QUANTIFYING EFFECTS OF CHANGING SPATIAL SCALE ON SPATIAL ENTROPY INDEX: USE OF FRACTAL DIMENSION

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ABSTRACT:

Quantifying landscape heterogeneity and its organization at different scales is essential for understanding ecosystems and landscapes. Among hundreds of landscape metrics, entropy-related index represents an efficient tool to quantify and characterize landscape patterns. A recent development is Spatial Entropy index (H_s), and it has been validated as flexible and effective in landscape pattern analysis. However, the effects of changing spatial scale on H_s has not been quantified. This paper applies the fractal method to measure the spatial scale (grain size) sensitivity of H_s. Using the initial land-use data of Yanhe watershed, which is located in northwest of China, eleven different spatial scales were created in order to investigate the scale effects on H_s. A linear log–log regression model was then constructed based on the power law to calculate the coefficient of determination (COD) of the model and the fractal dimension (FD) of H_s. The result indicates that Spatial Entropy index shows a robust fractal feature, and it decreases as the spatial scale (or grain size) becomes lager in a moderate degree. In total, we believe that this study will help us to get a better understanding of H_s, and to facilitate further applications of this entropy-related index.

1. INTRODUCTION

It is widely recognized that the study of landscape heterogeneity and its organization at different scales is essential for understanding ecosystems and landscapes (Turner, 1989; Levin, 1992; Chave, 2013). Landscape features have been identified to exist at multiple spatial and temporal scales (Anderson et al., 2010), these features are presented differently across spatial scales (Turner, 1990; Emilio Rafael et al., 2009). The study of landscape heterogeneity has progressed in recent decades through the use of methods based on the application of landscape metrics (e.g., Haines-Young and Chopping, 1996; McGarigal et al., 2012) and spatial statistics (e.g., Fortin et al., 2012). While all these studies have contributed to advance our understanding of landscapes, however, various problems still exist since most of them do not address the intrinsic causality and underlying dynamics of the patterns (see Li, 2000a; Li and Wu, 2004; Shao and Wu, 2008).

To address these persistent challenges of landscape analysis, some scholars highlight that holistic and thermodynamic based approaches are needed (Muller, 2000; Li, 2000a; Cushman, 2015; Nielsen, 2019). Since introducing the seminal work of Shannon entropy to the field of landscape ecology, entropy-related metrics have been rapidly developed and represent an efficient tool to quantify and characterize landscape patterns (Vranken et al., 2015), for example, Shannon diversity index, Simpson diversity index, contagion index (Li and Reynolds, 1994), quadratic entropy index (Díaz-Varela et al., 2016), etc. A recent derivation is the Spatial Entropy index (H_s), and it incorporates proximity as a key spatial component into the measurement of spatial heterogeneity (Wang and Zhao, 2018). Hs has been validated as flexible and effective in characterizing landscape patterns, however, the effects of changing spatial scale (or scale sensitivity) on this index has not been quantified.

Fractal method offers a general way to quantify the scale effect of landscape metrics (Li, 2000b). The term fractal, was coined by Mandelbrot (1967), and it stands for complex but self-similar shapes that repeat fundamental patterns at ever increasing and decreasing scale (Brown et al., 2002). By applying the fractal method to measure the length of Britain’s shoreline using different rulers, Mandelbrot (1967) shows that the self-similarity of the shorelines is invariant for some range of scales. Since then, this method has been applied to address the scaling issues of both social and natural phenomena (Wu and Qi, 2000; Li, 2000b). In particular, the spatial scale used to measure landscape patterns is similar to the ruler length in measuring the length of the shoreline. The relations between the landscape metrics and the corresponding grain sizes, represented by the coefficients in the power law relations (Wu, 2004; Feng and Liu, 2015), can be transformed into fractal dimensions, which can be used to investigate the scale effects of landscape metrics.

The primary aim of this study is to evaluate effects of changing spatial scale on Spatial Entropy index (H_s). Our interest specifically concerns the following aspects: (a) to what extent is Hs sensitive to changes in spatial scales; and (b) how to use fractal dimension to quantify the scale effects of H_s. The remainder of this paper is structured as follows. Section 2 briefly illustrates the case study area and experimental data used in this research, and introduces the notion of Spatial Entropy index, and fractal dimension method in general. Section 3 demonstrates the results and provides a discussion. Finally, Section 4 concludes the paper and outlines some further work.

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2. MATERIALS AND METHODS

2.1 Study Area and Data

Yanhe watershed is located in the hinterland of the Loess Plateau in China with a total area of approximately 7,725 km^2 (Fig. 1). The area follows a southeast-northwest gradient, with elevation ranging from 491 to 1787 m, and it belongs to semi-arid continental climate zone, with an annual average precipitation of 520 mm, and annual average temperature is about 8.8-10.2 ℃ (Wang, 2016).

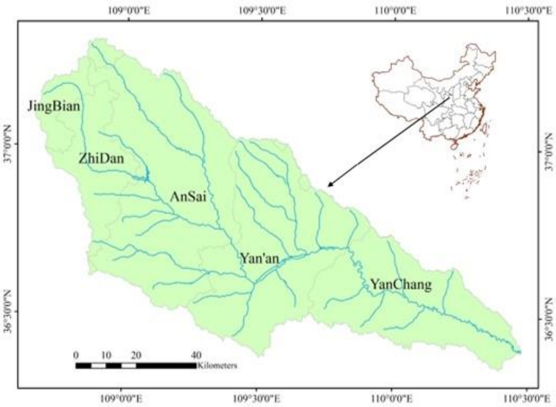

Figure 1. The location of study area.

A land-use map of Yanhe watershed for 2015 depicting different landscapes was used in this study (see Fig. 2), and it was provided by Resource Data Center of Chinese Academy of Sciences (http://www.resdc.cn). The main land-use types of this region include arable land (31.2%), grassland (52.4%), and woodland (14.9%). The rest (1.5%) contains urban, water bodies and other land-use types. The initial land-use map has a spatial resolution of 30 m, and then was resampled to other ten different spatial scales, which were defined as an increase by 30 m at each scale level. Therefore, the eleven spatial scales include 30 m, 60 m, 90 m, 120 m, 150 m, 180 m, 210 m, 240 m, 270 m, 300 m and 330 m. The resampling of the initial map was conducted on ArcGIS 10.2, and the Majority method was applied during this process. It should be kept in mind that some small land patches, especially the linear features such as rivers, disappeared at coarse spatial scales (Turner et al., 1989). Fortunately, as the number of such cells is low compared to other land-use types, this does not substantially change the composition of the land-use pattern of the region.

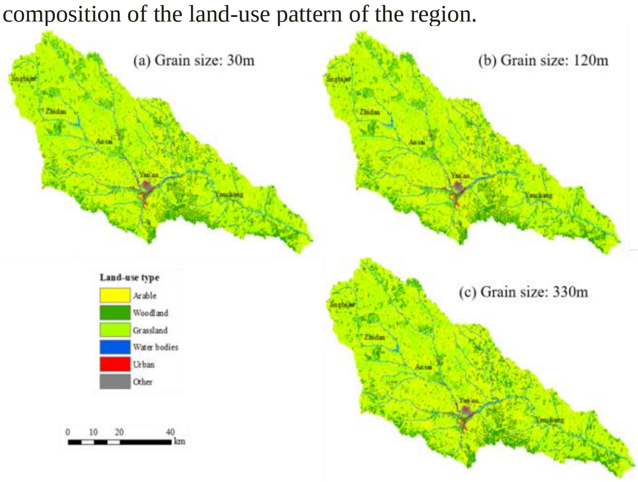

Figure 2. Land-use map of Yanhe watershed for 2015. Three different (a-c) grain sizes are represented.

2.2 Spatial Entropy Index as Heterogeneity Metrics

Entropy-related metrics represent an efficient tool to quantify and characterize landscape patterns. In particular, indices derived from information theory (i.e., Shannon entropy) have been extensively used to analyse the diversity of landscape heterogeneity (Vranken et al., 2015). The most widely used one, is Shannon diversity index (aka. Shannon-Wiener index), which is defined as:

$$H = -\sum_{i=1}^{n} p_i * \log_2 p_i \tag{1}$$

where p_i is the proportion of the landscape occupied by the class type i, and n is the total number of classes.

However, as many scholars pointed out, Shannon diversity index only reflects the compositional (i.e., richness and evenness), and it ignores the configurational information of landscape heterogeneity (Cushman, 2016). To address this problem, Claramunt (2005; 2012) highlighted that the fundamental properties that space generates and conveys should be considered when Shannon entropy is applied to spatial analysis. Following this perspective, a recent further derivation is the Spatial Entropy index (H_s) proposed by Wang and Zhao (2018). H_s, as Equation 2 shows, integrates proximity as a key spatial component into the measurement of spatial diversity. Proximity contains two aspects, i.e., total edge length and distance, and by including both aspects gives richer information about spatial pattern than metrics that only consider one aspect.

$$H_s = -\sum_{i=1}^{n} \frac{L_i}{d_i} p_i \log_2 p_i \tag{2}$$

$$L_i = \sum_{\substack{k=1 \\ i \neq k}}^{n} L_{ik} \tag{3}$$

$$d_i = \sum_{\substack{k=1 \\ i \neq k}}^{n} d_{ik} \tag{4}$$

where L_i is the total amount of edges between class i and other different classes (or patch types), and it equals to the sum of lengths of all edge segments involving the corresponding class (McGarigal et al., 2012). d_i denotes the sum of average distances between the different class centers. It should be noted that the distance that is considered in H_s might be any form that fulfils the metric properties of distance (e.g., Manhattan distance, Euclidean distance, contextual distance, cognitive distance). When different class centroids coincide, di can be taken as a relatively small constant (such as 0.5-unit length) in order to avoid the "noise" effect of null values in the calculations.

H_s has been validated as a flexible and objective measure in distinguishing and characterizing landscape patterns (cf. Wang and Zhao, 2018). However, the effects of changing spatial scale on H_s has not been quantified.

2.3 Fractal dimension for measuring scale effect

Fractal dimension offers a general way of investigating the scale effect of landscape metrics. Using the power law identified by Wu (2004), a linear log–log regression model was defined as:

$$\log M = a \times \log R + b \tag{5}$$

where M is the value of the landscape metrics, R denotes the spatial resolution (or grain size) of the land-use map, a is the slope, and b denotes the intercept of the linear log–log regression model.

Slope a is then transformed into a fractal dimension measure, which indicates to what extent a certain landscape metric is sensitive to changes of the spatial scales. This is written as:

$$FD = \begin{cases} -1-a & a \geq 0 \\ 1-a & a < 0 \end{cases} \quad (6)$$

where FD denotes the fractal dimension, and it quantifies the extent a certain landscape metric changes its value due to the change of spatial scales.

Given that the slope a in most linear log–log regression models of landscape ecology is in the range of [−1, 1], the value of FD falls within the range of [−2, 2]. A negative FD ($a > 0$) indicates that the value of the metrics increases as the cell size becomes larger (i.e., coarser scale), whereas a positive FD ($a < 0$) indicates that the value of the metrics decreases as the cell size becomes larger.

The coefficient of determination (COD, or R^2) of the linear log–log regression model, measures the degree the landscape metrics at different spatial scales accord with the log–log regression model. A COD value close to 1 means a robust fractal feature of the metrics, this is to say, this landscape metric exhibits a power law that is highly consist and robust over a range of scales (Wu, 2004).

According to the values of FD and COD, Feng and Liu (2015), in their comprehensive studies, defined four nominal scales to describe different degree of influence of spatial scales on the landscape metric respectively (see Table 1). For example, a “robust” fractal feature indicates the metric exhibits an obvious power law, while “none” means the metric does not exhibit a clear power law effect.

Fractal feature	COD range	Degree of influence	FD range
Robust	[0.7, 1.0]	Strong	[1.3, 2.0] & [-2.0, -1.3]
Moderate	[0.5, 0.7)	Moderate	[1.1, 1.3) & (-1.3, -1.1]
Weak	[0.3, 0.5)	Weak	[1.05, 1.1) & (-1.1, -1.05]
None	[0. 0.3)	None	[1.0, 1.05) & (-1.05, -1.0]

Table 1. Nominal categories of fractal feature and degree of influence of spatial scales on the landscape metric based on COD and FD (based on Feng and Liu, 2015)

3. RESULTS AND DISCUSSION

Taking Yanhe watershed as an example, the CODs and FDs of Shannon diversity index (H) and Spatial Entropy index (H_s) were calculated; the corresponding fractal features and scale influences were assessed (Fig.3; Table 2).

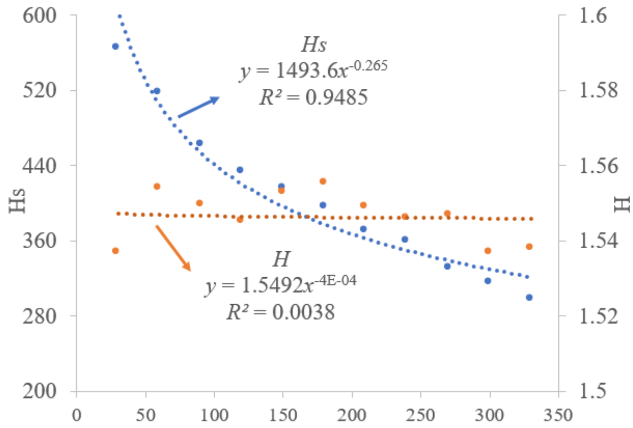

Figure 3. The results of Shannon diversity index and Spatial Entropy index.

Metrics	COD (R^2)		FD	
	Value	Feature	Value	Feature
H	0.0038	None	1.0004	None
H_s	0.9485	Robust	1.256	Moderate

Table 2. The CODs and FDs of Shannon diversity index and Spatial Entropy index

As mentioned above, a COD indicates the fractal feature while a FD indicates the influence of spatial scale on the metric being assessed. It is clear that the Spatial Entropy index (H_s) shows a robust fractal feature, and it decreases as the spatial scale (or grain size) becomes lager in a moderate degree. However, Shannon diversity index (H) exhibits no fractal feature, and it either scale-independent or randomly affected by spatial scale.

Generally speaking, the effects of changing spatial scale on landscape metrics are determined by three aspects, including the nature of the metrics, the experimental data and the landscape structure of the study area (Wu 2004; Feng and Liu, 2015). These factors may provide us a better understanding of the scale effects on H and H_s. First, the very nature (or the characteristic) of the landscape metrics, which plays the most important role in determining the scale effects of the landscape metrics. H quantifies the compositional information (i.e., richness and evenness) of a certain landscape; as grain size becomes larger, some small land patches and the linear features would be disappeared, however, these small patches are relatively low compared with other patches and then they do not substantially change the composition of the land-use pattern. H_s integrates proximity as a key factor, which contains total edge length and distance; as spatial scale becomes coarse, edge length between different classes (or patch types) decreases, and hence H_s has a positive fractal dimension. Second, the experimental data, that is to say the re-sampling method and the range of grain sizes (or the number of sampling points) used in the regression model, would affect the quantify of scale effects. The effects of re-sampling method have been demonstrated by Urban (2005). In this study, we applied Majority re-sampling method to create eleven changing spatial scales, and then constructed the log-log regression model. However, it should be noted that, on one hand, other re-sampling methods need to be further investigated; on the other hand, spatial scales ranging from 30 m to 330 m were used to establish the fractal law, however, this result may be not suitable for all scale ranges. The scale-independent interval in experimental data needs to be further discussed and explored. Future research should also develop multi-scale fractal methods to evaluate scale effects in order to avoid the uncertainty caused by the use of a single fractal dimension and its coefficient of determination (see Li 2000b). Third, the landscape structure of the study area, in some degree, also affect the results. The landscape data of Yanhe watershed only contains six categories with three main components; more complex landscapes should be investigated to assess the scale effects of H_s.

4. CONCLUSION

Quantifying the effects of changing spatial scale on landscape metrics is essential for landscape heterogeneity analysis. Spatial Entropy index (H_s) has been proposed as a flexible and efficient measure to characterize landscape heterogeneity. This study presents a fractal method to quantify the scale effects of H_s, and it rests on the generally accepted power law effect of landscape metrics to spatial scales reported in relevant literature (please refer to Wu, 2004; Forzieri and Catani, 2011). Two qualitative terms were used to summarize the scale effects of the landscape metrics: the fractal feature (i.e. coefficient of determination) which was used to quantify the extent that the landscape metrics accord to the power law, and the fractal dimension which was used to quantify the extent the landscape metrics change in response to change in spatial scales (Li, 2000b).

Application of the fractal method in the Yanhe watershed, China shows that the effects of changing spatial scale on Spatial Entropy index (H_s) accord to power law, and the fractal dimension value indicates H_s decreases as spatial scale becomes larger. The factors that may impact this result have been discussed and clarified. In total, through quantifying spatial scale effects on H_s, we believe it will help us to get a better understanding of H_s, and to facilitate the further application of this entropy-related index.

Our future studies will focus on the following aspects: (a) more complex landscapes should be incorporated to assess the scale effects; (b) different re-sampling methods need to be further investigated; and (c) multi-scale fractal methods should be applied to evaluate scale effects.

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