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Effects of changing spatial resolution on the results of landscape pattern analysis using spatial autocorrelation indices

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Abstract

Understanding the relationship between pattern and scale is a central issue in landscape ecology. Pattern analysis is necessarily a critical step to achieve this understanding. Pattern and scale are inseparable in theory and in reality. Pattern occurs on different scales, and scale affects pattern to be observed. The objective of our study is to investigate how changing scale might affect the results of landscape pattern analysis using three commonly adopted spatial autocorrelation indices, *i.e.*, Moran Coefficient, Geary Ratio, and Cliff-Ord statistic. The data sets used in this study are spatially referenced digital data sets of topography and biomass in 1972 of Peninsular Malaysia. Our results show that all three autocorrelation indices were scale-dependent. In other words, the degree of spatial autocorrelation measured by these indices vary with the spatial scale on which analysis was performed. While all the data sets show a positive spatial autocorrelation across a range of scales, Moran coefficient and Cliff-Ord statistic decrease and Geary Ratio increases with increasing grain size, indicating an overall decline in the degree of spatial autocorrelation with scale. The effect of changing scale varies in their magnitude and rate of change when different types of landscape data are used. We have also explored why this could happen by examining the formulation of the Moran coefficient. The pattern of change in spatial autocorrelation with scale exhibits threshold behavior, *i.e.*, scale effects fade away after certain spatial scales are reached (for elevation). We recommend that multiple methods be used for pattern analysis whenever feasible, and that scale effects must be taken into account in all spatial analysis.

Introduction

Landscapes are mosaics of patches that differ in size, shape, and contents (Risser *et al.* 1984; Forman and Godron 1986; Wu and Levin 1994). Numerous studies have shown that the spatial pattern of landscapes may have significant influences on ecological processes, such as population dynamics, biogeochemical cycling, and aspects of biodiversity (*e.g.*, Burgess and Sharpe 1981; Zonneveld and Forman 1990; Opdam 1991; Wiens *et al.* 1993; Wu *et al.* 1993; Wu and Vankat 1991a, b, 1995; Wu and Levin 1994). Therefore, identifying and characterizing spatial pattern across a range of scales (especially large ones) using various quantitative methods are often necessary in landscape ecological studies (Turner and Gardner 1991; Cullinan and Thomas 1992; Wu 1992a).

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In recent years, the importance of scale effects on spatial analysis and modeling has been increasingly emphasized in light of spatial heterogeneity and hierarchy theory (*e.g.*, Allen and Starr **1982;** Meentemeyer and Box **1987;** Morris **1987;** Turner *et al.* **1989;** Levin **1992;** Constanza and Maxwell **1994;** Wu *et al.* **1994;** Wu and Levin **1994).** Because of the spatial heterogeneity and hierarchical properties of landscape systems, understanding the effects of changing scale on the analysis of landscape patterns is critical to our ability to predict landscape dynamics across scales (Turner *et al.* **1989;** Wu and Levin **1994).** Identifying scales of landscape patterns and examining the effects of changing scales on pattern analysis are intrinsically related but two aspects of the pattern-scale problem in ecology. Both studies should shed light on the problems of pattern and scale, and thus facilitate the scaling up or scaling down of ecological information (Wiens **1989;** Levin **1992;** Wu **1992b).** However, little systematic investigation has been done as to how changing scale affects the results of spatial analysis (but see Turner *et al.* **1989),** although there has been a considerable amount of work done on the detection and characterization of spatial pattern (*e.g.*, Getis and Boots **1978;** Getis and Ord **1992;** O'Neill *et al.* **1988;** Fortin *et al.* **1989;** Legendre and Fortin **1989;** Turner and Gardner **1991;** Cullinan and Thomas **1992;** Wu **1992a).**

Detecting and characterizing spatial pattern in ecology dates back to the early work on plant community analysis (*e.g.*, Greig-Smith **1952;** Kershaw **1957).** Nevertheless, it was not until the recent development of landscape ecology that the classic blocking method originally developed by Greig-Smith began to be extended to larger scale studies, and that a number of new methods started being explored (*e.g.*, Milne **1988;** O'Neill *et al.* **1988;** Turner and Gardner **1991).** Recent reviews with examples of several classical and newly developed techniques for pattern analysis are available (*e.g.*, Turner and Gardner **1991;** Levin *et al.* **1993).** Cullinan and Thomas **(1992)** evaluated several methods (tests of non-randomness, grid blocking method, variance ratio analysis, spectral analysis, fractal dimension, correlation analysis) as to their suitability for detecting and characterizing landscape patterns and associated scales. Their data sets included two artificially generated Poisson random series and plant cover data along a transect, all of which were one-dimensional. Cullinan and Thomas **(1992)** asserted that tests of non-randomness and nearest-neighbor techniques were of limited use in the study of landscape patterns. In general, other methods showed varying ability to respond to changes in the scales of spatial patterns, with each method performing better for certain scales. Therefore, Cullinan and Thomas **(1992)** concluded that multiple methods should be used for examining landscape pattern and scale.

Based on actual landscape data from USGS land use maps and computer-generated random maps, Turner *et al.* **(1989)** investigated the effects of changing scale on landscape pattern analysis using different indices (diversity, dominance, and contagion). Spatial scale may refer to either the "grain" (*i.e.*, the spatial resolution) or the "extent" (*i.e.*, the total study area). Turner *et al.* **(1989)** found that three indices were all sensitive to the changes in spatial scale. They also showed that the scale effects on indices of dominance and contagion exhibited different patterns as the definition of scale changed from grain to extent. Specifically, both indices decreased with an increase in grain size, but increased as the extent increased, showing stair-step pattern as a result of being sensitive to the number of land cover types present (Turner *et al.* **1989).**

Although it is well known that changing scale will somehow affect the results of spatial analysis, the questions regarding "how" and "why" remain largely unanswered, and systematic investigations to address such issues are urgently needed. With increasing use of spatial autocorrelation analysis in landscape ecology, we believe that it is important to systematically investigate how changing scale affects the results of such analyses. In particular, based on two landscape data sets of Peninsula Malaysia, we have conducted a series of analyses by manipulating grain size across a range of scales to explore how this might affect the results of spatial autocorrelation analysis using three frequently practiced spatial autocorrelation indices – Moran coefficient, Geary ratio, and Cliff-Ord statistic.

Data and methods

The two data sets used for this study are geo-referenced digital data of elevation and above-ground biomass in Peninsular Malaysia (Fig. 1a, b; see Brown *et al.* 1994 for more details). Information in these data sets is represented using a rectangular lattice or grid, each cell of which has one or more values. Both data sets have *220* rows and 188 columns, with a grid cell size (the minimum or basic spatial unit, BSU) of *2.25* x *2.25* kilometers.

To change the grain size across a range of spatial scales, we systematically aggregated the data from the original spatial resolution to larger areal aggregates in the following way. Each BSU was treated as one basic unit, and therefore the grain size at this scale was expressed as 1 by 1. **A** *2* x *2* areal unit, then, corresponded to the grain size that contained four BSUs (two on each side). This was accomplished by aggregating four adjacent basic areal units, assigning the arithmatic mean of the four to the newly formed areal unit. This procedure was repeated until the entire region of the data sets was covered. In total, *20* different grain sizes (spatial scales) were created, ranging from 1 *x* 1 through *20* x *20* BSUs (*i.e.*, 1, 2^2, 3^2,. .., 20^2). Table 1 gives detailed information on the grain sizes, the number of areal units at grain size, and the starting position of aggregation at each scale.

In the aggregation process, sometimes the original data sets had to be modified (edge rows or columns were omitted or repeated) to obtain integer numbers of rows and columns. For example, in some cases we trimmed off the first 8 columns because they consisted mainly of zeros, representing ocean or areas of no concern. In some other cases, more rows were needed to maintain an integral number of rows for moving up to the next spatial scale, and we duplicated the first and/or last row. While this kind of modification was necessary only for technical convenience, we believed that this modification would not affect the results of our analysis because of the relatively large size of the dates.

Moran Coefficient (MC), Geary Ratio (GR) and Cliff-Ord statistic (CO) are among the most commonly used indices for the analysis of spatial autocorrelation in geographically referenced ecological data (Cliff and Ord 1973, 1981; Odland 1988; Goodchild 1986; Griffith 1988; Legendre 1993). These autocorrelation coefficients are defined as follows (Griffith 1988).

(1) Moran Coefficient

$$MC = \left(n \Big/ \sum_{i=1}^{i=n}\sum_{j=1}^{j=n} c_{ij}\right) \sum_{i=1}^{i=n}\sum_{j=1}^{j=n} c_{ij}(x_i-\bar{x})(x_j-\bar{x}) \Big/ \sum_{i=1}^{i=n} (x_i-\bar{x})^2 \qquad (1)$$

(2) Geary Ratio

$$GR = \left((n-1) \Big/ (2\sum_{i=1}^{i=n}\sum_{j=1}^{j=n} c_{ij})\right) \sum_{i=1}^{i=n}\sum_{j=1}^{j=n} c_{ij}(x_i-x_j)^2 \Big/ \sum_{i=1}^{i=n} (x_i-\bar{x})^2 \qquad (2)$$

(3) Cliff-Ord statistic

$$CO = \left(n \Big/ \sum_{i=1}^{i=n}\sum_{j=1}^{j=n} w_{ij}\right) \sum_{i=1}^{i=n}\sum_{j=1}^{j=n} w_{ij}(x_i-\bar{x})(x_j-\bar{x}) \Big/ \sum_{i=1}^{i=n} (x_i-\bar{x})^2 \qquad (3)$$

$$\text{with } \sum_{i=1}^{i=n} w_{ij} = 1 \text{ and } 0 \leq w_{ij} \leq 1 \qquad (4)$$

where n is the total number of areal units over the entire landscape, x_i and x_j are values of areal units i and j, and $\bar{x}$ is the mean of all areal units. c_{ij} denotes the connectivity between areal units i and j, and it takes a value of 1 if areal units i and j are adjacent and 0 otherwise). C = $\{c_{ij}\}$ is called the connectivity matrix (n X n). w_{ij} is the standardized connectivity between i and j, (*i.e.*, $w_{ij} = c_{ij} \sum_j c_{ij}$), and **W** = $\{w_{ij}\}$ is the standardized connectivity matrix (Griffith 1988).

Two areal units i and j are considered adjacent if they are within certain distance from each other. In practice, the values of c_{ij} and hence w_{ij} are determined simply by checking if two areal units i and j are immediately next to each other. In other words,

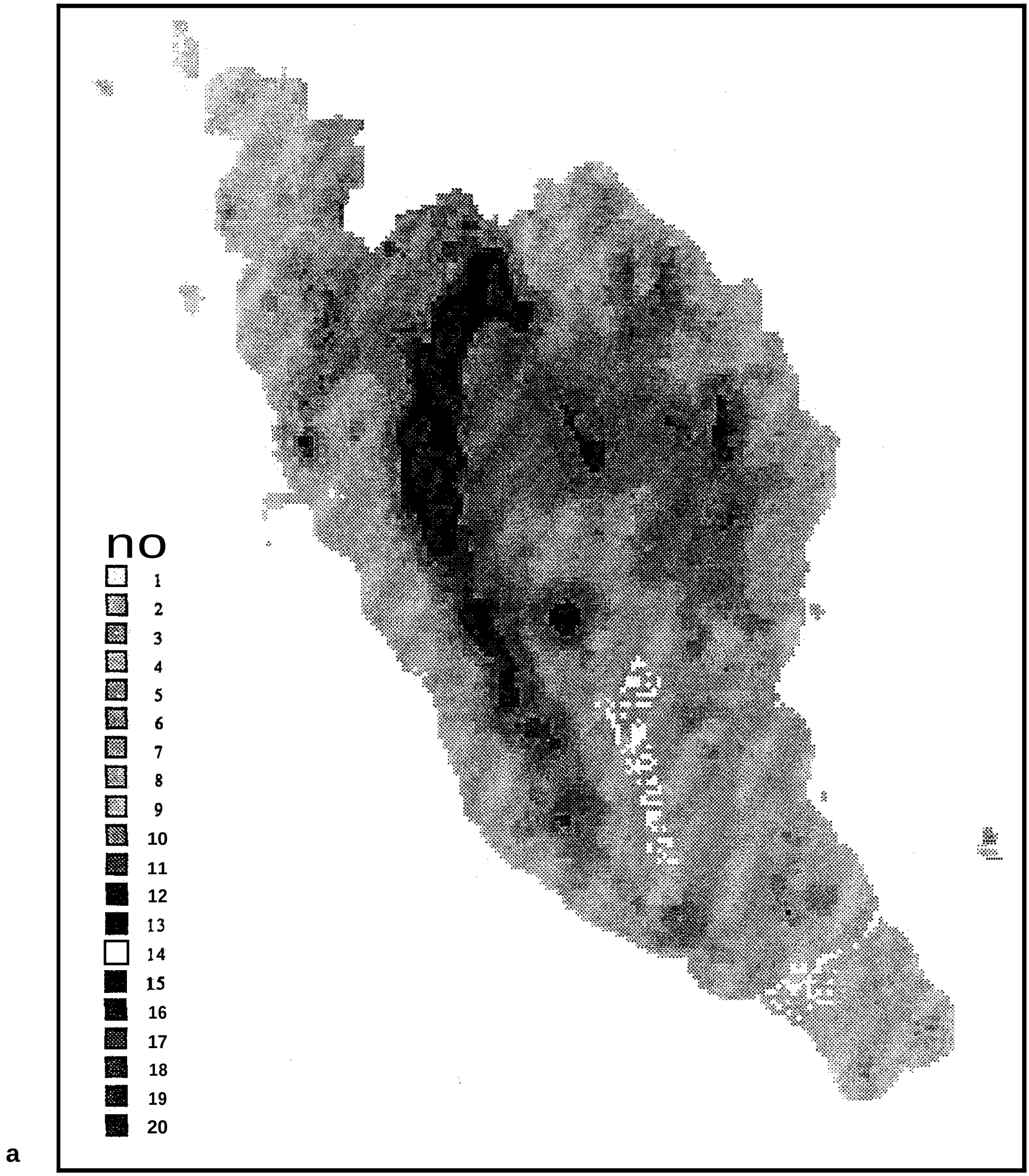
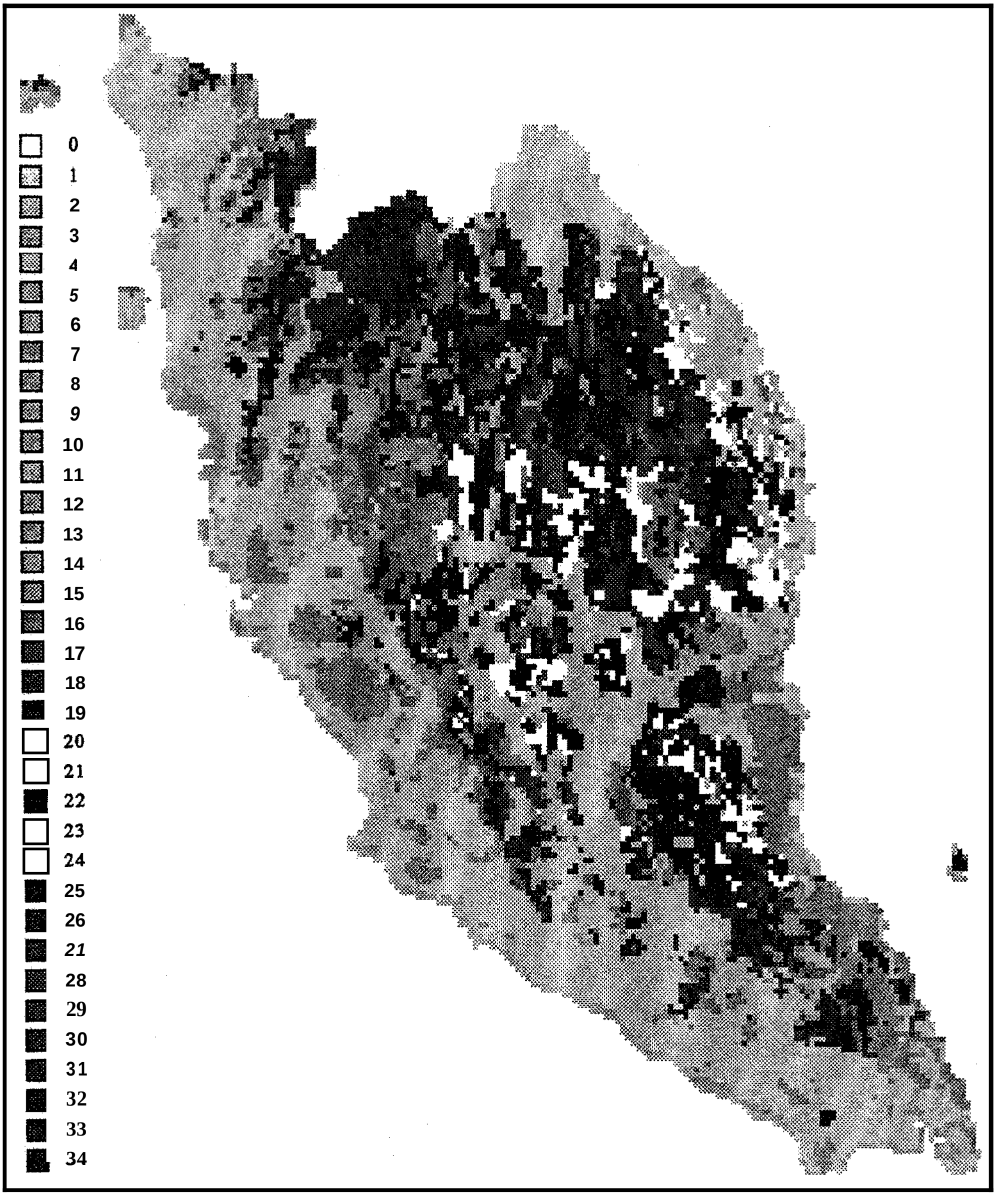


Fig. 1. The landscape data sets of Peninsular Malaysia: (a) elevation, where the actual altitude increases with the degree of darkness with category 0 denoting the sea level; (b) above-ground biomass in 1972, where areas with greater biomass are represented by darker pixels. **All** the data sets have 220 rows and 188 columns, and have a spatial resolution of 2.25 × 2.25 kilometers.

areal units i and j are regarded as being adjacent if they share a line. In our case where a regular rectangular lattice is used, a grid cell can only be adjacent to the neighboring cells on the four sides (*i.e.*, upper, lower, left, and right).

All three statistics have the following common properties: (1) there exists an expected value (mean) that corresponds to the case of no spatial autocorrelation, (2) the coefficient is able to discriminate between different spatial arrangements of the same set of values $\{x_i\}$ on a two-dimensional surface, and **(3)** all of them also have well established distributions based on conventional sampling theory (Griffith **1988;** Odland **1988).** The spatial correla-



b

Fig. Ib.

tion indices, as defined above, are determined by two factors: the value of each areal unit and the spatial relationship among all the areal units. In all our calculations, the spatial extent was fixed, so that our study was focused completely on the scale effects from a grain size point of view. We calculated the three spatial autocorrelation indices at each of the 20 spatial scales that were specified by different grain sizes for the two data sets. The three indices were used together for comparing their sensitivity to scale change and verifying the algorithm we developed. We realized that altering grain sizes would involve two closely related but different issues: change in the area of the spatial unit at different grain sizes and arrangement or configuration of spatial units at smaller scales to form higher level aggregates (*e.g.*, Wu *et* ***al.*** 1994). However, this study was concentrated only on the first issue.

Table 1. Layout of the aggregating scheme from the basic spatial unit (1 x 1 **BSU**) to larger areal unit aggregates (up to 20 x **20** BSUs). Grain size, starting row, and starting column are measured or denoted by the basic spatial units, while the numbers of rows and columns represent the actual numbers of the areal units corresponding to each spatial scales (grain sizes or levels of aggregation).

Grain size	#Areal units at each scale	Starting row	Starting column
1 x 1	220 x 180	3	9
2 x 2	110 x 90	3	9
3 x 3	73 x 60	4	9
4 x 4	55 x 45	3	9
5 x 5	44 x 36	3	9
6 x 6	36 x 30	4	9
7 x 7	31 x 26	4	7
8 x 8	27 x 23	4	5
9 x 9	24 x 20	**4**	9
10 x 10	22 x 18	3	9
11 x 11	20 x 16	3	11
12 x 12	18 x 15	4	9
13 x 13	17 x 14	3	7
14 x 14	15 x 13	5	7
15 x 15	14 x 12	6	9
16 x 16	13 x 11	7	11
17 x 17	13 x 11	*3*	2
18 x 18	12 x 10	4	9
19 x 19	11 x 9	7	11
20 x 20	11 x 9	3	9

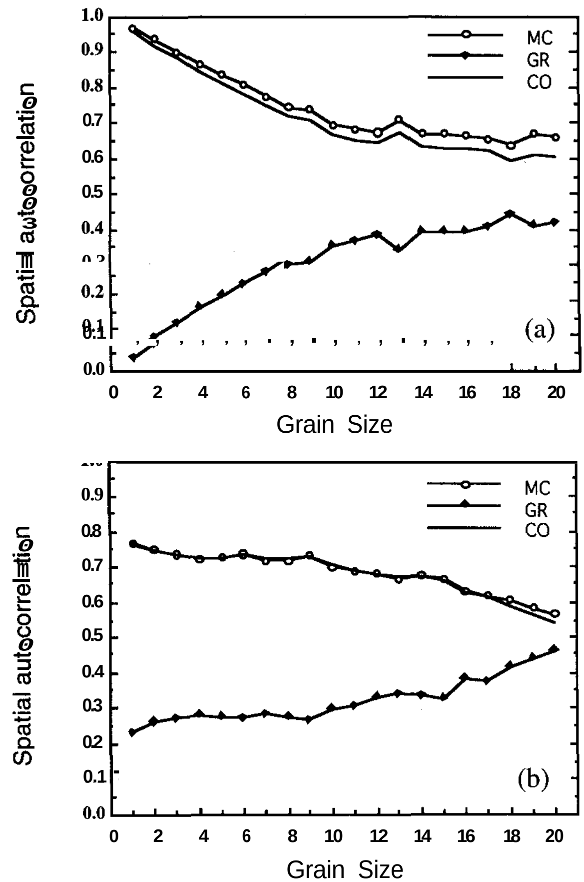


Fig. 2. Scale effect on spatial autocorrelation indices (Moran Coefficient – **MC**, Geary Ratio – GR, and Cliff-Ord statistic – CO): (a) elevation, and **(b)** biomass.

Constructing the connectivity matrix is usually the most critical step for calculating spatial autocorrelation indices (Griffith 1988). It is often the computational bottleneck that limits the size of the spatial data sets (Griffith 1990). There are, in total, 41,360 grid cells in our original data set (220 rows by 188 columns). This would produce a connectivity matrix of 41,360 by 41,360, which is too large for a personal computer to handle. Fortunately, the property of a regular rectangular lattice of data allows us to reduce the computational demand by changing the way of dealing with the connectivity matrix. In general, for a spatial data set with k rows and p columns, there are at most 4kp-2k-2p nonzero values in the connectivity matrix of kp x kp. Therefore, we can use a matrix of 4 x kp, instead of kp x kp, to record all the information contained in the connectivity matrix. By so doing, the computer memory usage can be reduced by a factor of kp/4, as compared to the conventional algorithm (*e.g.*, Griffith 1990). In this study, k and p are 220 and 188, so the computational demand is cut down by a factor of 10,340 (*i.e.*, 4 x 188 x 220 = 165,440 elements in the connectivity matrix in total).

Results and analysis

For the three autocorrelation indices used here, the values for both Moran coefficient and Cliff-Ord statistic usually fall in between -1 and 1, though they may exceed 1.0 for some weights and attribute values (Goodchild 1986). The theoretical value for no spatial autocorrelation for these two indices is -1/(n-1). **A** value of less than zero indicates a negative spatial autocorrelation, and a value larger than zero suggests a positive spatial autocorrelation. The value of Geary Ratio, on the other hand, ranges from 0 to 2, with 1 for no, larger than 1 for negative, and smaller than 1 for positive spatial autocorrelation. Therefore, a positive spatial autocorrelation is always detected if the computed value falls between 0 and 1, no matter which of the three autocorrelation coefficients is used.

We shall discuss the results of our analysis by addressing the following three related questions. (1) Based on the two landscape data sets, how does changing grain size affect he results of analysis using the three spatial autocorrelation correlation coefficients? (2) For a given spatial autocorrelation index, how do such scale-dependent changes vary with different types of landscape data? **(3)** Why do such differences occur for various types of landscape data?

To explore the first question above, we examined the sensitivity of the three autocorrelation coefficients to changes in spatial resolution by applying them simultaneously to the same data set. Figure 2 shows how the numerical values of these coefficients respond to increasing grain sizes. In all the analyses with the two data sets, the computed values for Moran coefficient and Cliff-Ord statistic are very closely related across a wide range of scales. This may be expected from a scrutiny of the similar formulation of the two indices (see Eqs. 1 and **3).** For the elevation data set, Moran coefficient and Cliff-Ord statistic decrease steadily from changing grain size affect the results of analysis using the three spatial autocorrelation correlation coefficients? (2) For a given spatial autocorrelation index, how do such scale-dependent changes vary 0.96 to about **0.68,** as the grain size increases from the minimum spatial unit to the 11 by 11 BSU aggregate, and then tend to level off (Fig. 2a; Table **2).** Geary ratio, on the other hand, increases almost linearly first from **0.038** to **0.37** as the grain size increases to the scale of 11 by 11 basic areal units, and then gradually levels off around the value of 0.4 (Fig. 2a; Table 2).

For the biomass data set, Moran coefficient and Cliff-Ord statistic again decline with increasing grain size (Fig. 2b). The decrease continues all the way to the grain size of 20 by 20 BSUs, but it seems more gradual (from 0.76 to 0.54 for the entire range of scales, see Table 2). Geary ratio shows a reversed trend with increasing spatial scale as it does for the elevation data set. All three indices show a rather distinctive change (through) around the grain size of 11 by 11 basic areal units in the data sets of elevation. We speculate that this may correspond to an abrupt change in spatial patchiness of some sort around that scale in the peninsular Malaysia landscape. However, we cannot completely rule out the possibility that it may be a result of some artifact in the data aggregation procedure. This phenomenon deserves further examination in future analysis of this type, especially when data sets of higher spatial resolution and larger extent are available.

Given the existence of obvious effects of changing scale on the results of spatial autocorrelation coefficients as demonstrated above, one of the questions in order is whether there is any generality about them. In this particular case study, we explore how scale effects manifest themselves with the different types of landscape data sets under con-

Table 2. Values of the three spatial autocorrelation coefficients for different data sets with changing grain size. The grain size is denoted by the basic spatial areal units (BSUs) for these data sets.

Grain size	Elevation			Biomass		
	MC	GR	CO	MC	GR	CO
1	0.9691	0.0382	0.9620	0.7647	0.2314	0.7691
2	0.9370	0.0764	0.9237	0.7468	0.2607	0.7416
3	0.8998	0.1180	0.8834	0.7336	0.2698	0.7339
4	0.8638	0.1609	0.8433	0.7227	0.2794	0.7237
5	0.8332	0.1961	0.8090	0.7246	0.2750	0.7242
6	0.8076	0.2259	0.7837	0.7333	0.2687	0.7360
7	0.7751	0.2630	0.7489	0.7173	0.2836	0.7202
8	0.7435	0.2999	0.7169	0.7190	0.2759	0.7272
9	0.7398	0.3092	0.7087	0.7318	0.2657	0.7324
10	0.6948	0.3558	0.6677	0.6997	0.2963	0.7064
11	0.6822	0.3695	0.6532	0.6862	0.3057	0.6900
12	0.6727	0.3891	0.6432	0.6763	0.3288	0.6779
13	0.7083	0.3454	0.6732	0.6671	0.3372	0.6679
14	0.6703	0.3961	0.6353	0.6750	0.3338	0.6732
15	0.6700	0.3947	0.6319	0.6669	0.3262	0.6605
16	0.6646	0.3948	0.6251	0.6294	0.3836	0.6271
17	0.6558	0.4095	0.6198	0.6174	0.3721	0.6146
18	0.6375	0.4428	0.5941	0.6054	0.4158	0.5859
19	0.6689	0.4140	0.6124	0.5839	0.4406	0.5603
20	0.6620	0.4217	0.6032	0.5644	0.4615	0.5453

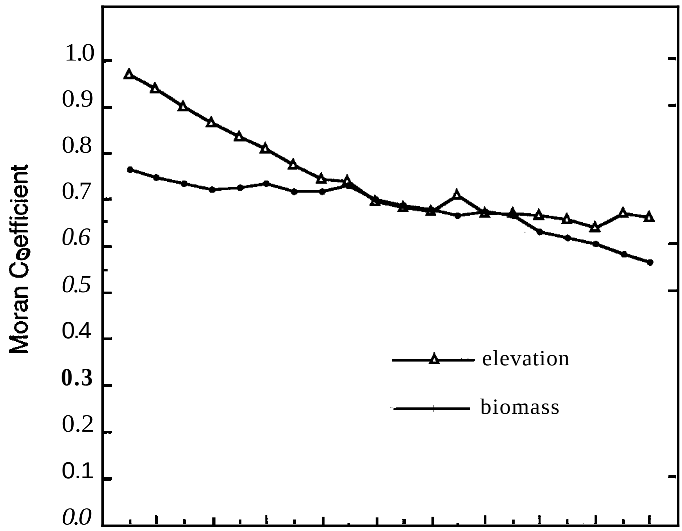


Fig. 3. Comparison of scale effects on Moran Coefficient among different landscape data sets.

Table 3. Values of Moran coefficient computed at the smallest, middle and largest spatial scales for the two different data sets. The changes in Moran coefficient between any two of the three grain sizes are also given in the table, with the percentage changes in the parentheses.

	MC value			A MC		
Data type	1 × 1	10 × 10	20 x 20	1x1 – 20x20	1 × 1 → 10 × 10	10x10 – 20x20
Elevation	0.9691	0.6948	0.6620	0.3071	0.2743 (89.3%)	0.0328 (10.7%)
Biomass	*0.1641*	0.6997	0.5644	0.2003	0.0650 (32.5%)	0.1353 (67.5%)

sideration. The answer to this question has already been touched upon earlier in the discussion of the results that show how the three indices are affected by changing scales using the same data sets. To further elucidate this question, however, we choose to use Moran coefficient to highlight the comparison (Fig. 3). The choice of Moran coefficient is based on the observation that the three indices used in this study are in good agreement, with Moran coefficient and Cliff-Ord statistic exhibiting great similarity in both pattern of change and numerical values.

From Fig. 3, some differences in the pattern of change in spatial autocorrelation with scale are appreciable. There is a noticeable contrast in the amplitude of decrease in the degree of autocorrelation from the smallest spatial unit (1 x 1 BSU) to the largest areal aggregate (20 x 20 BSUs) for the two data sets, with the maximum decrease of 0.3071 for elevation and a minimum of 0.2003 for biomass. In addition, the rate of decrease (*i.e.*, the steepness of each curve) is different for these data sets. For instance, the degree of spatial autocorrelation for biomass data drops appreciably more slowly than for elevation. Also, the biomass data set shows a faster changing pace over the larger spatial scales (from 10 x 10 BSU to 20 x 20 BSU areal aggregates) than smaller ones (from 1 x 1 BSU to 10 x 10 BSU aggregates), which is in contrast with elevation (Table 3).

Why does Moran coefficient show different scale effects for different types of landscape data sets? One way to explore this question is to examine the formulation of the autocorrelation index. The

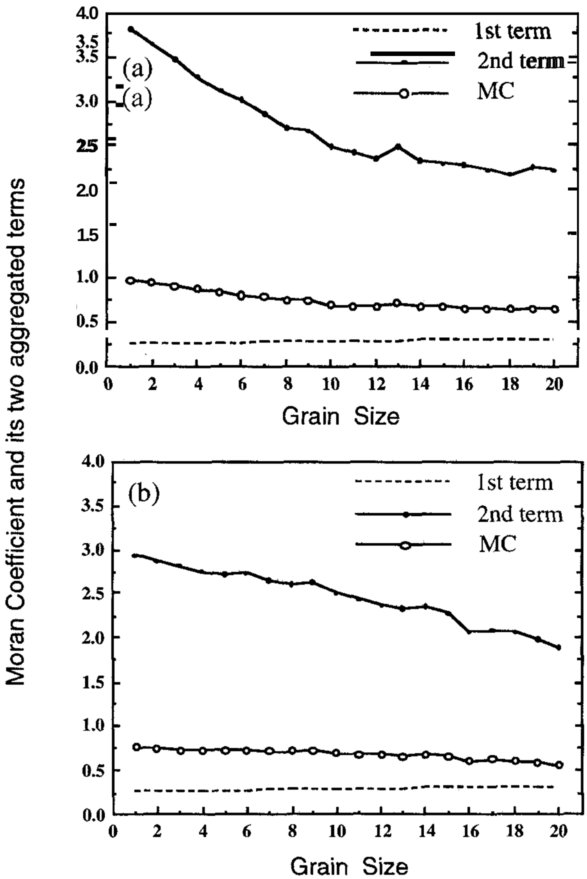


Fig. 4. Effect of changing spatial scale on Moran Coefficient and its two aggregated terms: (a) elevation, and (b) biomass.

formula used to calculare Moran coefficient may be decomposed into four terms: n, $\sum_{i=1}^{i=n} \sum_{j=1}^{i=n} c_{ij}$, $\sum_{i=1}^{i=n} \sum_{j=1}^{j=n} c_{ij}(x_i - \bar{x})(x_j - \bar{x})$, and $\sum_{i=1}^{i=n} (x_i - \bar{x})^2$ (see Eq. 3). It does not seem to make any sense to analyze scale effects using each term separately. However, when we regroup them into two terms, $n / \sum_{i=1}^{i=n} \sum_{j=1}^{j=n} c_{ij}$ and $\sum_{i=1}^{i=n} \sum_{j=1}^{j=n} c_{ij} (x_i - \bar{x})(x_j - \bar{x}) / \sum_{i=1}^{i=n} (x_i - \bar{x})^2$, we are able to gain insights into the question being addressed here. With increasing grain size, the first term exhibits a nearly linear increase, and the second term decreases which essentially resembles the behavior of Moran coefficient as a whole (Fig. 4a–b). Apparently, the decreasingtrend of the second term overwhelmes the increasing trend of the first term and, therefore, the overall pattern of change in spatial autocorrelation is primarily determined by that of the first term. **A** similar dissection of the formulas for Cliff-Ord statistic and Geary ratio can also be done, and the outcome is expected to be similar. The first term in the Moran coefficient formula is affected only by spatial aggregation or partitioning of the original data set, while the second term is influenced by both the manipulation of grain size and the numerical value of each grid cell. Therefore, the first term has the same response to all the data types of the same partitioning, whereas the second term presents different responses, for different landscape data sets due to their numerical differences.

Discussion and conclusions

It is common in landscape ecology to represent spatial data with a regularly divided rectangular lattice that is composed of a large number of equal-sized grid cells. The dimension of the grid cell determines the spatial resolution or grain size of the data set. Such geographically referenced data sets of different spatial resolutions are often used and spatial aggregation is frequently needed in landscape ecological studies. For instance, to assess and monitor the change in biomass in a region, one may use SPOT, Thematic Mapper, MSS, or AVHRR satellite data, each of which has a different spatial resolution (16 X **16** meters for SPOT, **30** X **30** meters for TM, **180** X 180 meters for MSS, and 1 X 1 kilometers for AVHRR). To advance our understanding of spatial processes in landscape ecology, therefore, it is critically important and absolutely imperative to first understand how changing spatial scale (*e.g.*, grain size) affects the results of spatial analysis of landscape patterns. Our study on spatial autocorrelation coefficients sheds some light on this issue.

Our study shows that both data sets (elevation and biomass) of Peninsula Malaysia are positively spatially autocorrelated across a range of scales (from 2.25 X 2.25 km to 45 X 45 km). From the results discussed earlier, it is clear that changing spatial scale significantly affects the values of all three autocorrelation indices. Therefore, spatial analysis of landscape pattern using these indices at single scales, in general, may provide little useful, or even misleading information. Specifically, as the grain size increases, the values of Moran coefficient and Cliff-Ord statistic decrease, while Geary ratio increases. In other words, the degreee of spatial autocorrelation as measured by these three indices, in general, decreases with increasing spatial scale. This result is not readily intuitive. It appears that for certain types of landscape data (*e.g.*, elevation), there exists a spatial threshold beyond which scale effects are no longer obvious. Yet, for other types of landscape data (*e.g.*, biomass) such a threshold does not seem to occur or, if it does, it would be on a much larger spatial scale that is beyond the range limit considered in our study. Although some geographical studies suggested that these three indices could behave differently (*e.g.*, Cliff and Ord 1973, 1981), we found no appreciable difference among them with regularly gridded data sets used in this study.

Given the scale effects, the results of all spatial analysis should be presented with explicit specification of the scale on which the study is conducted. Whenever feasible, an examination of scale effects on the analytical results across a range of scales that are relevant to the landscape pattern under investigation is most desirable. In the case of spatial autocorrelation analysis, the three indices do not seem to differentiate significantly from each other in terms of the ability to detect the scale effects according to our study. Yet, we concur with other researchers that multiple methods should be used wherever possible for the sake of comparison and verification (Turner *et al.* 1989; Cullinan and Thomas 1992). Now that landscape patterns and methods to analyze them are both scale dependent, an important task for landscape ecologists today is to develop not only techniques to detect characteristic spatial domains (Wiens and Milne 1989), but also the ways to scale up and down pattern and process in various landscapes (Turner, Dale and Gardner 1989; Constanza and Maxwell 1994; Wu and Levin 1994).

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