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Evaluating the effectiveness of landscape metrics in quantifying spatial patterns

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ABSTRACT

The effectiveness of landscape metrics in quantifying spatial patterns is fundamental to metrics assessment. Setting 36 simulated landscapes as sample space and focusing on 23 widely used landscape metrics, their effectiveness in quantifying the complexity of such spatial pattern components as number of patch types, area ratio of patch types and patch aggregation level, were analyzed with the application of the multivariate linear regression analysis method. The results showed that all the metrics were effective in quantifying a certain component of spatial patterns, and proved that what the metrics quantified were not a single component but the complexity of several components of spatial patterns. The study also showed a distinct inconsistency between the performances of landscape metrics in simulated landscapes and the real urban landscape of Shenzhen, China. It was suggested that the inconsistency resulted from the difference of the correlation among spatial pattern components between simulated and real landscapes. After considering the very difference, the changes of all 23 landscape metrics against changing of number of patch types in simulated landscapes were consistent with those in the real landscape. The phenomenon was deduced as the sign effect of spatial pattern components on landscape metrics, which was of great significance to the proper use of landscape metrics.

1. Introduction

Since the foundation of landscape ecology, the correlation between spatial patterns and ecological processes has always been one of the key topics of this discipline (Wu and Hobbs, 2002). To establish this correlation, the first step is to quantify landscape patterns (Hulshoff, 1995), which is a step that has been given substantial attentions by landscape ecologists (Turner, 2005). Generally speaking, there are two approaches to quantify landscape patterns: one is the approach of landscape metrics, mainly applied to categorical data with spatial interruption; and the other is the approach of spatial statistics, in which quantitative data are adapted to spatial continuity (Wu, 2000). In the studies on landscape patterns, the primary data mainly come from such categorization maps as vegetation, soil, and land use/land cover maps. Therefore, the former approach is more applicable than the latter (Fu, 1995). Because of the rapid development of GIS and RS technologies, and the availability of free and upgraded software packages, such as FRAGSTATS and APACK, landscape ecologists can easily obtain metrics for a certain landscape. Along with the tremendous progress in landscape ecology (Fu et al., 2008), landscape metrics have become common tools in landscape pattern monitoring, assessment and planning since the 1990s (Lausch and Herzog, 2002; Li and Wu, 2004; Schindler et al., 2007; Cushman et al., 2008).

However, we still do not fully understand landscape metrics even though their effectiveness has been a subject of studies and disputes since the beginning of the construction of these metrics. In recent decades, more focus has been paid to scale relations (Wu et al., 2000, 2002; Saura and Martinez-Millan, 2001; Lausch and Herzog, 2002; Shen et al., 2004; Wu, 2004; Uuemaa et al., 2005; Saura and Castro, 2007), the accuracy of source data (Shao et al., 2001; Shao and Wu, 2008), and the ecological implications of landscape metrics (Tischendorf, 2001; Lausch and Herzog, 2002; Bastin et al., 2002; Li and Wu, 2004; Li et al., 2005).

In essence, there are three steps in evaluating the effectiveness of landscape metrics: Firstly, it is to evaluate the effectiveness of landscape metrics in describing ecological processes, which is the ultimate objective in effectiveness evaluation; secondly, it is to evaluate the effectiveness of landscape metrics in quantifying spatial patterns with respect to the influences of spatial scales and data accuracy, which are important factors influencing the effectiveness of landscape metrics; and lastly, it is to evaluate the effectiveness of landscape metrics in quantifying spatial patterns, which is the primary step in effectiveness evaluation.

In contrast with flourish studies focusing on the former two steps of effectiveness evaluation, the latter is often overlooked. Only He et al. (2000) compared the performance of four aggregation

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Table 1
Varying parameters in generating simulated landscapes through SIMMAP.

Number of classes	Class abundance distribution			Patch aggregation
	One-class-dominated (d)	Systematically decreased (s)	Equally dominant (e)	
2	0.8, 0.2	0.6, 0.4	0.5 for both two classes	Clumped (c) $p = 0.55$
3	0.7, 0.15 for the other two	0.5, 0.33, 0.17	0.333 for all three classes	Moderately clumped (m) $p = 0.3$
5	0.64, 0.09 for the other four	0.34, 0.264, 0.198, 0.132, 0.066	0.2 for all five classes	Randomly distributed (r) $p = 0$
10	0.64, 0.04 for the other nine	0.19, 0.162, 0.144, 0.126, 0.108, 0.09, 0.072, 0.054, 0.036, 0.018	0.1 for all ten classes	

metrics under varied aggregation level. Frohn and Hao (2006) also discussed the effects of spatial aggregation on landscape metrics. Li et al. (2004) analyzed the responses of landscape metrics on different number of patch types, proportion of one patch type and aggregation level, respectively. Buyantuyev and Wu (2007) reported that the effects of thematic resolution on landscape metrics tend to show consistent general patterns, and Castilla et al. (2009) reported the impact of thematic resolution on the patch-mosaic model of natural landscapes. Bailey et al. (2007a,b) analyzed the influence of thematic resolution on metric selection for biodiversity monitoring, and compared the change of landscape metrics in three scales of thematic resolution. Peng et al. (2007) discussed the effects of changing number of patch types on landscape metrics. That is to say, all the existing studies on the effectiveness of landscape metrics in quantifying spatial patterns are limited to the effects on landscape metrics of changing single component of spatial patterns. While as Li and Wu (2004) stated, it was not one component, but the complexity of several components of spatial patterns that was quantified by landscape metrics. Therefore, there is a dearth of the study on evaluating the effectiveness of landscape metrics in quantifying several components of spatial patterns at the same time.

Landscape patterns originate from spatial heterogeneity, which can be mainly classified into five components (Li and Reynolds, 1994): (1) number of patch types; (2) proportion of each patch type; (3) spatial arrangement of patches, namely patch aggregation level; (4) patch shape; and (5) contrast between neighboring patches. Generally speaking, the former three are more important than the latter two in determining landscape patterns. Therefore, the effectiveness of landscape metrics in quantifying spatial patterns depends on the predictability of landscape metrics against changing these five components, especially the former three. Focusing on 23 widely used landscape metrics and based on simulated landscapes generated by the SIMMAP neutral landscape model, the aims of this study were to evaluate the effectiveness of landscape metrics in quantifying the complexity of such spatial pattern components as number of patch types, proportion of each patch type, and patch aggregation level, and to learn if landscape metrics perform in simulated landscapes as they do in real landscapes as reported by Peng et al. (2007), so as to highlight the factors influencing their effectiveness.

2. Methods

2.1. Simulation of neutral landscapes

Because they can systematically regenerate landscape patterns with the same statistical properties, neutral landscape models are widely used in landscape ecology to generate simulated landscapes (Shen et al., 2004; Li et al., 2008). As a widely used landscape generator, SIMMAP was used to create simulated landscapes. Based on a modified random cluster simulation method, SIMMAP was developed and described in details by Saura and Martinez-Millan (2000). In brief, the following six parameters are essential in simulation through SIMMAP: (1) linear dimension of the pattern (L), controlling spatial extent of simulated landscapes; (2) minimum mapped unit (m), influencing spatial grain of simulated landscapes; (3) neighborhood criterion (N), controlling how patches are built from initially random binary patterns with default 4-neigborhood criterion; (4) number of the classes (n), determining thematic resolution of simulated landscapes; (5) abundance of the classes (%), modifying classes abundances; and (6) Initial probability (p), determining fragmentation degree of obtained patterns.

In this study, landscapes were simulated by varying three simulation parameters, that is, n, %, and p, and the remainders are all constant, where $L = 500$, $m = 1$, and $N = 4$. In details, according to parameter settings in simulating landscapes with SIMMAP by Shen et al. (2004), the number of the classes was set to vary from 2, 3, 5 to 10, class abundance distribution varied from equally dominant (e), one-class-dominated (d), to systematically decreased (s), and three levels of patch aggregation were distinguished as clumped (c), moderately clumped (m), and randomly distributed (r) (Table 1). Therefore, 36 simulated landscapes were generated, and the grain and extent of spatial patterns were constant in the simulation, in order to exclude scaling effects.

2.2. Calculation of landscape metrics

The software package FRAGSTATS 3.3 was used to compute the selected landscape metrics, in which landscape metrics were divided into three levels: patch level, class level and landscape level. In this study, 23 widely used landscape metrics at landscape level were focused: number of patches (NP), patch density (PD), edge density (ED), mean patch size (MPS), patch size standard deviation (PSSD), patch size coefficient of variation (PSCV), landscape shape index (LSI), largest patch index (LPI), mean patch shape index (MSI), area-weighted mean patch shape index (AWMSI), perimeter-area fractal dimension (PAFRAC), mean patch fractal dimension (MPFD), area-weighted mean patch fractal dimension (AWMPFD), contagion index (CONT), aggregation index (AI), landscape division index (DIVISION), Shannon's diversity index (SHDI), Simpson's diversity index (SIDI), modified Simpson's diversity index (MSIDI), Shannon's evenness index (SHEI), Simpson's evenness index (SIEI), modified Simpson's evenness index (MSIEI), and landscape dominance index (DI). These 23 landscape metrics can also be grouped into four categories: area/density/edge (NP, PD, ED, MPS, PSSD, PSCV, LSI, and LPI), shape (MSI, AWMSI, PAFRAC, MPFD, and AWMPFD), contagion/interspersion (CONT, AI, and DIVISION), and diversity (SHDI, SIDI, MSIDI, SHEI, SIEI, MSIEI, and DI). The calculation and associated ecological meanings of these landscape metrics were detailed in the related studies (Fu, 1995; Gustafson, 1998; Fu and Chen, 2000).

2.3. Regression analysis between landscape metrics and spatial pattern components

In contrast with former unitary regression models used in characterizing landscape metrics against changing of spatial pattern components, the multivariate linear regression model was applied to validate the correlation between landscape metrics and several spatial pattern components simultaneously with the software package of SPSS 11.01. In details, 36 simulated landscapes were set as sample space. With the values of landscape metrics serviced as dependent variables, three varying parameters in SIMMAP, i.e. number of the classes, abundance of the classes, and initial probability, were input as independents in the regression analysis.

Among the three parameters, the values of number of the classes (n) and initial probability (p) can be entered into the regression model directly, while as a series of percentages, the parameter of "abundance of the classes" cannot. The proportion of the largest class in the simulated landscape (a_{max}) was used to represent the variable of "abundance of classes" in the regression model. When the number and sum of a set of data are constant, the evenness of numerical values of the array depends on the standard deviation. When the maximum of the array is also determinate, the range of the standard deviation is determined. The numerical change of other data except the maximum can only result in the change of standard deviation in the limited range. Therefore, a_{max} can quantify the core characteristics of the spatial pattern component of abundance of the classes.

As indicated in former study (Peng et al., 2007), many landscape metrics exhibit a logarithmic function relation against changing the number of patch types. Thus, the logarithm of number of the classes ($ln(n)$) was also input as an independent variable in the regression model. And two sets of independent variables (n, p, a_{max}) and ($ln(n)$, p, a_{max}), were entered into the regression model, respectively. The most effective regression equation was selected based on the value of the determination coefficient (R^2), when the regression equation passed the significance test of 0.05. If it failed to pass the significance test, it meant that the metric could not effectively quantify the corresponding components of spatial patterns represented by the independent variables, and what it mainly quantified were the other two of five spatial pattern components excluded from the regression model. The standard partial regression coefficient for each independent variable in the regression function was also calculated, which directly quantified the relative contribution of the corresponding independent variable to the dependent variable with the sign indicating negative or positive correlation. Namely, the standard partial regression coefficient was used to reflect the proportion of information associated with the components of spatial patterns quantified by landscape metrics.

3. Results

All the regression equations of 23 landscape metrics have passed the significance test of 0.05 (Table 2), which mean that all metrics are effective in quantifying spatial patterns. As most regression equations consist of two or three independent variables, it can be concluded that, the information expressed by landscape metrics is usually not on single component, but on the complexity of several components of spatial patterns. According to the number of independent variables in regression equations, 23 landscape metrics fall into three groups: (1) Type I metrics respond directly to only one independent variable, including LPI and DIVISION. Both metrics are highly correlated with the variable of a_{max}, which indicate that they mainly quantify the component of proportion of patch types; (2) Type II metrics involve in regression equations with two independent variables, including NP, PD, ED, MPS, LSI, AWMSI, PAFRAC, MPFD, AI, SHDI, SIDI, MSIDI, SHEI, SIEI, MSIEI, and DI. And among these 16 metrics, five (NP, PD, MPS, PAFRAC, and MPFD) are correlated with variables of $n/ln(n)$ and p, four (ED, LSI, AWMSI, and AI) with variables of p and a_{max}, Seven (SHDI, SIDI, MSIDI, SHEI, SIEI, MSIEI, and DI) with variables of $n/ln(n)$ and a_{max}, which show the emphasis of these metrics in quantifying spatial

Table 2
Regression functions and associated parameters for 23 landscape metrics.

Landscape metrics		Regression equation	R^2	Std. Error of the estimate	Std. partial regression coefficient			p-value		
Category	Metrics				$n/ln(n)$	p	a_{max}	$n/ln(n)$	p	a_{max}
Area/	NP	NP = 14675.7 + 26635.73 $ln(n)$ − 108796p	0.562	26937.023	0.411	−0.627		0.001	0.000	
Density/	PD	PD = 58702.82 + 106542.9 $ln(n)$ − 435185p	0.562	107748.094	0.411	−0.627		0.001	0.000	
Edge	ED	ED = 14965.71 − 19739.6p − 71.123a_{max}	0.866	1928.612		−0.879	−0.305		0.000	0.000
	MPS	MPS = 0.020 − 0.014 $ln(n)$ + 0.047p	0.668	0.010	−0.508	0.64		0.000	0.000	
	PSSD	PSSD = −0.045 − 0.105 $ln(n)$ + 0.474p + 0.006a_{max}	0.688	0.145	−0.105	0.435	0.53	0.037	0.000	0.000
	PSCV	PSCV = −5505.427 + 2792.106 $ln(n)$ − 9378.228p + 155.246a_{max}	0.618	2925.904	0.376	−0.472	0.752	0.007	0.000	0.000
	LSI	LSI = 188.071 − 246.745p − 0.889a_{max}	0.866	24.108		−0.879	−0.305		0.000	0.000
	LPI	LPI = −27.235 + 1.349a_{max}	0.919	8.928						0.000
Shape	MSI	MSI = 1.849 − 0.272 $ln(n)$ + 0.323p − 0.003a_{max}	0.565	0.145	−0.792	0.351	−0.36	0.000	0.005	0.014
	AWMSI	AWMSI = 16.817 − 95.811p + 0.847a_{max}	0.515	28.687		−0.546	0.465		0.000	0.000
	PAFRAC	PAFRAC = 1.787 − 0.036 $ln(n)$ − 0.625p	0.902	0.049	−0.939	−0.143		0.013	0.000	
	MPFD	MPFD = 1.171 − 0.007n + 0.130p	0.418	0.045	−0.385	0.52		0.006	0.000	
	AWMPFD	AWMPFD = 1.456 − 0.096 $ln(n)$ − 0.220p + 0.003a_{max}	0.739	0.080	−0.39	−0.336	0.505	0.001	0.000	0.000
Contagion/	CONT	CONT = −38.034 + 16.274 $ln(n)$ + 54.773p + 0.593a_{max}	0.96	3.557	0.58	0.73	0.76	0.000	0.000	0.000
Interspersion	AI	AI = 25.174 + 99.172p + 0.354a_{max}	0.866	9.693		0.88	0.302		0.000	0.000
	DIVISION	DIVISION = 1.212 − 0.01a_{max}	0.862	0.086						0.000
Diversity	SHDI	SHDI = 0.965 + 0.585 $ln(n)$ − 0.012a_{max}	0.981	0.079	0.642		−0.479	0.000		0.000
	SIDI	SIDI = 0.79 + 0.085 $ln(n)$ − 0.006a_{max}	0.979	0.026	0.299		−0.792	0.000		0.000
	MSIDI	MSIDI = 1.757 + 0.065n − 0.02a_{max}	0.957	0.124	0.324		−0.771	0.000		0.000
	SHEI	SHEI = 1.459 − 0.174 $ln(n)$ − 0.007a_{max}	0.951	0.031	−0.777		−1.158	0.000		0.000
	SIEI	SIEI = 1.464 − 0.159 $ln(n)$ − 0.008a_{max}	0.914	0.046	−0.639		−1.147	0.000		0.000
	MSIEI	MSIEI = 1.76 − 0.29 $ln(n)$ − 0.012a_{max}	0.957	0.048	−0.781		−1.161	0.000		0.000
	DI	DI = −0.965 + 0.415 $ln(n)$ + 0.012a_{max}	0.911	0.079	0.983		1.032	0.000		0.000

pattern components; and (3) Type III metrics behave against changing of all the three independent variables, including PSSD, PSCV, MSI, AWMPFD, and CONT, which mean that these metrics quantify more components of spatial patterns than the others.

For type II and III metrics, the emphasis in quantifying spatial pattern components can be concluded through comparing the absolute values of the standard partial regression coefficients of different independent variables, which is shown as the following: (1) NP, PD, MPS, and MPFD contain a little more information on patch aggregation level than that on number of patch types, while PAFRAC is far more affected by the latter; (2) ED, LSI, and AI focus on patch aggregation level far more than proportion of patch types, with AWMSI a little more; (3) SHDI is affected by number of patch types a little more than by proportion of patch types. On the contrary, SIDI, MSIDI and SIEI focus on the latter far more than the former, with SHEI, MSIEI and DI a little more; and (4) PSSD pays attention to proportion of patch types and patch aggregation level far more than number of patch types, while MSI focuses far more on the latter. PSCV reflects the information on proportion of patch types far more than that on the other two components. And CONT and AWMPFD display no significant focus on these three components of spatial patterns.

4. Discussion

4.1. Inconsistency between changes of landscape metrics against changing of number of patch types in simulated and real landscapes: a paradox

To test the results found in simulated landscapes, a comparison must be performed between the regression equations in simulated landscapes and those in real landscapes. As stated above, few studies focused on evaluating the effectiveness of landscape metrics in quantifying several components of spatial patterns simultaneously, with flourish studies on the impact of thematic resolution on landscape metrics. It was possible to compare the results in this study with former studies dealing with thematic resolution, with a focus on the response of landscape metrics against changing of the number of patch types. The study presented by Peng et al. (2007) was chosen in the comparison, because it was the only one reporting the impact of thematic resolution on all the 23 landscape metrics selected in this study.

According to regression equations, in simulated and real landscapes the response of landscape metrics can both be sorted into 3 types: monotonic decrease, monotonic increase, and irregularity. However, for 15 of these 23 landscape metrics, their behaviors with respect to the change of number of patch types were not consistent in simulated and real landscapes (Table 3). For example, in simulated landscapes three evenness indexes, SHEI, SIEI, and MSIEI, will decrease if the number of patch types is increased, while in real landscapes they behave irregularly. And for metrics of ED, LSI, LPI, AWMSI, AI and DIVISION, the variable of number of patch types is not involved in regression equations in simulated landscapes, in contrast with their monotonic change against the change of the very variable in real landscapes.

4.2. Difference of correlation among spatial pattern components between simulated and real landscapes

The reason for the paradox is the difference in correlation among spatial pattern components between simulated and real landscapes. As we know, there is an implicit assumption of inter-

Table 3
Consistency between the changes of landscape metrics against changing of number of patch types in simulated and real landscapes.

Landscape metrics	The changes of landscape metrics against increasing of number of patch types[a]			The consistency between the very changes of landscape metrics[b]		The sign of independent variables in regression equation[c]		
	In real landscapes	In simulated landscapes 1[d]	In simulated landscapes 2[e]	In real landscapes and simulated landscapes 1	In real landscapes and simulated landscapes 2	$n/ln(n)$	p	a_{max}
NP	↗	↗	↗	✔	✔	+	–	/
PD	↗	↗	↗	✔	✔	+	–	/
ED	↗	\	↗	×	✔	/	–	–
MPS	↘	↘	↘	✔	✔	–	+	/
PSSD	↘	↘	↘	✔	✔	–	+	+
PSCV	~	↗	~	×	✔	+	–	+
LSI	↗	\	↗	×	✔	/	–	–
LPI	↘	\	↘	×	✔	/	/	+
MSI	↗	↘	~	×	×	–	+	–
AWMSI	↘	\	~	×	×	/	–	+
PAFRAC	↗	↘	~	×	×	–	–	/
MPFD	↗	↘	↘	×	×	–	+	/
AWMPFD	↘	↘	~	✔	×	–	–	+
CONT	~	↗	~	×	✔	+	+	+
AI	↘	\	↘	×	✔	/	+	+
DIVISION	↗	\	↗	×	✔	/	/	–
SHDI	↗	↗	↗	✔	✔	+	/	–
SIDI	↗	↗	↗	✔	✔	+	/	–
MSIDI	↗	↗	↗	✔	✔	+	/	–
SHEI	~	↘	~	×	✔	–	/	–
SIEI	~	↘	~	×	✔	–	/	–
MSIEI	~	↘	~	×	✔	–	/	–
DI	~	↗	~	×	✔	+	/	+

[a] "↗", "↘", "\", and "~" means monotonic increase, monotonic decrease, irrelevance and irregularity, respectively, against increasing of number of patch types.
[b] "✔" and "×" means consistency and inconsistency, respectively, between the changes of landscape metrics against increasing of number of patch types in real and simulated landscapes.
[c] "+", "–", and "/" means positive correlation, negative correlation, and irrelevance, respectively, between landscape metrics and independent variables in multivariable linear regression equations.
[d] The changes of landscape metrics against increasing of number of patch types are judged only by the sign of the independent variable $n/ln(n)$ in multivariable linear regression equations.
[e] The changes of landscape metrics against increasing of number of patch types are judged by the sign of all the three independent variables in multivariable linear regression equations and the correlations between these variables and number of patch types.

independence among spatial pattern components in simulating landscapes through neutral landscape models. Generally speaking, this assumption is followed when contrasting two landscapes without correlation. However, in case studies of landscape ecology, it is unlikely to contrast irrelevant landscape patterns. The contrasts between landscapes with the same characteristics, or the same landscape in temporal series, are often performed. Among these landscapes, the components of spatial patterns are usually not independent but correlated with each other.

For example, in a real landscape, an increase in the number of patch types often results from division of former patch types into new ones, especially from division of patch types with a large proportion, as it is unlikely and worthless to divide patch types with a low proportion in common studies on landscape patterns. Because the total area of landscape is constant, the appearance of new types usually leads to proportion decrease of the former types, which certainly includes the decrease of proportion of the largest patch type. On the contrary, the decrease in the number of patch types is mainly due to amalgamation of patch types, which results in high proportion of newly generated patch types. Therefore, there is a negative correlation between number of patch types and proportion of the largest patch type.

Similarly, there is a negative correlation between number of patch types and patch aggregation level. When the number of patch types increases, number of patches will increase through the division of one patch into two or more patches. As patches of other types are usually unchanged, patch aggregation level in the whole landscape decreases as a result. When the number of patch types decreases, number of patches will decrease through a merging of patches. That is to say, several dispersed patches are merged into one patch. Considering the invariability of patches of other types, it can be suggested that patch aggregation level will increase.

4.3. Interpretation of changes of landscape metrics against changing of number of patch types in real landscapes through the results in simulated landscapes

As there is a significant difference of correlation among spatial pattern components between simulated and real landscapes, it is not reasonable to compare the results in real and simulated landscapes directly, and it is necessary to consider the correlation. That is to say, when the multivariable linear regression equations acquired in simulated landscapes are used to interpret the changes of landscape metrics against changing of number of patch types in real landscapes, it is determined not only by the regression parameter of the variable of number of patch types in the regression equation, but also by the regression parameters of the other two variables, proportion of the largest class and patch aggregation level, and by the correlation between the two variables and number of patch types.

Taking SHEI for example, the evenness index behaves irregularly in real landscapes, but should decrease in correspondence with an increase of the number of patch types according to regression parameter of the variable $ln(n)$ in the regression equation in simulated landscapes. However, according to the regression equation for SHEI (Table 2), the value of the metric is also determined by the variable of a_{max}, which is negatively correlated with number of patch types and has a negative regression parameter. Thus, the value of SHEI in the regression equation is composed of two parts, one decreasing against the increasing of number of patch types, and another increasing, which certainly results in the fluctuation of the value of SHEI.

Taking PSSD as another example, this index decreases against the increasing of number of patch types in real landscapes and shows the same behavior in simulated landscapes, as judged by the regression parameter of the variable of $ln(n)$ in the regression equation. According to the regression equation for PSSD (Table 2), there are three independent variables determining the value of the metric, $ln(n)$, p and a_{max}. However, two variables p and a_{max} have positive regression parameters in the regression equation, and correlate negatively with number of patch types, and the variable $ln(n)$ is positively correlated with number of patch types with a negative regression parameter. Thus, all these three changeable parts of PSSD in the regression equation will decrease if the number of patch types increases, which is consistent with the behavior of the metric in real landscapes.

After considering the correlations between variables of $ln(n)/n$, p and a_{max} and number of patch types, there are 18 of 23 landscape metrics showing consistency between the changes against changing number of patch types in simulated and real landscapes (Table 3). Furthermore, it is noticeable that the other 5 metrics of MSI, AWMSI, PAFRAC, MPFD, and AWMPFD all belong to the category of shape in the categorization of landscape metrics. It is not accidental, but due to the components of spatial patterns quantified by these metrics. Because of the categorization of these metrics, patch shape is their most focused component of spatial patterns. However, the component of patch shape is not set as a parameter in generating simulated landscapes through SIMMAP, and thus is not used as an independent variable in regression analysis. There is no doubt that the regression equation in simulated landscapes cannot interpret the behavior of these metrics in real landscapes.

4.4. Sign effect of spatial pattern components on landscape metrics: a deduction

It can be deduced that in a temporal series of spatial patterns of the same real landscape, the change of one spatial pattern component often results in varying of the other four spatial pattern components. That is to say, these five components of spatial patterns are correlated with each other in real landscapes. As it is not a single component but several components of spatial patterns that together determine the values of landscape metrics, when evaluating the monotonicity of the change of landscape metrics against changing of a certain component of spatial patterns, it is necessary to consider not only the correlation between landscape metrics and the very component, but also the correlations between landscape metrics and other components, and the correlations between the very component and other components as well, which is defined as sign effect of spatial pattern components on landscape metrics.

Generally speaking, if one of these landscape metrics may quantify five components of spatial patterns, the value of the metric can be acquired through the following equation:

$$\mathrm{LM} = a_0 + a_1 f_1(pc_1) + a_2 f_2(pc_2) + a_3 f_3(pc_3) + a_4 f_4(pc_4) + a_5 f_5(pc_5) \quad (1)$$

where LM is the value of the target landscape metric, a_i (i = 0–5) is constant, pc_i (i = 1–5) is independent variable characterizing the five components of spatial patterns, and f_i (i = 1–5) is the function of corresponding independent variable.

The correlations between the target component of spatial patterns and the five independent variables can be defined as C_i, which is a three-value function. Namely, when there is a negative correlation, the value of C_i is -1, while +1 and 0 are for positive correlation and non-correlation, respectively. A two-value function, F_i is also defined to quantify the correlation between pc_i and $f_i(pc_i)$, while +1 and -1 are for positive correlation and negative correlation, respectively. Because there are correlations between the five components of spatial patterns, these five independent variables are correlated with each other. All five changing parts in the equation, $a_i f_i(pc_i)$ (i = 1, 2, 3, 4, 5) must be considered to discuss the monotonicity of the change of landscape metrics against changing of the target component of spatial patterns. Supposing what pc_1 quantifies is the target component of spatial patterns, as a changing part of the value of target landscape metric, $S(pc_i)$, the change of $a_i f_i(pc_i)$ against changing of pc_1 can be judged through the following equation:

$$S(pc_i) = Sign(a_i) \times F_i \times C_i \tag{2}$$

where $Sign(a_i)$ is a sign function, a three-value function. When a_i is positive, it returns the value of +1, while -1 and 0 are for negative and zero, respectively.

It can be concluded that $S(pc_i)$ is also a three-value function. A value of +1 means that there is a monotonic increase of the value of $a_i f_i(pc_i)$ against increasing of pc_1, while -1 and 0 are for a monotonic decrease and irrelevance, respectively. Therefore, the monotonicity of the change of landscape metrics against changing of the target component of spatial patterns depends on the consistency among $S(pc_i)$.

5. Conclusions

Using a widely used neutral landscape model SIMMAP, the effectiveness of landscape metrics in quantifying the three spatial pattern components, i.e. number of patch types, proportion of each patch type, and patch aggregation level, was evaluated with the application of multivariate linear regression modeling. The results confirmed the previous conclusions that it was not one component, but the complexity of several components of spatial patterns that was quantified by most landscape metrics. Furthermore, a comparison was conducted between the results reported in this study and by Peng et al. (2007), focusing on the response of landscape metrics against changing of the number of patch types. The specious inconsistency in the comparison and associated factors were discussed, and the changes of landscape metrics in two studies were proved to be consistent.

As stated above, few studies before had focused on the effectiveness of landscape metrics in quantifying spatial patterns, and this study highlighted the necessity to analyze the very topic, with the deduced sign effect of spatial pattern components on landscape metrics. Recognizing the correlations among spatial pattern components, the deduced sign effect was important to the development, use and evaluation of landscape metrics. In other words, when dealing with the effectiveness of landscape metrics in quantifying spatial patterns, it was necessary to consider both correlations between landscape metrics and spatial pattern components, as well as correlations between the target component and other components.

However, to confirm the universality of the results, further case studies and theoretical analysis should be directed. Firstly, as only three of the five spatial pattern components were considered in this study, the other two components, i.e. patch shape and contrast between neighboring patches, should be introduced in regression analysis. Accordingly, because SIMMAP cannot generate simulated landscapes with special patterns of these two components, associated new approaches to simulating landscapes are also necessary. Secondly, it will significantly help to understand, apply and develop landscape metrics, to make a synthetic analysis on the effectiveness of landscape metrics in quantifying spatial patterns and associated ecological meanings, with consideration of the effects of scale relations and source data accuracy on landscape metrics. As stated above, synthetic analysis will comprise all these three steps in evaluating the effectiveness of landscape metrics. Thirdly, as only metrics at landscape level were introduced in this study, the behaviors of landscape metrics at patch level and class level should also be considered, and the comparison of the behaviors of landscape metrics at different level would be of great importance.

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