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RESEARCH ARTICLE

The transiogram as a graphic metric for characterizing the spatial patterns of landscapes

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Abstract
Context Landscape metrics play an important role in measurement, analysis, and interpretation of spatial patterns of landscapes. There are a variety of different landscape metrics widely used in landscape ecology. However, existing landscape metrics are mostly non-graphic and single-value indices, which may not be sufficient to describe the complex spatial correlation and interclass relationships of various landscapes. As a transition probability diagram over the lag distance, the transiogram, which emerged in recent years, essentially provides a new graphic metric for measuring and visualizing the auto and cross correlations of landscape categories.
Objectives To explore the capability of the transiogram for measuring spatial patterns of categorical landscape maps and compare it with existing landscape metrics.
Methods Sixteen commonly-used landscape metrics and transiograms (including auto- and cross-transiograms) were estimated and compared for land cover/use classes in four areas with different landscapes.
Results Results show that (1) these transiograms can provide visual information about the proportions, aggregation levels, interclass adjacencies, and intra-class/interclass correlation ranges of landscape classes; (2) sills and auto-correlation ranges of transiograms are correlated with the values of some landscape metrics; and (3) the peak height ratios of idealized transiograms can effectively represent the juxtaposition strength of neighboring class pairs.
Conclusions The transiogram can be an effective graphic metric for characterizing the auto-correlation of single classes (through auto-transiograms) and the complex interclass relationships, such as interdependency and juxtaposition, between different landscape classes (through cross-transiograms).

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Introduction

Landscape metrics are important for measuring, analyzing, and interpreting spatial patterns of landscapes. During last several decades, a number of landscape metrics were developed to describe and quantify the composition and arrangement of landscape categories (i.e., classes). They have been widely used in many aspects, such as biodiversity and habitat analysis, land use/land cover change evaluation, and landscape regulation. The most extensively studied topics related with landscape metrics are the relationships between various metrics and species richness and their habitat preferences. For instance, Bailey et al. (2007) found that landscape pattern is important for bee species, and thus it can be used to predict the diversity potential of bees. The evaluation of the landscape changes, especially urban growth and fragmentation, is also a main part of the exploitation of landscape metrics. Liu et al. (2017) suggested that landscape metrics can provide a new method to understand the patterns and related processes of urbanization in three dimensions. Moreover, the analysis of landscape regulation is a new and promising area in the use of landscape metrics (Li and Mander 2009). For example, landscape metrics were used in evaluating the influence of landscape factors on water quality (Shen et al. 2015) and the fire resilience of forests (Lee et al. 2009). Landscape metrics address the spatial composition and configuration of landscapes and are important tools for understanding, assessing, and monitoring changes in landscape pattern, which affect underlying ecological processes.

Landscape metrics are widely used due to easy calculation with easily obtained land cover data, from maps and remotely sensed images, and ready-to-use software such as FRAGSTATS, which needs a few or no parameterizations. There are several software packages available for calculating a variety of landscape metrics, such as FRAGSTATS (McGarigal et al. 2002), Patch Analyst in ArcGIS (Rempel et al. 2008), and Pattern in IDRISI (Eastman 2012). For example, FRAGSTATS provided around 43 landscape metrics at class level. However, these landscape metrics are all non-graphic and single-value indices, which may not be sufficient to describe the complex spatial patterns of various landscapes. In fact, as Li et al. (2005) stated, no index can fully describe the spatial pattern of a landscape. There are some limitations with the widely-used landscape metrics, which include some well-known limitations and the less-recognized correlation limitations. These well-known limitations are the sensitivity to data resolution (Wickham and Rhtters 1995), the sensitivity to study area extent (Turner et al. 1989), and the huge influence of data inaccuracy on the values of landscape metrics (Shao and Wu 2008). The correlation limitations are the disconnections between landscape metrics and ecological patterns or processes. For example, the relationships between some metrics and ecological processes may be confounded, due to the interactions among ecological processes and other attributes of the landscape (Hargis et al. 1999), and also due to the difficulties of quantifying the unique effects of habitat configuration on biotic responses caused by the correlation of configuration metrics and habitat abundance (Wang and Cumming 2011). Most of these limitations can be addressed, mitigated, or put in perspective, through careful data manipulation, result analysis and interpretation, and combination with other methods.

However, the interpretation of landscape metrics still remains difficult (Li and Wu 2004). Since landscape metrics have been linked to ecological patterns or processes, a primary concern is how easily they can be interpreted by a range of non-scientists, including politicians, land managers and, in some cases, the public, who are responsible for conservation planning and land management (Kupfer 2012). The evolution from solely indicator-based measures to methods that incorporate visualization techniques is an approach to make landscape analyses more interpretable (Kupfer 2012). Besides the requirement of improving interpretability, the need of measuring the new aspects of landscape pattern is also an urgent task. Some efforts have been made, for instance, the Morphological Spatial Pattern Analysis (MSPA) can describe the geometry and connectivity of image components and further classify and map individual pixels into core, patch, connector, perforation, and edge categories (Vogt et al. 2007, 2009; Soille and Vogt 2009). MSPA is available in the free software GuidosToolbox, which also contains some other spatial pattern analysis tools (Vogt and Riitters 2017). Sofia et al. (2014) proposed a new metric—the Slope Local Length of Auto-Correlation (SLLAC), which comes from the local analysis of slope self-similarity, for specifically measuring spatial heterogeneity of terraced landscapes. However, there is still a need for effective landscape metrics in measuring and interpreting landscape patterns in some aspects, particularly with visualization and convenience.

The transiogram concept was first introduced by Li (2007a) based on pioneer studies in geosciences (Schwarzacher 1969; Carle and Fogg 1996; Luo 1996; Carle and Fogg 1997; Ritzi 2000) and the variogram concept, mainly for providing transition probability parameters to the Markov chain geostatistical approach (Li 2007b; Li et al. 2015b; Yu et al. 2019). Theoretically, it is defined as a transition probability-lag function, but visually it is a transition probability diagram over the lag distance. The transiogram was first developed as a graphic correlation measure for categorical data to replace the transition probability matrix (TPM) of conventional Markov chain theory due to its capability of incorporating the complex spatial heterogeneity of categorical spatial variables into landscape simulation. However, it also can work as an independent metric to measure the spatial variability of categorical spatial variables, such as soil types and land cover classes. Li (2007a) analyzed the shape features of transiograms estimated from sample data of soil types and showed that the transiogram is an effective method for characterizing the intra-class auto-correlations of individual classes (through auto-transiograms) and the complex inter-class relationships, such as interdependency, juxtaposition and directional asymmetry, between different classes (through cross-transiograms). Our study indicates that the transiogram may work as a graphic and composite metric to measure the spatial patterns of landscape categorical maps. Compared with the traditional landscape metrics, transiograms represent the spatial patterns of landscape categories through graphic diagrams, which achieved the visualization of information. Nevertheless, the transiogram may also have some limitations on representing the spatial variability of landscapes, which need to be complemented.

In this paper, we use actual land cover data to explore the capability of the transiogram as a landscape metric through comparing it with other popularly-used landscape metrics. We firstly calculated the transiograms (both auto-transiograms and cross-transiograms) and sixteen commonly-used landscape metrics from the datasets of four corresponding study areas, and then we interpreted the results of transiograms and compared them with the values of those commonly-used landscape metrics. Through the comparison, we aim to explore the following questions: (1) What are the characteristics of the landscape transiograms and their relationships with traditional landscape metrics? (2) Do transiograms provide unique information compared with other landscape metrics? (3) What are the limitations of transiograms as a landscape metric? And finally, 4) can the transiogram work as an effective metric for measuring landscape characteristics?

Materials and methods

Data

We used actual land cover data to calculate the landscape metrics and transiograms. In order to test the general performance of transiograms, we randomly selected several pieces of a post-processed Connecticut land use/cover map for 2010. Six land use/cover types were considered for landscapes: developed land, crop/grass land, forest land, waterbody, wetland, and barren land. Four small land use/cover maps (clipped pieces) that contain all the considered patch types were finally used for this study (Fig. 1). These maps have a 30 m × 30 m pixel resolution and totally 240 × 200 pixels. The small example areas were used for linking the computed results, both transiograms and landscape metrics, with the visual interpretation of example images by human eyes, such as the class proportions and aggregation levels of different classes. Large images are too complex to interpret by human eyes. In addition, because the transiograms are estimated globally, using large images that contain different local patterns (i.e., different patterns in different subareas) may conceal the local features of landscape patterns that can be reflected on transiograms and visually interpreted. The main patch types (i.e., land use/cover classes) are forest land and developed land, due to the characteristics of the Connecticut land cover/use situation—Connecticut is the fourth most densely populated state in United States and around 50% of its surface is covered by forest. The minor class, barren land, was ignored in the analysis due to its low proportion (less than 3% for all four maps) and the unreliability of related metric values caused by data insufficiency (see Supplement IV for more information).

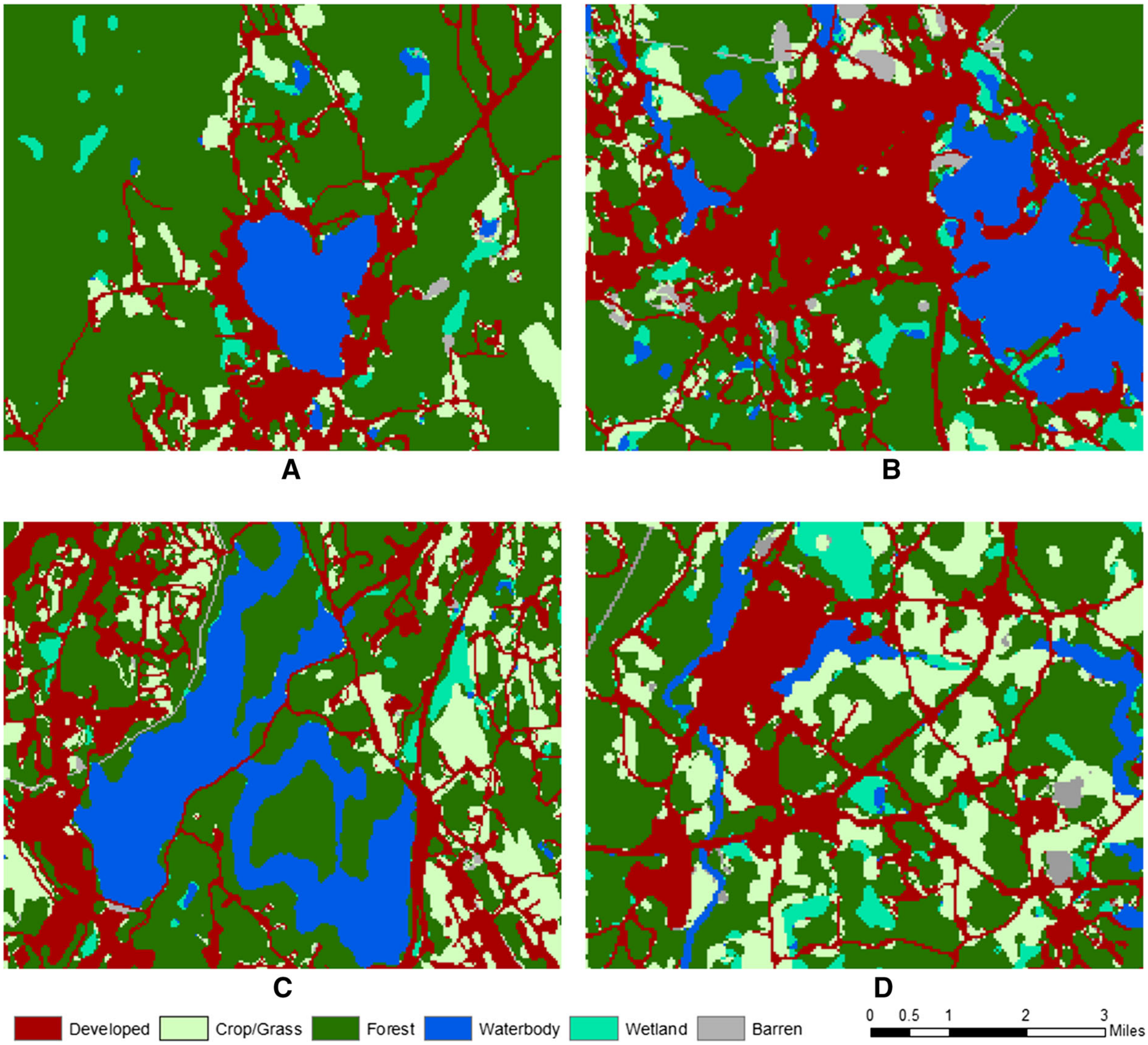


Fig. 1 The land use/cover maps of the selected study areas

Methods

Transiograms

A transiogram is a diagram formed by the values of the transition probabilities of one categorical field from one state (i.e., landscape class here) to itself or another state with increasing lag values from zero to a further distance. Theoretically, it is expressed as a transition probability-lag function:

$$p_{ij}(\mathbf{h}) = \Pr[z(\boldsymbol{x} + \mathbf{h}) = j | z(\boldsymbol{x}) = i]$$

where $p_{ij}(\mathbf{h})$ is the transition probability function of the categorical random variable Z from state i at location $\boldsymbol{x}$ to state j at location $\boldsymbol{x} + \mathbf{h}$ over the lag distance $\mathbf{h}$ (Li 2007a). Its value ranges from 0 to 1. The lag $\mathbf{h}$ can be a distance with an exact unit (e.g., feet or meters) or the number of spatial steps (i.e., the number of pixels or grid cells), which can be directional. Under the second-order spatial stationary assumption, the function is only dependent on the lag **h,** rather than on any specific location $\boldsymbol{x}$; therefore, transiograms can be estimated from sample data pairs in a space. $p_{ii}(\mathbf{h})$ denotes an auto-transiogram, representing the self-dependence of class i, and $p_{ij}(\mathbf{h})(i \neq j)$ denotes a cross-transiogram, describing the cross-dependence of class j on class i, with i defined as tail class and j defined as head class. Cross transition probabilities are asymmetric, which means $p_{ij} \neq p_{ji}$ for $i \neq j$; but if transiograms are estimated omni-directionally or bi-directionally, we have $p_{ij} \times p_i = p_{ij} \times p_j$. Transiograms have the following basic properties: (1) they are non-negative; (2) at any specific lag, values of transiograms with the same tail class sum to 1; (3) for mutually exclusive classes, transiograms should not have nuggets, that is, we have $p_{ii}(0) = 1$ for auto-transiograms and $p_{ij}(0) = 0$ or cross-transiograms of exclusive classes.

Normally, transiograms have two main parameters: sill and correlation range. Usually, a transiogram gradually approaches a stable value with increasing lag distance. The stable or approximately stable value is called *sill*. This means that auto-transiograms start from the origin point (0, 1.0) with a transition probability value of 1.0 and gradually decrease to their sills, while cross-transiograms start from the origin point (0, 0) and gradually increase to their sills. Sometimes, a cross-transiogram may have a peak or a series of peaks and troughs before gradually reaching their sills, which reflects the neighboring or alternate occurrence characteristics of the two involved classes. Theoretically, the value of the sill of a transiogram is equal to the proportion of the corresponding head class in the data used for estimating the transiogram (or in the study area if the data are representative of the study area). However, for a small research area, there may be some deviation between transiogram sills and corresponding class proportions due to the boundary effect and the fact that some transiograms may end before reaching their sills at longer lag distances (Li 2007a). Because boundary cells have fewer transitions relative to internal cells, the boundary effect means a class may have statistically biased smaller transition probabilities if it has a higher proportion to occur at boundaries of a research area. This effect is not apparent for relatively large research areas. The lag distance where the sill is stably approached is called *correlation range*. For auto-transiograms, it is the distance of self-dependence of the corresponding class, and for cross-transiograms, it is the distance of the interdependence of the two classes.

The transiograms directly estimated from real data are called real-data transiograms, including exhaustive transiograms and experimental transiograms, which reflect the spatial variation characteristics of the real data. Exhaustive transiograms are a special case of experimental transiograms, referring to those transiograms directly estimated from maps or images where data are exhaustive. Experimental transiograms refer to those directly estimated from sparsely sampled data. Free software, TGRAM, for experimental transiogram estimation and modelling was described in Yu et al. (2019). More interestingly, transiograms also can be directly calculated from a one-step TPM estimated from real data or expert knowledge (when no real data is available) (Schwarzacher 1969; Luo 1996; Li 2007a). Because this kind of transiograms are based on the first-order stationary Markovian assumption and have very smooth curves, they are called idealized transiograms (Li 2007a; Li et al. 2012). Idealized transiograms can capture the basic correlation characteristics of classes, and if available, their properties are significant in interpreting and modeling experimental transiograms. Therefore, even though they are not an exact reflection of real data or phenomena and are oversimple to some extent, understanding idealized transiograms is still necessary. In this paper, both idealized transiograms and experimental transiograms for the selected study areas are calculated.

The estimator for real data transiograms is given as

$$\hat{p}_{ik}(\mathbf{h}) = \frac{F_{ik}(\mathbf{h})}{\sum_{j=1}^{n} F_{ij}(\mathbf{h})},$$

where $F_{ik}(\mathbf{h})$ represents the frequency of transitions from class i to class k among data pairs with the spatial lag $\mathbf{h}$, and n is the total number of classes in a categorical spatial data set. When estimating the transition frequencies from sample data for experimental transiograms, the lag $\mathbf{h}$ considered is actually a lag interval [$\mathbf{h}$-$\Delta\mathbf{h}$/2, $\mathbf{h}$ + $\Delta\mathbf{h}$/2] around $\mathbf{h}$, due to the sparseness of sample data pairs (Li 2007a). Here the $\Delta\mathbf{h}$ is called lag tolerance width. That is, all data pairs within the lag interval are counted as the data pairs at lag $\mathbf{h}$. However, such a lag tolerance width also can be used to exhaustive transiogram estimation from exhaustive data to smooth the estimated transiogram curves.

For estimating experimental transiograms from sample data sets of landscape classes, one needs to first convert the sample data file into a required format

Table 1 The acronyms and names of the selected 16 class-level metrics

Group	Acronym	Name
Area and edge metrics	PLAND	Proportion of landscape
	LPI	Largest patch index
	ED	Edge density
	AREA_AM	Area-weighted mean patch area
Shape metrics	SHAPE_AM	Area-weighted mean shape index
	FRAC_AM	Area-weighted mean fractal dimension
Contrast metrics	CWED	Contrast weighted edge density
	TECI	Total edge contrast index
Aggregation metrics	CLUMPY	Clumpiness index
	PLADJ	Proportion of like adjacencies
	IJI	Interspersion/juxtaposition index
	COHESION	Patch cohesion
	AI	Aggregation index
	nLSI	Normalized landscape shape index
Subdivision metrics	PD	Patch density
	SPLIT	Splitting index

accepted by the software (e.g., Shapefile format is used in the TGRAM software). Inexperienced users may need several trials to find a suitable tolerance width so that the estimated experimental transiograms are relatively stable in their shape features. Another parameter is the maximum lag, which may be set to be equal to or smaller than the diagonal length of the study area if the study area is small. This parameter is not a concern when the sample data set is not very large. But when the sample data set is large, a very large maximum lag may increase the computation time a lot, while it is unnecessary to obtain experimental transiograms with long lags much longer than correlation ranges. Under this situation, one may set the maximum lag to the desired distance or the distance of the perceived longest correlation range. It should be noted that when the study area is too small or the sample data is too sparse, experimental transiograms may quickly go down or be out of order after or even before reaching their correlation ranges due to the lack of data pairs at longer lags. Experimental transiograms of extremely minor classes often tend to strongly fluctuate due to the lack of data pairs at many lags.

Landscape Metrics

Landscape metrics can be grouped into patch, class, and landscape levels. Some metrics are inherently redundant if they are representing the same information. More information about the interdependency of landscape metrics can be seen in Riitters et al. (1995). Users can choose among them based on the preference and different applications. We considered the commonly-used metrics in class-level after eliminating those that were inherently redundant (McGarigal 2002). In this paper, we calculated sixteen conventional class-level metrics for each landscape using the computer program FRAGSTATS 3.2 (McGarigal et al. 2002) (Table 1). The calculated results are all provided in Supplement I. These sixteen class-level metrics can be loosely grouped into five groups: area and edge metrics, shape metrics, contrast metrics, aggregation metrics, and subdivision metrics, according to the aspects of landscape patterns that they describe. In brief, area and edge metrics are the metrics that measure the size of patches and the amount of edge created by these patches. Shape metrics describe the geometric complexity and/or compactness of patch shapes. Contrast metrics deal with the magnitude of difference along patch edges between adjacent patch types. Aggregation metrics represent the aggregation level of patch types. Subdivision metrics are closely allied to the aggregation metrics and refer to the degree of subdivision of the classes.

Transiogram Estimation

Idealized transiograms in this paper were calculated from one-step TPMs estimated from exhausted data of the four land cover maps. For example, the one-step TPM $\boldsymbol{P}(1)$ of study area A is:

$$P(1) = \begin{bmatrix} p_{11}(0.883) & p_{12}(0.032) & p_{13}(0.075) & p_{14}(0.005) & p_{15}(0.003) & p_{16}(0.002) \\ p_{21}(0.067) & p_{22}(0.845) & p_{23}(0.080) & p_{24}(0.003) & p_{25}(0.003) & p_{26}(0.004) \\ p_{31}(0.013) & p_{32}(0.006) & p_{33}(0.976) & p_{34}(0.001) & p_{35}(0.003) & p_{36}(0.001) \\ p_{41}(0.013) & p_{42}(0.003) & p_{43}(0.009) & p_{44}(0.973) & p_{45}(0.003) & p_{46}(0.001) \\ p_{51}(0.015) & p_{52}(0.007) & p_{53}(0.096) & p_{54}(0.007) & p_{55}(0.871) & p_{56}(0.003) \\ p_{61}(0.065) & p_{62}(0.067) & p_{63}(0.087) & p_{64}(0.017) & p_{65}(0.018) & p_{66}(0.745) \end{bmatrix}$$

where each entry of $\boldsymbol{P}(1)$ represents a transition probability of one class (for self-transition) or a pair of class (for cross-transition) over one fixed spatial step (one pixel length, that is, 30 m at here) in study area A. Under the first-order stationary Markovian assumption, the n-step TPM $\boldsymbol{P}(n)$ can be calculated from the one-step TPM $\boldsymbol{P}(n)$ through self-multiplication, that is, we have

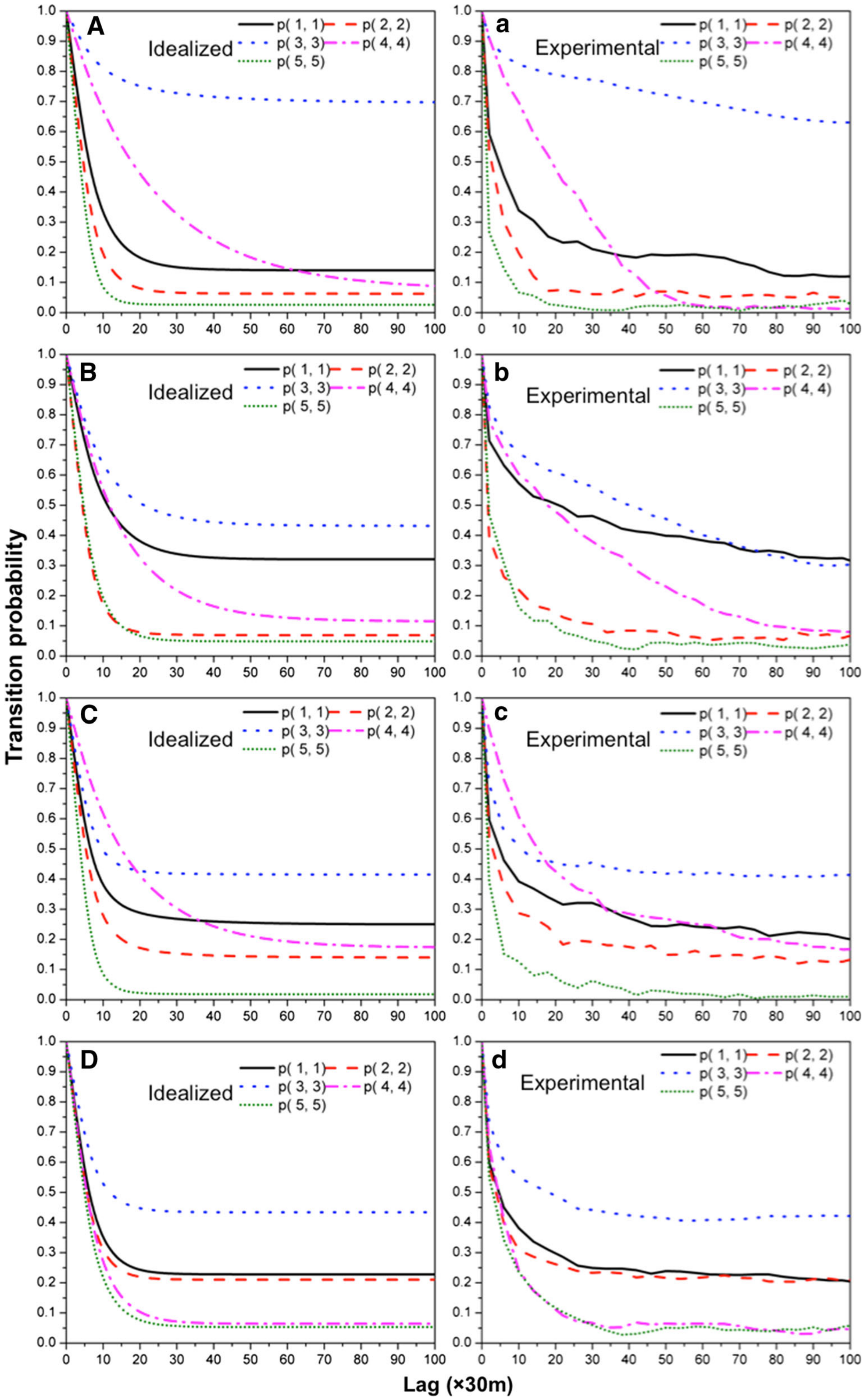
$$\boldsymbol{P}(n) = \boldsymbol{P}(1) \times [\boldsymbol{P}(1)]^{n-1} = [\boldsymbol{P}(1)]^{n}$$

As n increases, the calculated multi-step transition probabilities form a series of continuous diagrams (Schwarzacher 1969; Luo 1996; Li 2007a), which are the idealized transiograms of study area A.

Experimental transiograms in this paper are omnidirectional and calculated based on randomly selected sample data (2000 sample pixels, about 4% of the total pixels) from each of the four land cover maps. A tolerance width of 4 pixel lengths is used to make the transiograms stable in their shapes. The class proportions of each area and samples for the four study areas are provided in Table 2. Experimental transiograms are usually more feasible than exhaustive transiograms. First, although sample data account for only a small portion of the whole study area, they still represent the major spatial variability information and the approximate class proportions if not extremely sparse, while leaving sufficient space for possible class boundary uncertainty (i.e., avoiding taking crispy patch boundaries into account in transiogram estimation). Second, the land cover data may not be highly accurate and, in some cases, the exhaustive data is not available. Hence, experimental transiograms are more flexible and even may reduce the effect of noise. Third, for a relatively large study area with a large number of pixels, calculating experimental transiograms from sample data can save the computation time (for more information about computation time, see Supplement V), while exhaustive transiograms are actually similar to experimental transiograms as long as the sample data set is representative. All experimental transiograms estimated from the sample data sets of the

Table 2 Land cover/use class proportions in the four study areas (240 × 200 pixels for each map) and corresponding sample data sets (2000 pixels for each sample data set)

	Data	Class proportions (%)					
		Developed	Crop/grass	Forest	Waterbody	Wetland	Barren
A	Whole area	12.92	6.04	72.72	5.86	2.12	0.34
	Samples	13.16	6.23	72.55	5.52	2.24	0.30
B	Whole area	31.86	6.90	41.24	13.77	4.09	2.14
	Samples	31.67	6.64	42.12	12.96	4.34	2.27
C	Whole area	25.45	12.87	42.17	17.20	1.69	0.62
	Samples	25.90	13.97	41.18	17.11	1.44	0.40
D	Whole area	21.01	20.77	45.57	5.35	6.06	1.24
	Samples	21.18	20.54	45.23	5.81	5.93	1.31


A
Idealized
p(1, 1)
p(2, 2)
p(3, 3)
p(4, 4)
p(5, 5)
a
Experimental
p(1, 1)
p(2, 2)
p(3, 3)
p(4, 4)
p(5, 5)
B
Idealized
b
Experimental
C
Idealized
c
Experimental
D
Idealized
d
Experimental
Transition probability
Lag (×30m)

◀**Fig. 2** Idealized auto-transiograms (left column) and experimental auto-transiograms (right column) (1—developed land, 2—crop/grass land, 3—forest, 4—waterbody, 5—wetland). **A** and **a**—for Area A. **B** and **b**—for Area B. **C** and **c**—for Area C. **D** and **d**—for Area D. Note that p(i, j) denotes $p_{ij}(\mathbf{h})$ in legends for simplicity

four land cover maps are provided in Supplement II. In addition, although not examined here, all exhaustive transiograms of the four land cover maps are provided in Supplement III for comparison.

Results

Transiograms

Auto-transiograms

Idealized transiograms for the four areas were calculated using corresponding one-step TPMs. The idealized auto-transiograms of the four areas are shown in Fig. 2A–D. The *x*-axis of these transiograms is lag distance, of which the unit is pixel length (30 m in this study), and the *y*-axis is transition probability. They all start from point (0, 1.0) and smoothly decrease to stable values with increasing **h**. These idealized auto-transiograms are approximately exponential in their curve shapes. Idealized transiograms have stable sills and clear correlation ranges. The experimental auto-transiograms of the four areas are shown in Fig. 2a–d. Compared with idealized auto-transiograms, the sills and correlation ranges of experimental auto-transiograms are blurred. These experimental auto-transiograms are not smooth curves and some of them have some fluctuations (small peaks and troughs). The sill and auto-correlation range data of these auto-transiograms are provided in Table 3. The sill and auto-correlation range values (especially the range values) of the experimental transiograms were just approximately identified. Although the eventual sills of most experimental transiograms do not deviate too much from the sills of corresponding idealized transiograms, their correlation ranges are obviously

Table 3 The sills and correlation ranges of idealized and experimental auto-transiograms for the four cases as shown in Fig. 2

Area	Class	Idealized auto-transiogram		Experimental auto-transiogram	
		Sill	Range (pixels)	Sill	Range (pixels)
A	Developed	0.127	32	0.133	45
	Crop/grass	0.069	22	0.059	20
	Forest	0.707	40	0.668	85
	Waterbody	0.079	80	0.016	60
	Wetland	0.020	16	0.021	23
B	Developed	0.309	35	0.343	75
	Crop/grass	0.066	24	0.066	40
	Forest	0.456	40	0.336	85
	Waterbody	0.109	58	0.099	90
	Wetland	0.042	24	0.043	35
C	Developed	0.269	35	0.236	80
	Crop/grass	0.154	25	0.145	35
	Forest	0.395	25	0.415	30
	Waterbody	0.169	70	0.173	90
	Wetland	0.013	16	0.019	35
D	Developed	0.222	20	0.227	35
	Crop/grass	0.214	20	0.216	30
	Forest	0.439	25	0.417	35
	Waterbody	0.064	30	0.061	35
	Wetland	0.050	26	0.045	40

different. Their shapes show that they are not simply exponential, and the real data, especially the data of some classes (e.g., class 1, class 3 and class 4 in Fig. 2a, b), have very different (much longer or shorter) auto-correlation ranges or have multiple ranges.

Cross-transiograms

Figure 3 shows some of the idealized cross-transiograms and corresponding experimental cross-transiograms of the four cases (for more experimental transiograms, see Supplement II), and their sill and correlation range values are provided in Table 4. Idealized cross-transiograms are all smooth curves and most of them can be modeled perfectly by exponential functions, although some of them are not monotonically increasing, with a peak (or maximum value) occurring before reaching their sill values. Experimental cross-transiograms tend to have quite complex shapes. While some experimental cross-transiograms approximately follow the shapes of their corresponding idealized ones (e.g., Figure 3A), some others may deviate a lot, especially in the low lag section (assuming the maximum lag is sufficiently long and all experimental transiograms may reach a stable situation).

Cross-transiograms have different shapes, based on which we may loosely group them into three types. The first type, which is also the most common type, is the typical-shape cross-transiograms, whose shapes are normally approximately exponential (e.g., the idealized and experimental cross-transiograms $p_{(3,2)}$ from area A in Fig. 3A), starting from point (0, 0) and gradually increase to a stable value (i.e., sill) with increasing **h**. The second type is those peaked-shape cross-transiograms, which first increase and reach a peak value at a comparatively shorter distance and then gradually decrease to their sills (note that some experimental cross-transiograms may first have a relatively higher peak and then go through a series of peaks and troughs to decrease to their sills). This kind of cross-transiograms reflect the juxtaposition or neighboring characteristics of two classes (Li et al. 2012). For instance, the idealized cross-transiogram $p_{(2,1)}$ in Fig. 3A is an example of such kind of cross-transiograms, which means that the two classes (crop/grass land and developed land) frequently occur as close neighbors in area A. The experimental cross-transiogram $p_{(2,1)}$ in Fig. 3A actually has a similar shape, but with some extra complexity—the first peak is followed by a series of irregular fluctuations. The third type is those cross-transiograms of class pairs that are infrequent neighbors or non-neighbors. In this case, the cross-transiogram between a pair of classes normally has a low-value section first and then gradually approach to its sill. This shape style is uncommon but does exist. It occurs on some experimental cross-transiograms sometimes, but the corresponding idealized cross-transiograms tend to have a Gaussian model shape. The experimental cross-transiogram $p_{(4,2)}$ from area C in Fig. 3D is an example of this kind of cross-transiograms. Here the $p_{(4,2)}$ (for waterbody and cross/grass land) is relatively flat with low values within the lag value of 10 pixels and then gradually increase to the sill. It tells that these two classes are infrequent neighbors, even though it is not so obvious because the low-value section is too short. Checking the map C in Fig. 1, we can find that waterbodies basically do not border on the crop/grass land class in the map. However, compared with the typical-shape cross-transiograms, the cross-transiograms of infrequent-neighbor classes have much lower values in the low-lag section (see $p_{(4,2)}$ in Fig. 3C, D).

Transition probabilities are typically asymmetric, which means the transition probabilities from class *i* to class *j* are different from the transition probabilities from class *j* to class *i* at the same distance (e.g., Figure 3B). For example, the idealized cross-transiograms between forest and waterbody in area B, are different—the $p_{(3,4)}$ is 0.07 while the $p_{(4,3)}$ is 0.34 at the lag of 10 pixels. This also holds for experimental cross-transiograms. But unless transition probabilities are estimated uni-directly, the difference is only on the magnitude of transition probability values (i.e., curve height) rather than on transiogram shapes. All the transiograms with the same head class should reach to the same sill, which is the proportion of the head class (e.g., Figure 3C, D). This is more obvious for the idealized transiograms, as shown in Fig. 3C, in which all the idealized cross-transiograms approach to the exact same value. However, there are some uncertainties on experimental cross-transiograms. For example, the experimental cross-transiograms in Fig. 3D only approximately approach the proportion value of the head class but do not reach the exact same value. Even though the cross-transiograms with the same head

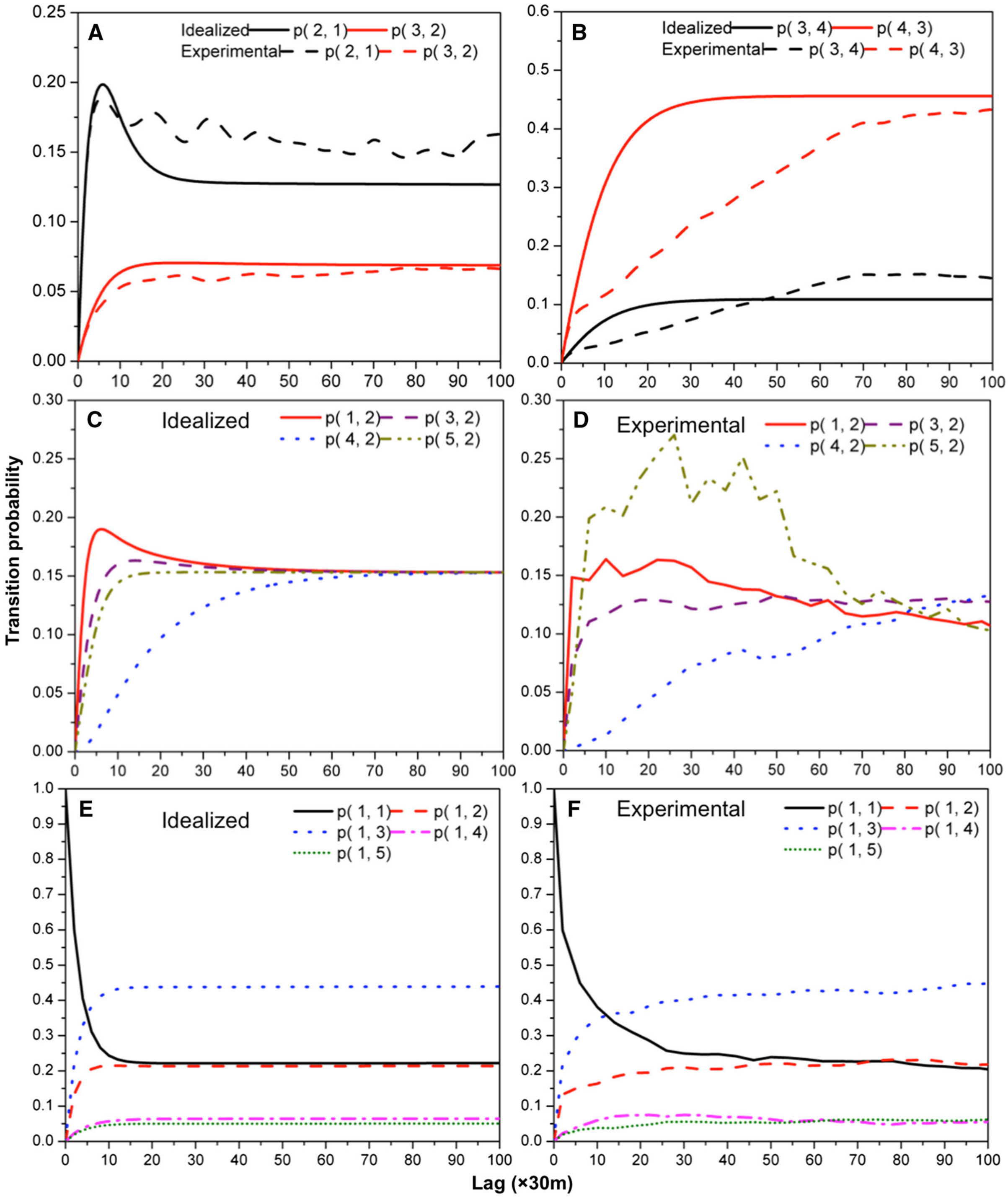


Fig. 3 Examples of idealized cross-transiograms and experimental cross-transiograms (1—developed land, 2—crop/grass land, 3—forest, 4—waterbody, 5—wetland). **A** for Area A. **B** for Area B. **C**, **D** for Area C. **E**, **F** for Area D, including a whole subset of transiograms with the same tail class

Table 4 The sills and correlation ranges of corresponding idealized and experimental cross-transiograms, as shown in Fig. 3

Area	Cross-transiogram symbol[a]	Idealized cross-transiogram		Experimental cross-transiogram	
		Sill	Range (pixels)	Sill	Range (pixels)
A	$p_{(2,1)}$	0.127	22	0.150	40
	$p_{(3,2)}$	0.069	18	0.067	20
B	$p_{(3,4)}$	0.109	26	0.147	80
	$p_{(4,3)}$	0.456	30	0.424	70
C	$p_{(1,2)}$	0.153	30	0.121	60
	$p_{(3,2)}$	0.153	24	0.129	20
	$p_{(4,2)}$	0.153	60	0.131	90
	$p_{(5,2)}$	0.153	18	0.121	70
D	$p_{(1,1)}$	0.222	20	0.231	40
	$p_{(1,2)}$	0.214	18	0.225	30
	$p_{(1,3)}$	0.438	15	0.435	30
	$p_{(1,4)}$	0.064	18	0.055	25
	$p_{(1,5)}$	0.051	15	0.050	25

[a]Symbol p(2,1) denotes transiogram $p_{21}(\mathbf{h})$ and corresponds to the legend style in Fig. 3

class reach the same sill, their shape characteristics do reflect the distinct interactions between the head class and other classes before they reach the same sill. They have different correlation ranges and different curve shapes. For example, $p_{(1,2)}$ in Fig. 3C has a peaked shape (i.e., has a peak at the low lag section) with a correlation range of 30 pixels, while $p_{(5,2)}$ in Fig. 3C has a typical shape with a correlation range of 18 pixels.

From Fig. 3, we find that the idealized and experimental cross-transiogram pair between two classes have some differences. First, most of the idealized and experimental cross-transiogram pairs have different correlation ranges and usually the correlation ranges of idealized cross-transiograms are smaller. For instance, the correlation range of the idealized cross-transiogram $p_{(4,3)}$ of area B is 30 pixels and the corresponding experimental cross-transiogram has a correlation range of around 70 pixels (Fig. 3B). Second, an idealized and experimental cross-transiogram pair may reveal different relationships between the two classes. For example, the idealized cross-transiogram $p_{(5,2)}$ in area C has a typical shape (Fig. 3C), while the corresponded experimental cross-transiogram has a peaked shape, showing a juxtaposition relationship of these two classes (Fig. 3D). These are reasonable, because the idealized transiograms were calculated from a one-step TPM based on the first-order stationary Markovian assumption, which cannot capture the non-Markovian effect of spatial data and the features of measured multiple-step (or longer-lag) transition probabilities (Li 2007a). If we check the land use/cover map of area C. It can be seen that wetland patches (class 5) are very close to crop/grass patches (class 2) but only part of the former touch the latter. This explains the short-distance adjacency relationship of wetland and crop/grass land. The idealized cross-transiogram does not catch this characteristic because immediate adjacency happens only for part of wetland patches. Third, even if the idealized and experimental cross-transiogram pair reveal the same relationship, there are still some differences between them. For example, both the idealized cross-transiogram and the experimental cross-transiogram from crop/grass land to developed land (i.e., $p_{(2,1)}$ in Fig. 3A) reveal the interclass adjacency situation between the two classes; however, the experimental cross-transiogram has a series of peaks and gradually decreases through undulation after the first peak, while the idealized one has only one peak in the short lag section around the 8 pixels lag value. On the other hand, sometimes the difference between idealized cross-transiogram and corresponding experimental cross-transiogram could be small. The idealized and corresponding experimental cross-transiograms in Fig. 3E, F have similar sills and

Table 5 Spearman's correlation coefficients between the two feature values of auto-transiograms and landscape metrics

Landscape metric	Idealized auto-transiogram		Experimental transiogram	
	Sill	Range	Sill	Range
PLAND	0.971**	–	0.968**	–
LPI	0.786**	–	0.743**	–
ED	0.750**	–	0.820**	–
AREA_AM	0.687**	0.705**	0.612**	0.711**
SHAPE_AM	–	–	–	–
FRAC_AM	–	–	–	–
CWED	0.823**	–	0.883**	–
TECI	–	–	–	–
CLUMPY	–	0.722**	–	0.596**
PLADJ	–	0.813**	–	0.659**
IJI	–	–	–	–
COHESION	–	0.672**	–	0.662**
AI	–	0.806**	–	0.639**
nLSI	–	–	–	–
PD	–	–	–	–
SPLIT	− 0.844**	− 0.641**	− 0.776**	− 0.649**

−Means that correlation is not statistically significant

**Means that correlation is significant at the 0.01 level

ranges. And they comply with the rule that the values of transiograms with the same tail class sum up to 1 at any specific lag.

Comparison with Landscape Metrics

Relation with landscape metrics by sills and autocorrelation ranges

The selected sixteen conventional landscape metrics (Table 1) represent different aspects of landscape variability, and their values for the four study areas and five different patch types (i.e., classes) can be seen from Supplement I. In order to explore the physical meanings of the two features of auto-transiograms (i.e., sill and correlation range), we calculate their spearman's correlation coefficients with the 16 landscape metrics (Table 5). It is clear that sill has a very strong positive correlation with PLAND (landscape proportion). Since the sill of a reliable auto-transiogram approximately reflects the proportion of the corresponding class, that is, it should be approximately equal to the PLAND value of the class, this result is normal. The sill also has significant correlation with the LPI, which is reasonable for small study areas because one class with a higher proportion probably has a lager LPI. ED is the total length of edge of one patch type divided by its total area and CWED is the sum of the lengths of contrast-weighted edge segments divided by the total landscape area. Therefore, sill also has significant positive correlation with ED and CWED.

Another important finding is that autocorrelation range has significant positive correlation with some aggregation index including CLUMPY, PLADJ, COHESION and AI. This means that autocorrelation range can reflect the aggregation level of different classes. Since class patch size has positive influence on the value of autocorrelation range, the autocorrelation range actually represents a patch-size-weighted aggregation level of a class. Among these metrics, AREA_AM and SPLIT have significant correlation with both of sill and autocorrelation range. The larger AREA_AM implies the possibly higher sill and larger autocorrelation range, especially for the small research area. SPLIT is a subdivision index. A higher SPLIT value means that the class is subdivided into more or smaller patches. Hence its correlations with sill and autocorrelation range are strongly negative. Both sill and autocorrelation range have no correlation with shape metrics (SHAPE_AM and FRAC_AM) and contrast metrics (TECI). Hence, transigorams cannot reveal the geometric complexity and the magnitude of difference between adjacent patch types by their two basic feature values.

Reflection of interclass relationships on cross-transiograms

At the class level, the landscape metrics measure the landscape characteristics of the target class, and reveal the relationships of the target class with all other classes as a whole. Unlike landscape metrics, cross-transiogram can reveal the interclass relationship between two classes. Thus, one can use a cross-transiogram alone (by regarding all other classes as one class) or several cross-transiograms together to explore the interclass relationships of a class with other classes.

For example, a cross-transiogram can indicate whether there is a juxtaposition (or neighboring) relationship between a pair of classes. Figure 4 shows some examples of idealized cross-transiograms of neighboring classes in the four areas. We can find that all of these cross-transiograms have a high peak at a short lag distance and gradually decrease to their sills. The relative peak height over the sill in each cross-transiogram is different, but the peak height ratios (i.e., ratios between peak relative height (PRH), peak height (PH), and sill) of the paired cross-transiograms between two classes are the same if the transiograms are estimated omni-directionally or bi-directionally (Table 6), because they represent the same juxtaposition relationship. However, for different pairs of classes, their cross-transiogram peak height ratios are different. The peak height ratios reflects the magnitude of neighboring or juxtaposition strength between two classes. The larger the ratios of PRH/Sill and PRH/PH, or the smaller the ratio of Sill/PH, the stronger the juxtaposition tendency of the class pair.

Among the landscape metrics, CLUMPY and PLADJ measure the adjacencies of a specific class, COHESION measures the physical connectedness of a specific class, and IJI measures the interspersion or intermixing of a class, with all other classes. It is difficult to use the values of these metrics to interpret the interclass relationships of any two specific classes. Taking the developed land class and the waterbody class in the study area B as an example, the IJI values of them are 79.32 and 79.78 (see Supplement I), which are approximately equal. Since a higher IJI value indicates a greater interspersion of the corresponding class among other classes, one can conclude on the basis of the IJI values that there is no difference between the two land cover classes in terms of their interspersion or intermixing among other classes in the study area B. However, much more interclass information can be obtained through related transiograms (Fig. 5). The cross-transiograms involving them show that they have different interactions with other classes.

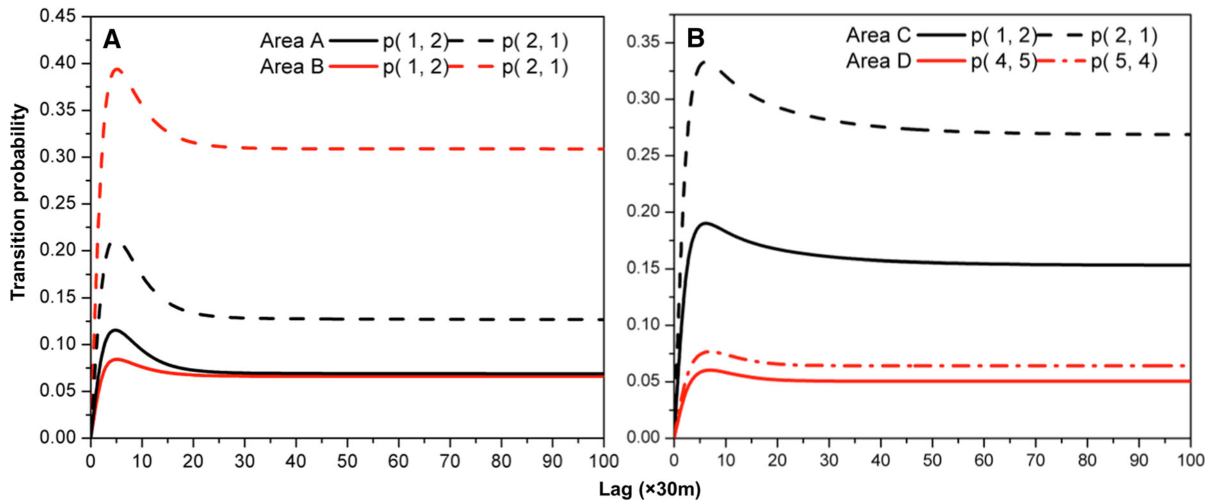


Fig. 4 Some idealized cross-transiograms of neighboring classes in the four areas (1—developed land, 2—crop/grass land, 4—waterbody, 5—wetland)

Table 6 The peak height ratios of idealized cross-transiograms of neighboring classes in the four areas (1—developed land, 2—crop/grass land, 4—waterbody, 5—wetland)

Study area	A		B		C		D	
Transiogram	$p_{(1,2)}$	$p_{(2,1)}$	$p_{(1,2)}$	$p_{(2,1)}$	$p_{(1,2)}$	$p_{(2,1)}$	$p_{(4,5)}$	$p_{(5,4)}$
Peak height (PH)	0.118	0.218	0.085	0.398	0.191	0.336	0.061	0.077
Sill	0.069	0.127	0.066	0.309	0.154	0.269	0.051	0.064
Peak relative height (PRH)[a]	0.049	0.091	0.019	0.089	0.038	0.067	0.010	0.013
PRH/Sill	0.71	0.72	0.29	0.29	0.25	0.25	0.20	0.20
PRH/PH	0.42	0.42	0.22	0.22	0.20	0.20	0.16	0.17
Sill/PH	0.58	0.58	0.78	0.78	0.81	0.80	0.84	0.83

[a]PRH = PH–sill

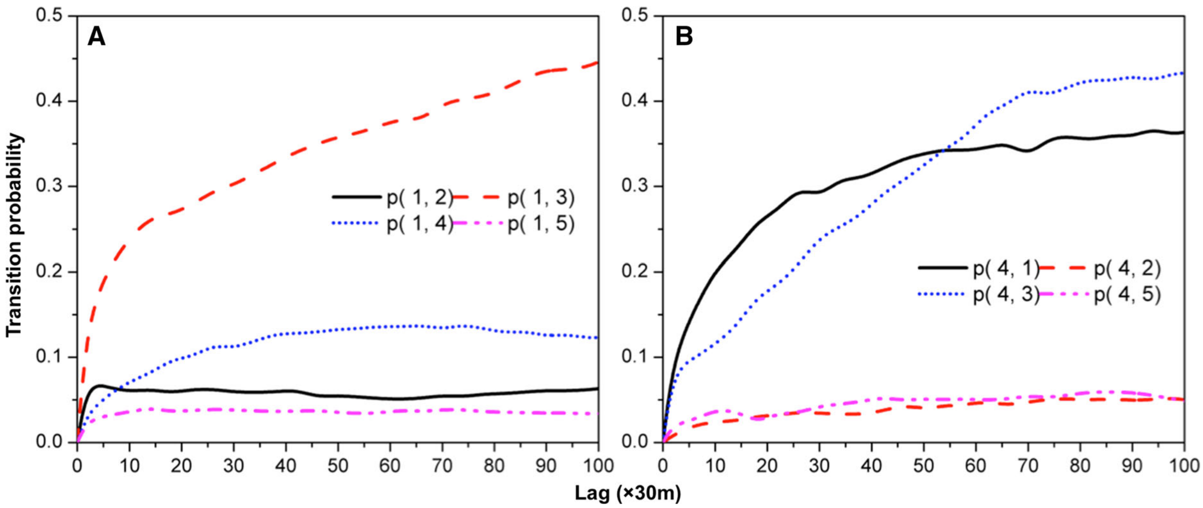


Fig. 5 The experimental cross-transiograms of developed land (left) and waterbody (right) in the study area B.(1—developed land, 2—crop/grass land, 3—forest, 4—waterbody, 5—wetland)

For example, the cross-transiogram $p_{(1,2)}$ between developed land and crop/grass land shows a neighboring characteristic with a correlation range of 7 pixels, but the cross-transiogram $p_{(4,2)}$ between waterbody and crop/grass land shows a typical ordinary correlation with a correlation range of 20 pixels.

Discussions

The sixteen metrics considered in this study are commonly used metrics in many studies. For instance, Frank et al. (2013) applied SHAPE and PD to the assessment of landscape aesthetics and concluded that they are able to assess and monitor landscape diversity and naturalness. Fan and Myint (2014) selected four metrics (PLAND, LPI, PD and AI) to measure the urban landscape fragmentation of Phoenix. These four metrics were also incorporated into an urban growth potential model to simulate the urban growth processes of Jinan City, China (Kong et al. 2012). Midha and Mathur (2010) chose the PD, ED, and IJI to assess the fragmentation of two constituent protected areas and compare the magnitude between them. Li et al. (2015a) analyzed the relationships between landscape metrics (PLAND, PD, LPI, ED, SHAPE, COHESION) and water quality in coastal China and found these metrics are important for illustrating the degradation of water quality. Lee et al. (2009) found that the spatial heterogeneity of forests (both of composition and configuration) has a strong impact on burn severity and they used landscape metrics, including LPI, PD, and AI, to represent landscape structure. In general, previous studies on the use of landscape metrics have demonstrated the important values of landscape metrics in landscape ecology, which raise the hope that transiograms and their features may also have potentials in landscape ecological analysis.

The transiograms represent the transition probabilities of land cover/use classes over different lag distances. They are graphic composite measures, which can represent the information of multiple aspects of variability of landscape classes. Different from real-data transiograms derived from spare sample data (experimental transiograms) or exhaustive data (exhaustive transiograms), idealized transiograms can be simply derived from a one-step TPM. Idealized transiograms can capture basic spatial variation features of classes (e.g., auto-correlation ranges, cross-correlation ranges, juxtaposition tendencies), but miss more-complex characteristics of spatial autocorrelations and interclass relationships, such as multiple peaks, troughs, or multiple ranges, that are exhibited on real-data transiograms. The real-data transiograms are able to capture complex features of spatial relationships of classes, but sometimes it is difficult to extract accurate information from them due to their over-complexity. Although idealized transiograms are comparatively simple, they are useful in interpreting real-data transiograms. Therefore, even though it is preferable to use experimental transiograms in most cases, the idealized transiograms are still important and probably more useful to some users, especially inexperienced users, in landscape pattern interpretation due to their simplicity in curve shape and unambiguity in range, sill and peak height values.

We consider the transiogram as a new graphic landscape metric for measuring and visualizing spatial variability of landscape classes. Compared with traditional landscape metrics, transiograms are visual measures of the complex spatial intra-class and interclass relationships, which make them, to some extent, easier to interpret about their implications. The most significant merit of transiograms is that cross transiograms measure interclass relationships. However, there are some weaknesses in transiograms that should not be ignored. Although experimental transiograms estimated from sample points can eliminate the noise of misclassification to some extent, they may not accurately reflect the real class proportions if sample data deviate from the truth in class proportions, and their shapes sometimes may be too complex to explain accurately in detail. Idealized transiograms depend on one-step TPMs, which may not be available or may contain some effect of noise if they are estimated from exhaustive data that contain much noise (note that traditional landscape metrics should also have this problem if estimated from data with much noise, such as classified remote sensing images without post-processing).

If used for spatial description of different species, the features of transiograms might relate to the dynamic activities of different species (e.g., home range size, perception range, dispersal abilities). For example, the autocorrelation range of a land use/cover type might link with the home range of a species if the species tend to move within patches of the land use/cover type. The cross-correlation range and neighboring strength of two land use/cover types might link with the dispersal ability of a species. In addition, transiograms may be used to describe the spatial patterns of various landscape categories that are formed naturally or divided by humans, including ecological function zones and plant species.

Landscape metrics, including transiograms, address the spatial variability of landscapes and may play an important role in exploratory and descriptive landscape analysis. Landscape pattern is linked to critical ecological processes, such as biodiversity and other ecological values of the landscapes. The measurement of landscape pattern is necessary for understanding the functioning of landscapes and is a prerequisite to the study of pattern–process relationships. The simplicity and quick calculation of landscape metrics ensure that they can meet the demand of understanding rapid environmental changes. As a part of geospatial data analysis, landscape metrics provide background information and scenario testing of environmental policies to policymakers and resources mangers. Therefore, even though landscape metrics and transiograms have some limitations, it is worthwhile to make effort to apply them in real world studies, such as land cover spatial and temporal changes.

Although in this study we used only small images as study areas, the transiogram can be applied to large maps. Computation time depends on the size of data (number of pixels used) and the computer program (e.g., given the same data set, using different computer languages and different programming strategies may result in different computation time), but it is generally not a big concern in practice due to the following reasons: (1) Experimental transiograms are estimated from sample data, of which the size is usually not very large (usually hundreds to thousands of sample data), so they can be computed quickly. (2) Idealized transiograms are calculated from a TPM, which can be estimated from map data much more easily, and the further calculation step from the TPM to idealized transiograms needs almost no time. (3) The estimation of exhaustive transiograms from a large classified image or map is indeed time-consuming or impractical if they are estimated omni-directionally, because it needs to count numerous pixel pairs in all directions with many different lags (i.e., separate distances of data pairs). However, the use of exhaustive transiograms is not much necessary, because their curve shapes are very similar to the experimental transiograms estimated from a representative randomly-selected sample data set as a small portion of the pixels of the same image/map, thus providing little extra valuable information (see Supplement II and Supplement III). Transiograms have been used in some real case studies with very large data sets. For example, Zhang et al. (2017, 2018) used the Markov chain geostatistical approach for post-processing pre-classified Landsat images to detect the urban horizontal and vertical growth in megacities in East Asia, in which full Landsat images and experimental transiograms estimated from sample data sets for the large areas were used.

This study is still preliminary with limitations, which may be explored in future studies. First, the analysis of the landscape metrics and transiograms in this study has no link with any specific applications. Second, not all landscape metrics are included; therefore, comparisons between existing landscape metrics and transiograms may not be sufficiently comprehensive. Third, we examined only one scale of observations without considering multiple grains and extents. Fourth, due to the complexity of spatial variability, our results and conclusions are, to some extent, limited to the situations we examined. Hence, further study may still be needed for a comprehensive understanding of transiograms as a new, graphic landscape metric.

Conclusions

This study provides some further understanding of the class-level landscape metrics, transiograms, and the relationships between them. It shows that the transiogram may serve as a new, graphic landscape metric with some unique features. Landscape researchers may gain some insight into the ability of transiograms for measuring some new aspects of landscape patterns. The differences between idealized transiograms and experimental transiograms are also analyzed. They can be used separately or together according to actual needs as they have their own advantages and weaknesses. A peak height ratio concept based on idealized transiograms is also presented for quantitatively representing the juxtaposition strength of neighboring landscape class pairs.

While auto-transiograms can provide information on the proportions of landscape classes and their individual aggregation levels, cross-transiograms can provide information on the proportions of landscape classes, interclass adjacency types, and interclass correlation ranges. The peak height ratios of idealized cross-transiograms can be good indices to reflect the neighboring or juxtaposition strength of neighboring class pairs. Therefore, transiograms, as a new graphic landscape metric, represent some different aspects of landscape variability. Comparison shows that transiogram sills are correlated with some conventional landscape metrics (PLAND, LPI, AREA_AM, ED, CWED, and SPLIT), and transiogram auto-correlation ranges are also correlated with some conventional landscape metrics (CLUMPY, PLADJ, COHESION, AI, AREA_AM, and SPLIT). However, transiograms have some characteristics different from conventional landscape metrics: (1) As diagrams, transiograms provide visual information, making them to some extent more interpretable intuitively; for example, class proportions, auto/cross-correlation ranges, and neighboring relationships can be intuitively interpreted from transiograms. (2) Cross-transiograms are able to capture complex interclass relationships, which include interdependency and juxtaposition (i.e., neighboring) relationships between classes. (3) Transiograms can be estimated from real data or calculated from a TPM, and these transiograms estimated using different ways may be used together. While idealized transiograms clearly reveal the basic dependency features of landscape classes that are implied in one-step transition probabilities, experimental transiograms reveal more complex dependency features of landscape classes that are contained in sample data in different spatial lag distances.

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