Scale variance analysis coupled with Moran's I scalogram to identify hierarchy and characteristic scale

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Available online: 06 Sep 2011
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(Received 8 February 2010; final version received 7 October 2010)

Scale variance is highly sensitive to multi-scale patterns of variables, which is advantageous in identifying spatial hierarchy and characteristic scale(s). However, the significance of peak(s) in scale variance cannot be statistically tested, and different spatial patterns may be obtained when different zoning systems are used to calculate scale variance. To address these two problems, this study compared the scale levels with peaks in scale variance and the scale levels at which there were breaks in the nature of spatial autocorrelation as identified by shifts in Moran’s I scalogram. The estimates for three simulated landscapes showed that accordance between scale levels identified employing the two methods can be used to evaluate the significance of peaks in scale variance and choose a more reasonable zoning system. The approach of scale variance analysis coupled with Moran’s I scalogram was also applied to the Xilin River Basin of Inner Mongolia, China. The most vital characteristic scale (64 × 32 km) identified for the growing-season net ecosystem productivity (NEP) of the basin was validated by other spatial pattern analysis methods such as semi-variogram, Moran’s I correlogram, and wavelet variance analyses, and the directionality of the chosen zoning systems was found to be similar to the orientation of actual dominant vegetation type patches. The results demonstrate that Moran’s I scalogram can be used to improve the interpretation of the results of scale variance analysis and increase the reliability of scale variance analysis for landscapes having a repetitive patch pattern or gradient variation and that the proposed approach is suitable for identifying the hierarchy and the characteristic scales of patterns or processes. In summary, this study used a simple approach to solve two problems in scale variance analysis, thereby improving the methodology and enhancing the theoretical basis of multi-scale analysis.

Keywords: zoning and scaling system; scale break; multi-scale analysis; repetitive patch pattern; spatial gradient variation

1. Introduction

With few exceptions, ecological systems have hierarchy (Allen and Star 1982, O’Neill et al. 1986, Wu 1999). The hierarchy of an ecologically complicated system needs to be clearly identified as it is important in the exploration of spatial patterns and ecological processes at distinct hierarchical levels and their relationships among hierarchical levels and the translation of information across scales (upscale or downscale). In addition, the identification of hierarchy would greatly simplify studies of complex systems.

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Scale variance analysis, developed by Moellering and Tobler (1972), is one of the few methods used to identify spatial hierarchy in ecology and geography. In general, variance (including scale variance) gradually decreases with increasing analysis scale (Dungan et al. 2002). However, variance may suddenly increase at a certain scale level and then decrease again, having an overall decreasing trend and local peak(s). A peak in the variance may imply that there is high variability of spatial heterogeneity at the corresponding scale level, which is indicative of the average size of dominant clusters or the range of the influence of the main ecological process (i.e., characteristic scale) and hierarchy in the landscape. The magnitude of the peak indicates the relative contribution of the pattern or process at that particular scale level to the total variability of the whole system. Therefore, scale variance analysis can be used to detect the hierarchical level or spatial scale at which studies should be targeted (Moellering and Tobler 1972, Wu et al. 2000, Zhang 2006, Wu 2007).

Scale variance analysis has been used in remote sensing (e.g., Townshend and Justice 1988, 1990, Justice et al. 1991, Barnsley et al. 1997), but it has seldom been applied in ecology (Wu 2007). In one of a few ecological studies, Wu et al. (1994) used the scale variance method to analyze the multi-scale and hierarchical spatial pattern of a Canadian conifer landscape and detected patchiness at two scales.

The greatest merit of scale variance analysis is its sensitivity to changes in spatial patterns at multiple scales. Thus, this method is especially suitable for variables with inconspicuous multi-scale patterns. Some common methods (such as simple variance and semi-variance analyses) may fail to detect multi-scale patterns where scale variance analysis can. Studies of simulated landscapes with neatly organized nested patch hierarchies have shown that results obtained using the simple variance method may be similar to those obtained from scale variance analysis in detecting multi-scale patterns; however, the results are not as clear as those obtained from scale variance analysis (for instance, Wu et al. 2000, Figure 3). For simulated landscapes with less neatly organized nested patch hierarchies and real landscapes, however, results obtained using the simple variance method may be unreliable, and sometimes obvious hierarchical levels are not detected (for instance, Wu et al. 1994, 2000, Figure 4). For simulated landscapes, semi-variance analysis does not seem to be able to clearly identify the hierarchical levels that apparently exist in the landscapes (Wu et al. 2000). A graph of spatial autocorrelation against scale level (scalogram) may indicate a multi-scale structure; however, sometimes it is not as easy to interpret as scale variance analysis. In addition, scale variance analysis is much simpler to compute and explain than complicated computational methods, such as spectral analysis and wavelet analysis, while being no less accurate or effective (Townshend and Justice 1988, 1990, Wu 2007).

However, scale variance analysis also has limitations. For example, the decomposition of variance is based on averages. For regularly (evenly) spaced data in grid cells, the nested sampling method, with gradually aggregated spatial grains generally in $2^n$ or $2^{2n}$ (where $n$ is 0 or any positive integer), potentially misses the scale level at which a break may occur. For example, variability at scale levels (grain sizes) near $32 \times 32$ and $32 \times 64$ cells can be detected, but variability between these grain sizes cannot be detected because they were not sampled. In addition, scale variance analysis may produce ambiguous results for two main reasons: first, scale variance analysis cannot test the statistical significance of a peak, making it difficult to determine whether an inconspicuous peak implies a real characteristic scale; second, different zoning definitions for the same size of aggregated units lead to differences in identified spatial patterns for the same landscape. The chosen zoning system affects the way in which the ecological system is perceived. However, it is not known which zoning system is more reasonable to use. These two problems have seriously limited the method being used widely.
A break in Moran’s I spatial autocorrelation coefficient can be statistically tested, in contrast to other common spatial pattern analysis methods such as simple variance, semivariance, and wavelet variance analyses. A change among statistically significant positive, zero, and negative values of Moran’s I indicates a change in the nature of spatial autocorrelation as a result of the variation in spatial heterogeneity, which may imply a new hierarchy (Fortin and Dale 2005). This study attempts to use Moran’s I scalogram to solve the problems of identifying a significant peak and choosing a reasonable zoning system to improve the suitability and reliability of scale variance analysis.

In this study, three landscapes exhibiting more and less neatly organized nested patch hierarchies (i.e., a repetitive patch pattern) were artificially constructed as simulated landscapes, and the growing-season net ecosystem productivity (NEP) over the entire Xilin River Basin of Inner Mongolia, China (as a real landscape), which has a gradient variation, was modeled. For each landscape, scale variance analysis was conducted to identify possible characteristic scales, Moran’s I scalogram was developed to test the significance of peaks in scale variance, and the most reasonable zoning system(s) was chosen by comparing the scale breaks identified employing the two methods. For the Xilin River Basin, the results of scale variance analysis coupled with Moran’s I scalogram were compared with the results of other spatial pattern analysis methods such as semi-variogram, Moran’s I correlogram, and wavelet variance analyses to verify the suitability of the proposed approach in identifying hierarchy and the characteristic scale. This study is expected to provide new insights into the science of scale.

2. Methods

2.1. Generation of simulated landscapes

Three simple simulated landscapes were generated to illustrate how scale variance works and changes with varying spatial patterns. Simulated landscape 1 (SL1) comprised $32 \times 32$ cells, including 7 patch types represented by 7 integers. SL1 had obvious hierarchy with distinct patch patterns at $1 \times 1$, $8 \times 8$, and $16 \times 16$ scale levels (Figure 1a).

Simulated landscape 2 (SL2) was based on SL1. It also comprised $32 \times 32$ cells, but nearly one-fifth of cells were replaced by an additional patch type, forming clusters of $4 \times 8$ cells. The three similar hierarchical levels could still be identified through visual inspection, although the spatial pattern was not as clear as in SL1 (Figure 1b). The $4 \times 8$ cell clusters were not dominant in SL2, and thus it was assumed that the $4 \times 8$ scale level would not be identified as one of hierarchical levels.

2.2. Scale variance analysis

Scale variance analysis was conducted for each landscape to identify possible characteristic scales. Moran’s I scalogram was developed to test the significance of peaks in scale variance, and the most reasonable zoning system(s) was chosen by comparing the scale breaks identified employing the two methods. For the Xilin River Basin, the results of scale variance analysis coupled with Moran’s I scalogram were compared with the results of other spatial pattern analysis methods such as semi-variogram, Moran’s I correlogram, and wavelet variance analyses to verify the suitability of the proposed approach in identifying hierarchy and the characteristic scale. This study is expected to provide new insights into the science of scale.
Simulated landscape 3 (SL3) was also based on SL1, but more than one-third of cells were replaced by an additional patch type, forming twice as many $4 \times 8$ cell clusters as there were in SL2 (Figure 1c). Because of the dominance of $4 \times 8$ cell clusters, it was assumed that the $4 \times 8$ scale level would be identified as one of hierarchical levels in SL3. The sensitivity of scale variance to the change in spatial patterns was investigated by comparing the results for SL2 and SL3. In addition, the $1 \times 1$ hierarchical level in SL3 was obvious as in SL1 and SL2, but there was no $16 \times 16$ hierarchical level.

2.2. Real landscape description

The real landscape is situated in the Xilin River Basin of Inner Mongolia, China ($43^\circ26'-44^\circ39'N$ and $115^\circ32'-117^\circ12'E$), with an area of 11,024 km$^2$. The zonal vegetation is typical steppe, mainly composed of *Leymus chinensis* + grass + forbs steppe (*L. chinensis* steppe) and *Stipa grandis* + bunchgrass steppe (*S. grandis* steppe). Largely degraded steppe is dominated by *S. krylovii*, *Artemisia frigida*, and shrub (Jiang 1988, Li et al. 1988, Chen and Wang 2000). A digitalized vegetation and land cover type map with spatial resolution $1 \times 1$ km was obtained from the Chinese Ecosystem Research Network. The initial 62 plant association types were combined into 17 current vegetation and land cover types using ArcGIS software (Figure 2).

The basin belongs to a continental mid-temperate zone. The average annual air temperature is $0.2^\circ C$, and the annual precipitation is 350 mm. Altitude, climate conditions, soil types, and vegetation composition and distribution have horizontal gradient variations from upriver to downriver.
in the southeast to downriver in the northwest (Jiang 1985, Li et al. 1988, Wang and Cai 1988, Bai et al. 2000). The southeastern area has a climate similar to the semi-humid forest-steppe climate of the western piedmont of the southern Daxinganling Mountains. This area is colder and more humid than the northwestern area, having annual precipitation of about 400 mm on average and exceeding 500 mm in rainy years. It is dominated by Chernozems and dark Kastanozems soil types. The northwestern area has a semiarid steppe climate, warm and dry with annual precipitation of about 250 mm on average and less than 200 mm in dry years. The area is dominated by typical and light Kastanozems soil types. Precipitation is the most critical factor influencing the distribution of plant productivity and carbon sequestration across the Xilin River Basin (Li et al. 1988, Bai et al. 2000). Influenced by the southeast–northwest gradient variation in precipitation, plant productivity also differs along this gradient.

2.3. Modeled growing-season net ecosystem productivity

Growing-season NEP was modeled employing the Grassland Landscape Productivity Model (GLPM). The GLPM estimates carbon and water fluxes for each cell over the entire study region. The GLPM was developed on the basis of the Ecosystem Productivity Process Model for Landscape (Zhang et al. 2003) with major references to the Boreal Ecosystem Productivity Simulator (Liu et al. 1997, 1999), Forest-BGC (Running and Coughlan 1988), and BIOME-BGC (Running and Hunt 1993). The GLPM consists of submodels for the energy transfer, physiological regulation, water cycle, and carbon cycle. NEP is one of the most important model outputs (Figure 3). Zhang et al. (2009) described the GLPM in detail and validated and analyzed the modeled carbon fluxes over the Xilin River Basin and the area further west.

Figure 3. Spatial pattern of the growing-season net ecosystem productivity (kgC m\(^{-2}\) yr\(^{-1}\)) in the Xilin River Basin of Inner Mongolia, China.
2.4. Improved scale variance analysis

2.4.1. Scale variance analysis

Scale variance analysis can be based on raster data commonly used in geographic information systems for spatial pattern analysis. After rasterizing the entire study area into a grid of cells, spatial data are systematically reconstructed several times so that a nested data hierarchy is produced. In this study, the finest grain size (scale level) was a 1 (the number of row, NR) \times 1 (the number of column, NC) cell. The broader grain sizes progressively increased in integral powers of 2 (i.e., \(2^n (n = 1, 2, 3, \ldots)\); e.g., \(1 \times 2 (or 2 \times 1), 2 \times 2, 2 \times 4( or 4 \times 2)\) cells) to form different aggregated units representing a nested hierarchy of grain sizes. The value for each aggregated unit was the average of all its constituent 1 \times 1 cells, and cells with no data were not counted. Four zoning and scaling systems (ZSSs) were used to aggregate cells. The zoning system is such that aggregated units may have different spatial configurations even if they are of the same size; for instance, zoning with 2 \times 4 and 4 \times 2 cells. In the cases of the first and second ZSSs (ZSS1 and ZSS2), there were less differences between the number of rows (NRs) and the number of columns (NCs) for the same size of aggregated units; however, for all scale-level scenarios in ZSS1, the NRs were not greater than the NCs, and on the contrary, for all scale-level scenarios in ZSS2, the NRs were not less than the NCs. In the cases of the third and fourth ZSSs (ZSS3 and ZSS4), there might be greater differences between the NRs and NCs for the same size of aggregated units; however, for all scale-level scenarios in ZSS3, the NRs were not greater than the NCs, and on the contrary, for all scale-level scenarios in ZSS4, the NRs were not less than the NCs (Table 1). These combinations of zone and scale level provided cluster orientations and sizes that were most likely.

The variance for the entire system is gradually decomposed to obtain scale variance at each scale level. The statistical model is

\[
X_{ijk...z} = \mu + a_i + b_{ij} + \gamma_{ijk} + \cdots + \omega_{ijk...z}
\]

where \(X_{ijk...z}\) is the value of a spatial unit at the finest grain size, \(\mu\) is the grand mean over the entire data set based on the finest grain size, the other items represent the effects of respective levels (such as \(a, b, \gamma, \) and \(\omega\) levels), and \(\gamma\) represents the effect of the highest level. Moellering and Tobler (1972) deduced equations based on the above model to compute the total sum of squares and partitioned sums of squares (SS) at each scale level. Dividing SS by the respective standardized degree of freedom gives the scale variance at the corresponding scale level (Moellering and Tobler 1972, Wu et al. 2000, Wu 2007).

For each ZSS, a computer program was developed to calculate SS and scale variance at all scale levels. A scalogram for each ZSS, which plots values of the logarithm of SS against scale level, was created to identify the scale level(s) at which peak(s) in scale variance and further spatial hierarchy occurred.

2.4.2. Scale variance analysis coupled with Moran’s I scalogram

The same ZSSs used in the previously described scale variance analysis were again used here. For each scale-level scenario in each ZSS, only Moran’s I with minimum lag distance (equal to the grain length of an aggregated unit) was calculated using RookCase software v0.96 (Sawada 1999). Moran’s I scalogram was plotted against grain size (scale level) for each ZSS.
Table 1. Zoning and scaling systems for calculating scale variance and Moran’s $I$.

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Moran’s $I$ coefficient was transformed into $Z(I)$ on the basis of a normal distribution:

$$Z(I) = \frac{I - E(I)}{\sqrt{\text{Var}(I)}}$$

The significance of each Moran’s $I$ coefficient was tested by comparing $Z(I)$ with the $Z'$ value from a standard normal distribution $N(0,1)$ at probability level 0.05. $Z(I) > Z'$ or $Z(I) < -Z'$ indicates statistically significant positive or negative spatial autocorrelation, respectively; $-Z' < Z(I) < Z'$ indicates statistically non-significant spatial autocorrelation or a random pattern. A statistically significant variation in the spatial autocorrelation at a particular scale level determined from Moran’s $I$ scalogram (e.g., from significant negative to positive or non-significant autocorrelation, or from non-significant to significant negative or positive autocorrelation, or from significant positive to non-significant autocorrelation) indicates a possible pattern break at that particular scale level, which may imply the formation of a new system and the occurrence of a new process (Legendre and Legendre 1998, Fortin and Dale 2005).

It was assumed that if the scale level corresponding to the peak in scale variance is the same as the scale level at which the break in Moran’s $I$ scalogram occurs, then the significance of the peak in scale variance at this scale level could be verified. However, for a ZSS, only when all the scale levels with peaks in scale variance are the same as those having breaks in Moran’s $I$ scalogram is the corresponding zoning strategy believed to be reasonable, and these scale levels are indeed the characteristic scales for the hierarchical pattern or process.

### 2.5. Other spatial pattern analyses

#### 2.5.1. Semi-variance analysis

Global spatial statistics such as those used in semi-variance analysis are usually based on the assumption that the process being studied is stationary. In other words, the parameters of the process, such as mean and variance or covariance, should be the same in all parts of the study area and in all directions; that is, there is no ‘true gradient’ in the process (Fortin and Dale 2005). However, the striking gradient of decreasing precipitation and thus ecosystem productivity from the southeast to northwest in the Xilin River Basin violates this intrinsic assumption. To satisfy this assumption, semi-variance analysis can only be applied to the spatial extent in which precipitation and ecosystem productivity were relatively constant. The spatial range in which precipitation has significant positive autocorrelation (i.e., the characteristic scale of precipitation) could be to this extent.

The sampling pairs at different lag distances were selected omnidirectionally. The lag distance had a minimum of 1 km and progressively increased by 1 km until reaching 75 km, nearly half the extent of the entire basin. This tentative extent was larger than the characteristic scale of precipitation with gradient variation (54–56 km) identified by the trend of Moran’s $I$ correlogram, which varied from significant positive values at shorter lag distances to negative ones at larger lag distances (according to Fortin and Dale, 2005).

The semi-variance value at each lag distance was calculated and semi-variogram produced. The lag distance at which the semi-variogram leveled off is indicative of the threshold range of spatial autocorrelation. At this range, there is a transition from a pattern with strong positive autocorrelation to a random pattern or a pattern with weaker autocorrelation or without autocorrelation, implying a characteristic scale.
2.5.2. Spatial autocorrelation analysis

The lag distance had a minimum of 1 km and progressively increased by 1 km until reaching 75 km. Value of Moran’s $I$ for each lag distance class was calculated using RookCase software v0.96 (Sawada 1999).

The progressive (sequential) Bonferroni correction was used to test the significance of Moran’s $I$ owing to the lack of independence in the NEP data. The Bonferroni-corrected probability level $a' = \frac{a}{d}$ was obtained by dividing the probability level $a$ (usually 0.05) by the number of lag distance classes $d$ (i.e., 1, 2, 3, . . ., 75) separately (Legendre and Legendre 1998; Fortin et al. 2002; Fortin and Dale 2005). Consequently, $a' = \frac{0.05}{1} = 0.05$ ($d = 1$), $a' = \frac{0.05}{2} = 0.0025$ ($d = 2$), and so on up to $a' = \frac{0.05}{75} = 0.000667$ ($d = 75$). Thus, spatial autocorrelation is not evaluated by uniform measurement, and the requirement for significance testing is higher for sample pairs with larger lag distances.

The normal $Z$ value for each distance class can be calculated and compared with the $Z'$ value from the standard normal distribution $N(0,1)$ at the corresponding progressive Bonferroni-corrected level. $Z > Z'$ or $Z < -Z'$ indicates significant positive or negative spatial autocorrelation, respectively, and $-Z' < Z < Z'$ indicates insignificant spatial autocorrelation.

Moran’s $I$ correlogram is obtained by plotting Moran’s $I$ against the lag distance class. If Moran’s $I$ correlogram indicates significant positive autocorrelation values at shorter distances through zero to significant negative values at larger distances, then the variable changes along the spatial gradient. A non-autocorrelation or random pattern is detected at the critical distance at which Moran’s $I$ reaches or crosses the expected value. The correlogram may also present single or multiple repetitive variations in patchiness, with successive values of Moran’s $I$ being positive, zero, negative, zero, positive, zero, negative, and so on. A single variation implies a large patch, and multiple repetitive variations imply a series of repeating patches. The characteristic scale corresponds to the critical lag distance at which Moran’s $I$ begins to shift from a positive to a negative value (Fortin and Dale 2005).

2.5.3. Wavelet variance analysis

Representative transects with directions corresponding to the southeast–northwest gradient of altitude, climate condition, soil, and vegetation type in the Xilin River Basin were selected. The first transect, D, was along the southeast–northwest diagonal line of the rectangular grid framing the basin. The 2nd to 40th transects were parallel to transect D at intervals of one cell. These 40 transects in the middle of the southeast–northwest gradient covered more than one-third of the entire basin.

The one-dimensional continuous wavelet module of the Matlab 7.0 wavelet toolbox was used to calculate wavelet transforms. For a single transect, only wavelet transforms ranging between scale levels of 1 and 32 km could be derived because of the limited length of the single transect (around 100 km). To obtain the wavelet transform and wavelet variance at broader scale levels, all 40 transects were combined into one transect 3980 km in length. Although the combined transect was long enough to enable the calculation of a wavelet transform at a much broader scale than 100 km, the maximum analysis scale could not be larger than the length of a single transect because the identified characteristic scale was based on a single transect.

The selected wavelet functions were db1 (the same as the Haar wavelet), db6, and db10 within the Daubechies family of wavelets, bior2.8, bior3.5, and bior6.8 within the biorthogonal family of wavelets, sym3 and sym8 within the Symlets family of wavelets, and Morlet,
Meyer, and Mexican hat wavelets. These wavelet functions with different forms and amplitudes give different values of the wavelet transform.

The wavelet variance at each scale level was calculated on the basis of wavelet transforms, and a wavelet variance scalogram was constructed for each wavelet function. The peak in wavelet variance can be used to determine the characteristic scale at which the pattern changes strikingly, and the height of the peak may indicate the relative contribution of the pattern at this scale to the overall pattern (Bradshaw and Spies 1992, Dale and Mah 1998, Zhang 2006).

3. Results

3.1. Simulated landscapes

3.1.1. Simulated landscape 1

For SL1, the scale variance was the same when ZSS1 and ZSS2 or ZSS3 and ZSS4 were used (Figures 4a and b). For all four ZSSs, Moran’s $I$ repeatedly had statistically significant negative or positive values. In ZSS1 and ZSS2, the three peaks in scale variance were in complete accordance with not only the three breaks in Moran’s $I$ scalogram at the $1 \times 1$ (varying from significant negative to positive autocorrelation) and $8 \times 8$ and $16 \times 16$ (both varying from non-significant to significant negative autocorrelation) scale levels (Figure 4a) but also the three set hierarchical levels for SL1 (Figure 1a). Analyses verified these three peaks in scale variance and that the corresponding three scale levels were characteristic scales.

In ZSS3 and ZSS4, the three peaks in scale variance occurred at the $1 \times 1$, $4 \times 8$, and $8 \times 16$ scale levels, but the peak at the $8 \times 16$ scale level failed to reach statistical significance according to Moran’s $I$ scalogram (Figure 4b). In addition, the $4 \times 8$ and $8 \times 16$ scale levels were not the same as the hierarchical levels set for SL1.

In summary, for SL1, ZSS1, and ZSS2 were more reliable than ZSS3 and ZSS4 in identifying hierarchy and characteristic scales.

3.1.2. Simulated landscape 2

As for SL1, when ZSS1 was used in SL2, the three peaks in scale variance at the $1 \times 1$, $8 \times 8$, and $16 \times 16$ scale levels were in complete accordance with both the three breaks in

![Figure 4](http://example.com/figure4.png)  
Figure 4. Scalograms of scale variance and Moran’s $I$ obtained using four zoning and scaling systems for simulated landscape 1 in Figure 1. The larger open diamonds indicate the peaks in scale variance, and the larger open squares indicate the statistically significant variations in Moran’s $I$ among positive, zero, and negative values. The zoning and scaling systems are presented in Table 1.
Moran’s $I$ scalogram (Figure 5a) and the three hierarchical levels set for SL2 (Figure 1b). Analyses again verified these three peaks in scale variance and that the corresponding three scale levels were characteristic scales.

The peak in scale variance at the $8 \times 8$ scale level in SL2 was not as obvious as that in SL1 because of the presence of $4 \times 8$ cell clusters in SL2 (Figures 4a and 5a). However, there was no true peak in scale variance at the $4 \times 8$ scale level in SL2 in visual inspection. The value at the $4 \times 8$ scale level was actually a little lower than the true peak at the $8 \times 8$ scale level as the new $4 \times 8$ cell clusters did not dominate SL2 in terms of number. Moran’s $I$ scalogram statistically showed that there was no pattern break at the $4 \times 8$ scale level (Figure 5a), indicating the non-significance of scale variance at this scale level. Indeed, scale variance analysis coupled with Moran’s $I$ scalogram evaluated the visual inspection carried out in scale variance analysis alone, which was more or less arbitrary. This demonstrates one of the main purposes of the proposed approach.

In contrast to the results for SL1, the scale levels with peaks in scale variance for SL2 varied more greatly among different ZSSs. The peaks in scale variance were for $1 \times 1$, $4 \times 4$, $8 \times 8$, and $16 \times 16$ scale levels in ZSS2, $1 \times 1$, $4 \times 8$, and $8 \times 16$ scale levels in ZSS3 and $1 \times 1$, $4 \times 2$, $8 \times 4$ and $16 \times 8$ scale levels in ZSS4; however, the peaks at $4 \times 4$, $8 \times 16$, and $4 \times 2$ scale levels failed to reach statistical significance according to Moran’s $I$ scalogram (Figures 5b, c and d).

In summary, for SL2, ZSS1 was more reliable than other ZSSs in identifying hierarchy and characteristic scales.

3.1.3. Simulated landscape 3

In ZSS1, one of the peaks in scale variance indeed occurred at the $4 \times 8$ scale level owing to there being more $4 \times 8$ cell clusters in SL3 than in SL2; however, Moran’s $I$ scalograms still

![Figure 5](image-url)
showed a break at the 8 × 8 scale level as for SL2 with less 4 × 8 cell clusters (Figures 5a and 6a). Therefore, scale variance is more sensitive than Moran’s I to a change in the size and orientation of dominant clusters. There was an inconspicuous peak in scale variance at the 16 × 16 scale level; however, it was not verified by Moran’s I scalograms (Figure 6a) nor the set dominant clusters (Figure 1c).

All the scale levels with peaks in scale variance for SL3 were the same as those for SL2 when ZSS2 and ZSS4 were used; however, the peaks at the 4 × 4, 16 × 16, and 4 × 2 scale levels failed to reach statistical significance according to Moran’s I scalogram (Figures 5b, d, 6b and d).

In ZSS3, the two peaks in scale variance at the 1 × 1 and 4 × 8 scale levels were in complete accordance with the two breaks in Moran’s I scalogram (Figure 6c) and the set size and orientation of the dominant clusters in SL3 (Figure 1c). Analyses verified these two peaks in scale variance and that the two corresponding scale levels were characteristic scales. Furthermore, it was demonstrated that the scale variance at the 4 × 8 scale level increased and became a significant peak when the number of 4 × 8 cell clusters increased and became dominant.

In summary, for SL3, ZSS3 was more reliable than other ZSSs in identifying hierarchy and characteristic scales.

The above three examples of simulated landscape demonstrate that when a ZSS was used, if all the scale levels with peaks in scale variance (S_SV) were the same as the scale levels at which there were breaks in Moran’s I scalogram (S_MI), then they must be the same as the hierarchical levels set for the simulated landscape (S_SL), and the ZSS was accepted; if not all S_SV were the same as S_MI, then not all S_SV were the same as S_SL, and the ZSS was rejected. The results imply that no matter whether S_SL is known, from the accordance between S_SV and S_MI, it is possible to test the significance of peaks in scale variance and choose a suitable zoning system to identify hierarchy and characteristic scales of patterns or processes.

Figure 6. Scalograms of scale variance and Moran’s I obtained using four zoning and scaling systems for simulated landscape 3 in Figure 1. Symbols and their meanings are the same as those in Figure 4.
3.2. Real landscape

There was a peak in the scale variance for the growing-season NEP at the 64 × 32 km scale level when ZSS2 or ZSS4 was used, which was the same scale level at which significantly positive spatial autocorrelation of NEP changed to non-autocorrelation according to Moran’s I scalogram of NEP (Figures 7b and d). Thus, the significance of a peak in scale variance was preliminarily verified using Moran’s I scalogram and the 64 × 32 km scale level might be a characteristic scale when ZSS2 or ZSS4 was used. However, there were greater differences between the two scale breaks identified by scale variance analysis and Moran’s I scalogram when ZSS1 or ZSS3 was used (Figures 7a and c). Thus, the peak in scale variance was not significant when ZSS1 or ZSS3 was used. In summary, for the Xilin River Basin ZSS2 and ZSS4 were more reliable than ZSS1 and ZSS3 in identifying hierarchy and characteristic scales.

The inherent hierarchical levels of an ecological variable in a real landscape are usually unknown, in contrast to the case of a simulated landscape. Consequently, the identification of hierarchy and characteristic scale for the growing-season NEP employing scale variance analysis coupled with Moran’s I scalogram was compared with those employing semi-variogram, Moran’s I correlogram, and wavelet variance analyses.

When the lag distance (h) was 1 km, the growing-season NEP had extremely strong spatial autocorrelation and negligible semi-variance. As h increased from 1 to 6 km, the semi-variance rapidly increased, and correspondingly, autocorrelation rapidly decreased (but was still strong). When h was around 9–13 km, the semi-variogram leveled off and reached the sill, which indicated the threshold range between stronger and weaker autocorrelation. As h increased from 13 to 45 km, the semi-variance slowly increased, and autocorrelation was not strong. When h was larger than 45 km, a different semi-variogram was obtained, that is, NEP seemed to have nested semi-variogram characteristics (Figure 8).

![Image of graphs showing scale variance and Moran’s I for different zoning and scaling systems](image-url)

Figure 7. Scalograms of scale variance and Moran’s I obtained using four zoning and scaling systems for the growing-season net ecosystem productivity in the Xilin River Basin of Inner Mongolia, China. The larger open diamonds indicate the peaks in scale variance, and the larger open squares indicate insignificant spatial autocorrelation in Moran’s I scalogram. The zoning and scaling systems are presented in Table 1.
Thus, three characteristic scales were identified: $6 \times 6$, $9 \times 9$–$13 \times 13$, and $45 \times 45$ km. The breaks at the $6 \times 6$ km and $9 \times 9$–$13 \times 13$ km scale levels indicate shifts in the intensity of autocorrelation from extremely strong to moderately strong and from strong to weak positive autocorrelation, respectively. The break at the $45 \times 45$ km scale level indicates a new hierarchy and a change in the dominant ecological process due to the direct interaction between process and pattern at the same hierarchical level.

Moran’s $I$ of the growing-season NEP continuously decreased as the lag distance increased, varying from significantly positive through zero to negative values, which indicated that NEP varied along a gradient over the entire basin (Fortin and Dale 2005). Spatial autocorrelation was extremely strong, but rapidly decreased with increasing lag distance when $h$ was smaller than the critical scale of 11 km. This was especially true for a 1–6 km lag distance, for which the decrease was most rapid. Spatial autocorrelation gradually decreased as $h$ increased above 11–13 km. There was another critical scale at a lag distance of 49–52 km, where Moran’s $I$ correlogram leveled off around the expected non-autocorrelated value (Figure 9). The two scales of $6 \times 6$ km and $11 \times 11$–$13 \times 13$ km signify breaks in the degree of autocorrelation, and the scale of $49 \times 49$–$52 \times 52$ km signifies a break in the nature of autocorrelation (i.e., from positive to negative autocorrelation).

For most selected wavelet functions, three obvious peaks or inflexion points in the wavelet variance for the growing-season NEP could be detected at the similar finer ($11 \times 11$–$19 \times 19$ km), intermediate ($41 \times 41$–$58 \times 58$ km), and broader ($78 \times 78$–$100 \times 100$ km) scale levels (Figure 10).

In summary, for the growing-season NEP, the above three spatial pattern analysis methods could detect a characteristic scale near $45 \times 45$ km ($2025$ km$^2$), which was very close in terms of size (but not orientation) to the characteristic scale $64 \times 32$ km ($2048$ km$^2$) identified by scale variance analysis coupled with Moran’s $I$ scalogram, except that in this proposed approach, NRs of the spatial grain may differ from NCs because of a zoning effect.

4. Discussion

This study used three simulated landscapes to show that we can both test the significance of peaks in scale variance and choose a reasonable zoning system from the accordance between
the scale levels with peaks in scale variance and the scale levels at which there are breaks in Moran’s $I$ scalogram. The usefulness of the proposed approach was also demonstrated for the growing-season NEP in the Xilin River Basin of Inner Mongolia, China, by comparing results with those obtained using other spatial pattern analysis methods. Thus, it is concluded that Moran’s $I$ scalogram can be used to improve the interpretation of the results of scale variance analysis and increase the reliability of scale variance analysis, and that the approach of scale variance analysis coupled with Moran’s $I$ scalogram is suitable for identifying hierarchy and the characteristic scales of patterns or processes.

For the simulated landscapes with set hierarchical levels, the characteristic scales identified by the proposed approach were in perfect accord with the size and orientation of the set dominant clusters, and thus, they were closely associated with variations in repetitive patches of the landscapes. In the case of the Xilin River Basin, the characteristic scale
identified by the proposed approach is the most crucial for NEP because the variation in NEP at this scale level contributes most to the total spatial variability of NEP over the entire basin. This characteristic scale indicates a spatial gradient variation in NEP, which is mainly controlled by the southeast–northwest gradient of decreasing precipitation in the basin (Jiang 1985, 1988; Li et al. 1988, Bai et al. 2000). Therefore, the inherent break in the spatial pattern or ecological process decides the identified characteristic scale.

Spatial gradient variance and repetitive patch patterns are the two most common forms of spatial heterogeneity. The proposed approach can deal with these two forms, implying the universality of the approach on a theoretical basis. The scalograms of scale variance and Moran’s I and scale breaks greatly differ between the two types of landscape because of their conspicuously different spatial patterns. In the landscapes with gradient variations, a given ecological process usually varies continuously, although not evenly, along the gradient (Wu et al. 2000). Scale variance notably decreases with increasing scale level. As Moran’s I varies from positive through zero to negative values as the scale level increases, the spatial pattern shifts from positive autocorrelation through non-autocorrelation to negative autocorrelation, implying the change in a dominant process influencing spatial pattern. The critical characteristic scale is the scale level at which spatial autocorrelation becomes insignificant and scale variance has a peak. On the other hand, in landscapes with repetitive patches, patterns present sharp and discontinuous variations and clear boundaries among neighboring patches as nested patch hierarchies are more ‘neatly’ organized (Wu et al. 2000). Scale variance again decreases as the scale level increases, but the breaks are much more obvious and sharper than those in landscapes with gradient variations. Moran’s I varies, possibly repeatedly, among positive, zero, and negative values as the scale level increases. The characteristic scales are the scale levels at which Moran’s I coefficients have statistically significant variations and scale variance values have local peaks.

Besides enhancement of the theoretical basis, the proposed approach also improves the methodology of multi-scale analysis. In the case of simulated landscapes, the proposed approach can more easily identify possible scale breaks with increasing scale level, whereas methods employing a semi-variogram or Moran’s I correlogram might not be able to identify obvious scale breaks or be easily interpreted (although they might for some real landscapes). For example, the semi-variogram for SL1 seemed to indicate a scale break at a lag distance of 8 cells, the threshold range of spatial autocorrelation (Figure 11a). However, the semi-variogram could not detect the $1 \times 1$ and $16 \times 16$ hierarchical levels set for SL1 (Figure 11a). In addition, only the $1 \times 1$ characteristic scale in SL1 could be detected.

![Figure 11](image-url)
using Moran’s $I$ correlogram (Figure 11b). It is difficult to clearly explain the confusion of the Moran’s $I$ correlogram in the case of a landscape with a repetitive patch pattern (Fortin and Dale 2005), although it might be easy for a landscape with a gradient pattern (e.g., Figure 9).

Compared with the proposed approach, the use of semi-variograms is more effective in spatial dependence or autocorrelation analysis and spatial interpolation than in multi-scale analysis. Robertson and Gross (1994) assumed that spatial dependence reflects hierarchy from a scale of individual plants, to scales of population, community, regions, or landscapes, and even global ecosystems, and thus, the semi-variogram of an ecological variable increases in steps as the lag distance increases. Their study revealed two hierarchical levels for pH of agricultural soil, and thus, they were able to check this theoretical assumption. However, some studies have suggested that a semi-variogram fails to clearly identify hierarchy in real landscapes. For example, Meisel and Turner (1998) pointed out that although semi-variograms can be used to detect multi-scale patterns on their artificial maps it is unlikely to do so in real landscapes. In this study, after the semi-variance values for NEP increased slowly and even decreased over a long distance, they suddenly increased as $h$ changed from 45 to 54 km and then leveled off and reached another sill (Figure 8). This semi-variogram trend could imply a new hierarchy for NEP at around $45 \times 45$ km according to the assumption proposed by Robertson and Gross (1994). However, the significance of changes in semi-variograms cannot be tested using the method itself, which increases uncertainty in identifying characteristic scales. Scale variance analysis overcomes this shortcoming by coupling with Moran’s $I$ scalogram, with which the significance of changes in scale variance is tested so that hierarchy and characteristic scales can be ascertained.

In conclusion, only Moran’s $I$ analysis has the advantage of testing the significance of pattern variation at possible scale breaks among the four single methods considered. However, not all significant variations in Moran’s $I$ scalogram imply characteristic scales,
and thus, another method that is sensitive to pattern variation such as scale variance analysis is needed to calibrate the results obtained from Moran’s I scalogram. Only after pattern variations are mutually verified are the corresponding characteristic scale(s) and reasonable zoning system(s) determined. In other words, when only a single method is used, whether it be scale variance analysis or Moran’s I scalogram, the conclusions may not be sound.

However, although the proposed approach might identify lower hierarchical levels in simulated landscapes, in a real landscape, it might be sensitive to only the level that signifies a break in the nature of the spatial pattern and the occurrence of a new dominant process, and insensitive to lower levels that signify breaks in the intensity of spatial patterns. However, this requires the investigation of a variety of simulated and real landscapes as there are few examples of the application of scale variance analysis.

In any case, the proposed approach of scale variance analysis coupled with Moran’s I scalogram concurrently performs scale effect, zoning effect, and multi-scale pattern analysis, which is essential to elucidate spatial heterogeneity and further understand complex ecological systems and can provide a vital basis and framework for upscaling or downscaling across scales, the key to the science of scale.

Acknowledgments

This study was supported by the National Natural Science Foundation of China (No. 30870430; No. 30500076) and the National Natural Science Foundation of China for Major International (Regional) Joint Research Project (No. 31061140359). We are grateful to the Chinese Ecosystem Research Network (CERN) for digital vegetation maps, the China Meteorological Administration for meteorological data, and the Inner Mongolia Grassland Ecosystem Research Station of the Chinese Academy of Sciences for field-based ecological and environmental measurements. We appreciate the anonymous peer reviewers, who provided helpful comments and suggestions that significantly improved our analysis and article.

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