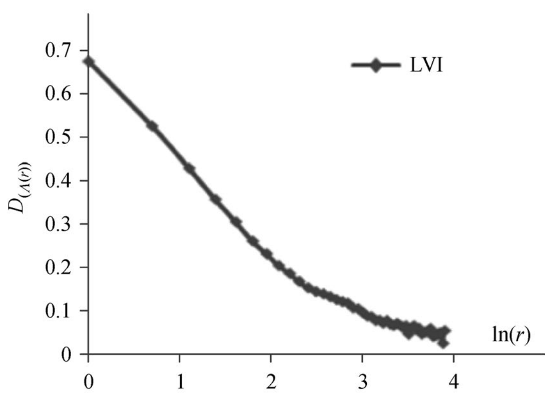
(e) Data set (e)



(f) Data set (f)



(g) Data set (a)



(h) Data set (b)

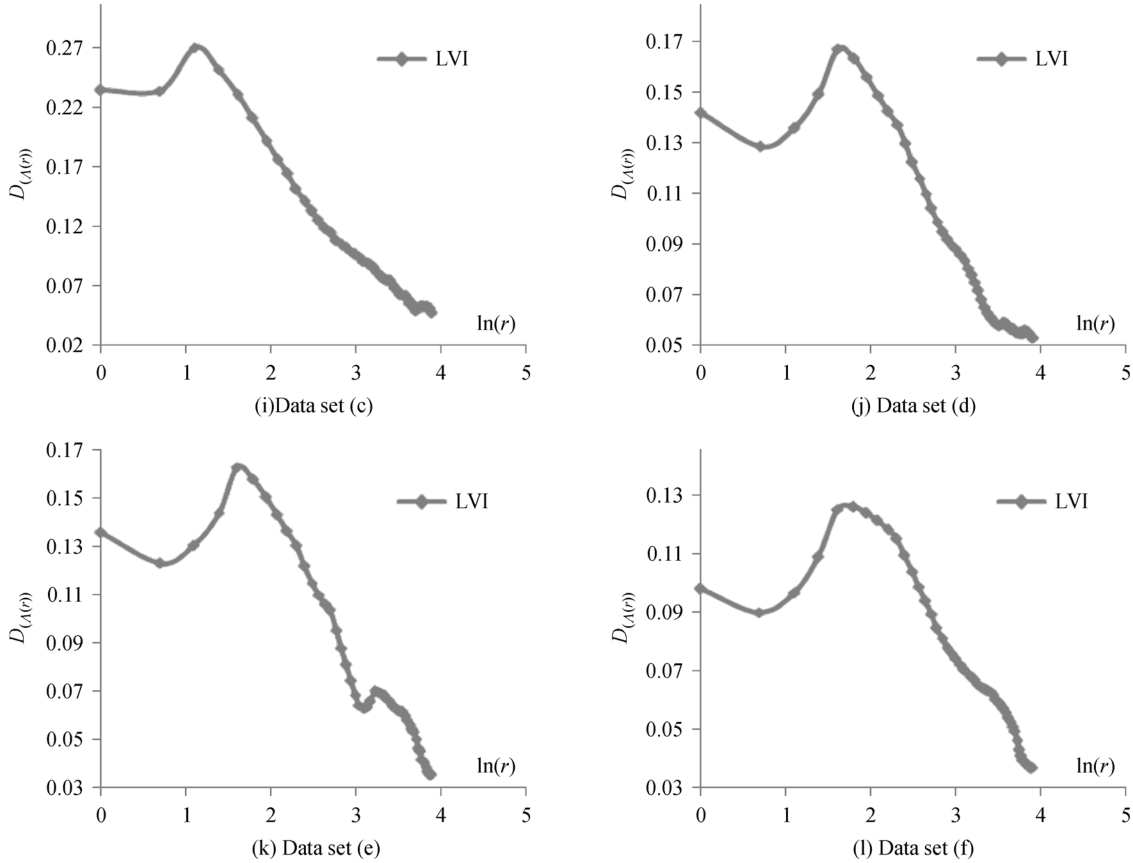


Fig. 4 Analysis results of the lacunarity value and LVI.

4(a) and 4(g) are the lacunarity analysis result and LVI analysis result of the regular pattern respectively. Figure 4(a) shows that the lacunarity value decreased to zero in small decrements as the box size increased although with a rather small bounce. Whereas Fig. 4(g) shows that the LVI value vibrated with a larger range and the zero value indicated the characteristic scale in the regular pattern. Figures 4(b) and 4(h) show that the lacunarity and LVI analyses' results for the random pattern are similar, except in terms of the curvature. The curve of the Fig. 4(b) is concave, whereas that of the Fig. 4(h) is more linear. The difference in the results for the different types of aggregated pattern is noticeable. The lacunarity analyses of the four different aggregated patterns followed an S-shape. Although the four patterns are different from one another, only minimal differences are observed in the corresponding curves. All LVI curves have a single peak, which indicated the characteristic scales in the pattern. The characteristic scale of pattern (c) is 3, whereas those of pattern (d), (e) and (f) are 5, which are the ordinal of peak points. The abscissa of the peak in Fig. 4(i) is different from Figs. 4(j), 4(k) and 4(l), indicates that LVI can detect the characteristic scale.

The differences among Figs. 4(c)–4(f) are not large, while the differences among Figs. 4(i)–4(l) are large, indicating that the LVI analysis is sensitive to the data set's extent and points' density. The simulation results prove that the LVI analysis can well identify different spatial patterns, and detect the characteristic scales in the pattern, which are huge improvements compared with the lacunarity analysis.

3.2 Pattern analysis of the slopes

The segmentation process generated five types of slope. This study selected the CL and LL slopes as the research objects. To compare the results obtained using the two different methods, the common lacunarity values are also calculated. The results are displayed in Fig. 5.

The lacunarity and LVI analyses' results of the Suide area are shown in Figs. 5(a) and 5(b), respectively. Figure 5(a) shows that the two slope types exhibit an aggregated pattern. Given that the lacunarity value is 1/P when the size of the box is equal to the grain of the map, where P is the density of the study objects, the CL slope covered more area in Suide than the LL slope. Figure 5(b) indicates that both slope types have characteristic scales because of the existence of the distinct peaks in the curve. The characteristic scales of the LL and CL slope are 85 m, but densities of the two slope types are different. For the

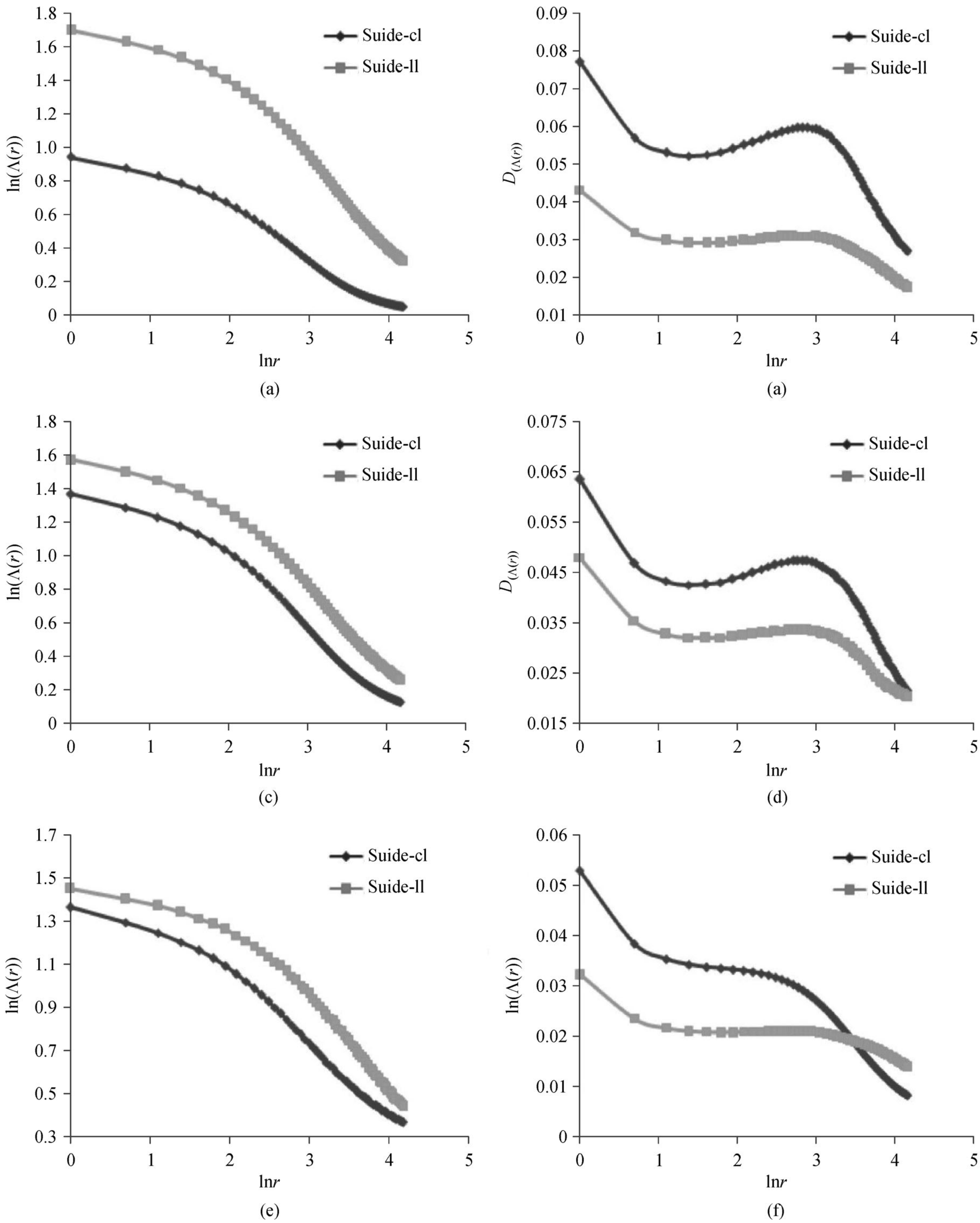


Fig. 5 Lacunarity and LVI analysis.

Ganquan area, the analysis results are similar to that of the Suide area, except that the characteristic scales of the two slope types are 80 m. The analysis results for the Yijun area is complicated. The lacunarity analysis shows that the density of the CL slope is larger than that of the LL slope, but the characteristic scale of the former (65 m) is smaller than that of the latter (80 m). This phenomenon can be explained as follows. Although the CL slope covered more area than the LL slope, and the former is more fragmented than the latter. In other words, compared with the LL slope, the CL slope is aggregated with small areas, which makes the corresponding characteristic scale small. The difference between the two slope types is clearly illustrated in Fig. 6; dark areas in Figs. 6(a) and 6(b) represent the CL

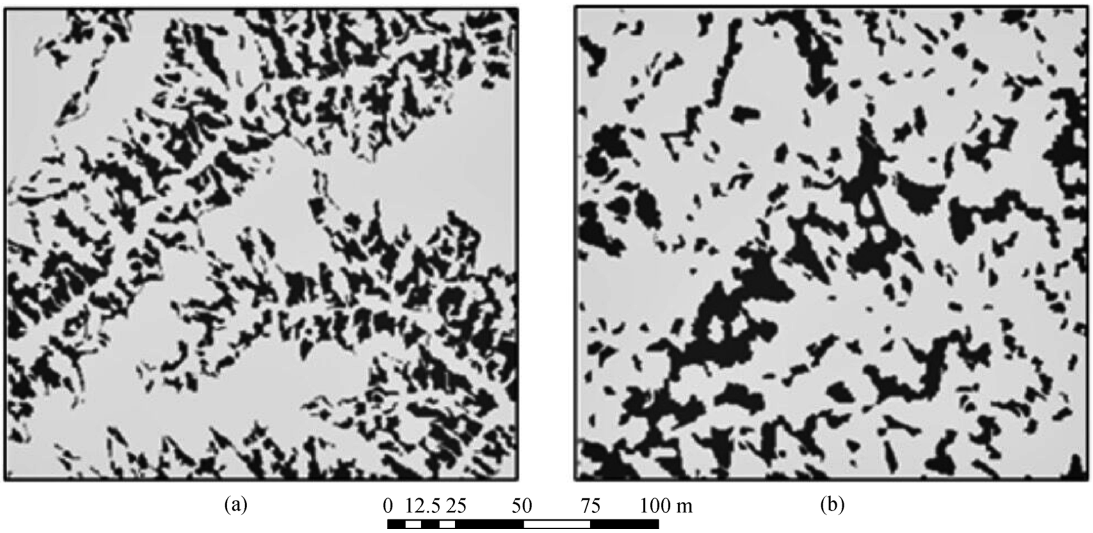


Fig. 6 CL (a) and LL slopes (b) of Yijun

and SL slopes, respectively. According to the figure, the LL slope is more aggregated than the CL slope.

4 Discussion and conclusions

Lacunarity analysis is crucial in exploring the spatial pattern and distribution of geography objects. Although common lacunarity analysis can judge if the spatial pattern is regular, random and aggregated, this method cannot provide additional information, especially for the aggregated pattern. In addition, this analysis cannot detect the characteristic scales of the spatial patterns. Therefore, this study proposed a new index called LVI, which can be easily calculated on the basis of the lacunarity value. The calculations in LVI is easier than those in other spatial pattern analysis methods.

This study used six kinds of simulation data sets to verify the superior efficiency of LVI analysis over the common lacunarity analysis. The experiment results showed that the former can easily distinguish the types of spatial patterns from the form of the curves. Furthermore, for the aggregated pattern, the LVI analysis can detect the characteristic scales from the data accurately. The results from analyzing different kinds of aggregated pattern data (e.g. changing the extent of the study area, study object's density and aggregation intensity) showed that the LVI analysis can avoid the influence of the factors.

This study selected three sample areas, namely, Suide, Ganquan and Yijun, to evaluate the application of LVI. The high-resolution DEMs are used as the basic data. An object-oriented method was applied for the detection of loess slope pattern and its characteristic scale. Subsequently, the spatial pattern of the CL and LL slope in the three test areas are investigated using LVI. The analysis results show that both slopes display an aggregated pattern and have characteristic scales. The characteristic scales of the CL and LL slopes for Suide and Ganquan are 85 m and 80 m, respectively, whereas those for Yijun are 65 m and 80 m, respectively. This study used LVI to analyze slope patterns, and it has the potential to be applied in the field of ecology and other sciences.

LVI analysis has its advantages, but it is not perfect. First, unlike the lacunarity analysis curve, LVI loses the density information of the study objects. However, the density is easier to obtain than the characteristic scales. LVI can still serve as a support for the common lacunarity analysis. Second, no matter lacunarity analysis or LVI, they are based on the classification of three categories of spatial pattern. If the pattern is aggregated, it is of interest to determine the sizes and characteristic scales of the clumps and their density. If the pattern is regular, it is of interest to know the characteristics of the spacing and its variability. If the analysis suggests that the pattern is random, is it possible to evaluate the characteristics of that randomness and to distinguish patterns that truly are random? (Dale, 2000) This is the problem that the whole spatial pattern analysis face. Third, LVI is proposed on the basis of lacunarity analysis. Although it can show the additional information of aggregated pattern which lacunarity analysis cannot do, it still inherits other defects of lacunarity analysis. Dale (2000) suggested that estimates of scales of pattern identified by lacunarity cannot consistently detect known features in multi-scaled patterns. Lacunarity looks at only one block at a time, therefore losing information on the spatial relationship between blocks of high density and blocks of low density (Saunders et al., 2005). In application experiment, LVI improves its interpretation and makes the differences between the results for different slope patterns more obvious. Even with this modification, however, LVI does not give results from which the characteristics of the slope patterns can be easily deduced. LVI is a good complement to the lacunarity analysis and spatial pattern analysis, and is also effective in the exploration of slope pattern, but this does not mean that LVI can completely replace other methods. For example, wavelet analysis cannot detect the distributions of regular and random. In contrast to lacunarity, it can indicate both the scales of patchiness and positions in space or time (Dale and Mah, 1998). It emphasized the importance of using multiple methods including LVI to examine information of patterns.

Acknowledgements We are grateful for the financial support from the National Natural Science Foundation of China (Grant Nos. 41930102, 41571383, 41771415, 41801321, and 41701450). We sincerely appreciate the editor's encouragement. The constructive criticisms and suggestions from anonymous reviewers are also gratefully acknowledged.

References

Allain C, Cloitre M (1991). Diffraction on Fractals. Scaling Phenomena in Disordered Systems. New York: Springer

Anderson C D, Rosenberg M S (2016). Spatial pattern analysis. In: David Gibson ed, Oxford Bibliographies in Ecology. New York: Oxford University Press

Cao Y Z (1983). Slope features and soil erosion on the loess region. Geogr Res, 2(3): 19–28 (in Chinese)

Dale M R T, Mah M (1998). The use of wavelets for spatial pattern analysis in ecology. J Veg Sci, 9(6): 805–814

Dale M R T (2000). Lacunarity analysis of spatial pattern: a comparison. Landsc Ecol, 15(5): 467–478

Dale M R T, Gibson D J (2002). Spatial pattern analysis in plant ecology. Q Rev Biol, 15(1): 195–196

Dale M R T, Dixon P, Fortin M J, Legendre P, Myers D E, Rosenberg M S (2002). Conceptual and mathematical relationships among methods for spatial analysis. Ecography, 25(5): 558–577

Dikau R, Brabb E E, Mark R M. (1991). Landform classification of New Mexico by computer. Open-File Report.

Dougherty G, Henebry G M (2002). Lacunarity analysis of spatial pattern in CT images of vertebral trabecular bone for assessing osteoporosis. Med Eng Phys, 24(2): 129–138

Drăguț L, Blaschke T (2006). Automated classification of landform elements using object-based image analysis. Geomorphology, 81(3–4): 330–344

Falcon-Lang H J (2003). Late carboniferous tropical dryland vegetation in an alluvial-plain setting, joggins, Nova Scotia, Canada. Palaios, 18 (3): 197–211

Gao Y, Alexander E C Jr, Barnes R J (2005). Karst database implementation in minnesota: analysis of sinkhole distribution. Environmental Geology, 47(8): 1083–1098

Gefen Y, Meir Y, Mandelbrot B B, Aharony A (1983). Geometric implementation of hypercubic lattices with noninteger dimensionality by use of low lacunarity fractal lattices. Phys Rev Lett, 50(3): 145–148

Gefen Y, Aharony A, Mandelbrot B B. (1984). Phase transitions on fractals. iii. infinitely ramified lattices. Journal of Physics A General Physics, 17(6): 1277–1289

Greig-Smith P (1979). Pattern in vegetation. J Ecol, 67(3): 755–779

Hammond E H (2005). Analysis of properties in land form geography: an application to broad-scale land form mapping. Ann Assoc Am Geogr, 54(1): 11–19

Heltshe J F, Ritchey T A (1984). Spatial pattern detection using quadrat samples. Biometrics, 40(4): 877–885

Heupel M R, Simpfendorfer C A (2005). Quantitative analysis of aggregation behavior in juvenile blacktip sharks. Marine Biology (Berlin), 147(5): 1239–1249

Huang X L, Ding H, Na J M, Tang G A (2017). Theories and methods of space-for-time substitution in geomorphology. Acta Geogr Sin, 72 (1): 94–104

Keersmaecker M L D, Frankhauser P, Thomas I (2003). Using fractal dimensions for characterizing intra-urban diversity: the example of Brussels. Geogr Anal, 35(4): 310–328

Kristensen L, Olsen J, Weiner J, Griepentrog H W. (2006). Describing the spatial pattern of crop plants with special reference to crop–weed competition studies. Field Crops Research, 96(2–3): 0–215

Larsen D R, Bliss L C (1998). An analysis of structure of tree seedling populations on a lahar. Landsc Ecol, 13(5): 307–323

Li F Y (2010). DEM and image-based loess slope segmentation. In: 3rd International Congress on Image and Signal Processing

Li S J, Xiong L Y, Tang G A, Strobl J (2020). Deep learning-based approach for landform classification from integrated data sources of digital elevation model and imagery. Geomorphology, 354: 107045

Lin B, Yang Z R (1986). A suggested lacunarity expression for sierpinski carpets. J Phys Math Gen, 19(2): 49–52

Mandelbrot B B, Wheeler J A (1983). The fractal geometry of nature. Am J Phys, 51(3): 286–287

McGarigal K (2016). Concepts of scale. In: Landscape ecology course notes. Amherst: Massachusetts University

McIntyre N E, Wiens J A (2000). A novel use of the lacunarity index to discern landscape function. Landsc Ecol, 15(4): 313–321

Oliver M A, Webster R (1986). Semi-variograms for modelling the spatial pattern of landform and soil properties. Earth Surf Process Landf, 11(5): 491–504

Perry J N, Liebhold A M, Rosenberg M S, Dungan J, Miriti M, Jakomulska A, Citron-Pousty S (2002). Illustrations and guidelines for selecting statistical methods for quantifying spatial pattern in ecological data. Ecography, 25(5): 578–600

Plante M, Lowell K, Potvin F, Boots B, Fortin M J (2004). Studying deer habitat on Anticosti Island, Quebec: relating animal occurrences and forest map information. Ecol Modell, 174(4): 387–399

Plotnick R E (1996). The ecological play and the geological theater. Palaios, 11(3): 207–208

Reiji K, Naru T (2014). Climate of the Loess Plateau. In: Restoration and Development of the Degraded Loess Plateau, China, 22–33

Sadahiro Y (2005). Spatiotemporal analysis of the distribution of urban facilities in terms of accessibility. Pap Reg Sci, 84(1): 61

Saunders S C, Chen J, Drummer T D, Gustafson E J, Brosofske K D (2005). Identifying scales of pattern in ecological data: a comparison of lacunarity, spectral and wavelet analyses. Ecol Complex, 2(1): 87–105

Shaw D C, Chen J, Freeman E A, Braun D M (2005). Spatial and population characteristics of dwarf mistletoe infected trees in an old-growth douglas-fir/western hemlock forest. Revue Canadienne De Recherche Forestière, 35(4): 990–1001

Tang G A, Li F Y, Liu X J, Long Y, Yang X (2008). Research on the slope spectrum of the Loess Plateau. Science in China Series E: Technological Sciences, 51(S1): 175–185

Tarolli P, Sofia G (2016). Human topographic signatures and derived geomorphic processes across landscapes. Geomorphology, 255: 140–161

Urban D L, O'Neill R V, Shugart H H Jr (1987). A hierarchical perspective can help scientists understand spatial patterns. Bioscience, 1987(37): 119–127

Williams E A, Wentz E A (2008). Pattern analysis based on type, orientation, size, and shape. Geogr Anal, 40(2): 97–122

With K A, King A W (1999). Dispersal success on fractal landscapes: a consequence of lacunarity thresholds. Landsc Ecol, 14(1): 73–82

Wu H, Li Z L (2009). Scale issues in remote sensing: a review on analysis, processing and modeling. Sensors (Basel), 9(3): 1768–1793

Wu J, Jones K B, Li H, Loucks O L (2006). Scaling and Uncertainty Analysis in Ecology II Concepts of Scale and Scaling. Amsterdam: Springer

Zhao M W, Li F Y, Tang G A (2012). Optimal scale selection for DEM based slope segmentation in the Loess Plateau. Int J Geosci, 1(3): 37–43

Zhou Y, Tang G A, Yang X, Xiao C C, Zhang Y, Luo M L (2010). Positive and negative terrains on northern Shaanxi Loess Plateau. J Geogr Sci, 20(1): 64–76