Landscape Ecology **13:** 347–362, 1998.

Scale detection in real and artificial landscapes using semivariance analysis

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(Received 4 June 1997; Revised 7 January 1998; Accepted 1 February 1998)

Key words: scale detection, semivariance analysis, semivariogram, spatial heterogeneity, spatial statistics, ungulate foraging, Yellowstone National Park

Abstract

Semivariance analysis is potentially useful to landscape ecologists for detecting scales of variability in spatial data. We used semivariance analysis to compare spatial patterns of winter foraging by large ungulates with those of environmental variables that influence forage availability in northern Yellowstone National Park, Wyoming. In addition, we evaluated (1) the ability of semivariograms to detect known scales of variability in artificial maps with one or more distinct scales of pattern, and (2) the influence of the amount and spatial distribution of absent data on semivariogram results and interpretation. Semivariograms of environmental data sets (aspect, elevation, habitat type, and slope) for the entire northern Yellowstone landscape clearly identified the dominant scale of variability in each map layer, while semivariograms of ungulate foraging data from discontinuous study areas were difficult to interpret. Semivariograms of binary maps composed of a single scale of pattern showed clear and interpretable results: the range accurately reflected the size of the blocks of which the maps were constructed. Semivariograms of multiple scale maps and hierarchical maps exhibited pronounced inflections which could be used to distinguish two or three distinct scales of pattern. To assess the sensitivity of semivariance analysis to absent data, often the product of cloud interference or incomplete data collection, we deliberately masked (deleted) portions of continuous northern Yellowstone map layers, using single scale artificial maps as masks. The sensitivity of semivariance analysis to random deletions from the data was related to both the size of the deleted blocks, and the total proportion of the original data set that was removed. Small blocks could be deleted in very high proportions without degrading the semivariogram results. When the size of deleted blocks was large relative to the size of the map, the corresponding variograms became sensitive to the total proportion of data removed: variograms were difficult or impossible to interpret when the proportion of data deleted was high. Despite success with artificial maps, standard semivariance analysis is unlikely to detect multiple scales of pattern in real ecological data. Semivariance analysis is recommended as an effective technique for quantifying some spatial characteristics of ecological data, and may provide insight into the scales of processes that structure landscapes.

Introduction

Spatial and temporal ecological heterogeneity results from a variety of hierarchically organized structuring forces (Allen and Starr 1982; O'Neill et al. 1986; Holling 1992). At broad scales, geomorphological and climatic factors exert a strong influence on ecological patterns (Delcourt and Delcourt 1988). At intermediate scales, control may be provided by the shape and location of land forms, and the existing distribution patterns of vegetative and animal populations (Swanson et al. 1988). At finer scales, constraints are provided by biotic interactions at the community, population and individual levels (Watt 1947; Danielson 1991; Hansen and Urban 1992). The interaction of these structuring forces across multiple scales is hypothesized to create landscapes that exhibit characteristic patterns of resource distribution. However, it remains difficult to detect multiple scales of variability in ecological data and to relate these scales to the processes that generated the patterns (Carlile et al. 1989; Cullinan and Thomas 1992; Kotliar and Wiens 1990; Levin 1992; Ward and Salz 1994).

One of the most widespread tools for detecting spatial or temporal scales of variability is the semivariogram, originally developed by mining engineers to assess the dominant scale of spatial variability in soil samples (Matheron 1963; David 1977; Rossi et al. 1992). Semivariograms and related measures (e.g., covariogram, correlogram) may be applied to linear or two-dimensional data sets and traditionally have been used for two broad purposes: quantification of the scale of variability exhibited by natural patterns of resource distributions (i.e., soil type, habitat type, biomass, etc.), and identification of the spatial or temporal scale at which a sampled variable exhibits maximum variance. The latter application is common in sampling design (Ball et al. 1993; Istok et al. 1993) to avoid problems in statistical analyses, whereas the former has been used by ecologists seeking enhanced understanding of how patterns of environmental heterogeneity influence ecological processes (Legendre and Fortin 1989; Turner et al. 1991; O'Neill et al. 1991; Bell et al. 1993; Kareiva and Wennergren 1995). The coincidence in the scales of variability of different ecological features, for example plants and soil nutrients (Greig-Smith 1979) or seabirds and their prey (Schneider and Piatt 1986), can indicate the possibility of direct linkages.

Although we selected semivariance analysis for the present study, a growing variety of tools for the analysis of spatial scale must be recognized. Additional methods for the analysis of scale in landscape patterns include lacunarity analysis (Plotnick et al. 1993; Plotnick et al. 1995), spectral analysis (Legendre and Fortin 1989), the paired quadrat technique (Greig-Smith 1983), and a variety of fractal-based methods (Krummel et al. 1987; for a thorough review, see Sugihara and May 1990). An excellent review of the application of these techniques to the analysis of spatial scales is provided in Gardner (1998).

The initial objective of this study was to use semivariogram analysis to compare scales of variability in spatial patterns of winter foraging by large ungulates, and of environmental variables that influence forage availability either directly or by influencing snow accumulation (e.g., vegetation type, slope, aspect, elevation), in northern Yellowstone National Park, Wyoming. Elk (*Cervus elaphus*) and bison *Bison bison*) make foraging choices at a variety of spatial scales, but the environmental parameters that are most important at various scales are not well known. Prior research suggested that elk responded to coarse-grained variation in the landscape during winter (Pearson et al. 1995; Turner et al. 1997). We examined spatial variability of a set of environmental factors to seek congruence in the dominant scale(s) of variability that might identify the scales (sensu Senft et al. 1987) at which elk make foraging choices.

Initial analyses led to fundamental questions concerning application and interpretation of semivariance analysis of landscape data. Identification of major scales of landscape pattern proved to be problematic, and the spatially discontinuous nature of the foraging data appeared to disrupt semivariance results. A subsequent objective of this study thus became an assessment of the effectiveness and limitations of this approach by using neutral landscape models (Gardner et al. 1987; Gardner and O'Neill 1991). Neutral landscape models are computer-generated maps that are neutral to the physical and biotic processes that shape real landscapes, and they provide a basis for statistical tests of observed landscape patterns (With and King 1997). Analysis of neutral landscape models has contributed much to ecologists' understanding of landscape pattern, and our analysis extends their use to detection of spatial scales of variability using semivariance analysis. We evaluated (1) the ability of semivariograms to identify known scales of pattern in artificial maps constructed with one or more distinct scales of pattern, and (2) the influence of the amount and spatial distribution of absent data on semivariogram results and interpretation.

Methods

Semivariance analysis

Semivariance analysis examines the contribution to the total sample variance made by the average variance of all pairs of points that are separated by a specific lag distance. Thus, adjacent objects are compared first, then every other object, then every third, and so on; the separation or lag distance ranges from 1 (adjacency) to a possible maximum of one-half the spatial size of the data set (larger lags eliminate points from the analysis). The standard equation for the semivariogram is:

$$\gamma(\mathbf{h}) = \frac{1}{2N(\mathbf{h})}\sum_{i=1}^{n(\mathbf{h})}(x_i - y_i)^2, \qquad (1)$$

where $\gamma(\mathbf{h})$ = semivariance at lag distance h; $N(\mathbf{h})$ = number of pairs separated by distance h; x_i = value at the start, or tail, of the pair; y_i = value at the end, or head, of the pair.

Semivariograms, which plot semivariance against lag distance, typically increase from a theoretical Y-intercept of zero (the 'nugget'), and level off at the maximum semivariance (the 'sill'), which occurs at and beyond a particular lag distance (the 'range'). The range identifies the distance beyond which pairs of objects no longer exhibit spatial autocorrelation. Those objects separated by distances less than the range exhibit some degree of correlation. Tobler (1970) summarizes this relationship as the first law of geography, which states that nearby objects are more likely to be similar than are widely separated objects. Semivariance analysis assumes the data are both stationary (i.e., variance is due to separation distance alone) and anisotopic (i.e., no directional trends occur in the data), assumptions that are often difficult to meet when using environmental data (Burrough 1986). Furthermore, it is difficult to interpret quantitatively the results of semivariance analysis due to their unknown confidence limits and the complications imposed by nested environmental variables (Lacaze et al. 1994). For our purposes, these limitations did not preclude the qualitative identification of overt peaks or inflections in semivariogram plots which corresponded to the scale of spatial patterns under analysis. Future attempts to quantify the relationships described herein will need to confront these methodological constraints, possibly by turning to correlogram analysis or other techniques.

A continuous curve is normally obtained by fitting a recognized model (e.g., spherical, linear, circular, exponential) to the discrete points of the semivariogram (McBradney and Webster 1986). Range and sill can then be derived from the continuous model. Researchers may choose to examine further either the discrete semivariance data, the continuous mathematical model, or the difference between the two (i.e., the residuals). In the present study we concentrated on the raw semivariance plots, and identified local peaks or valleys that corresponded to the spatial patterns in the analyzed maps. The nugget was assumed to be zero for all artificial maps, while the Yellowstone data sets showed non-zero nuggets due to the grain of the data (100×100 m cells). All semivariance analyses were computed by using the GSLIB package (Deutsch and Journel 1992), and our own UNIX interface scripts.

Covariograms are computed in much the same manner as semivariograms, except that the average covariance between all points separated by a fixed lag distance is plotted; the covariance is therefore a declining function. Correlograms (essentially the covariogram divided by the sample variance) have several statistical advantages over semivariograms, despite the fact that semivariance analysis remains the most commonly used of this family of techniques. Legendre and Fortin (1989) argue convincingly that correlograms should be preferred over semivariograms, for two important reasons. First, the statistical significance of each correlation coefficient in a correlogram can be tested, using the Bonferroni method for multiple comparisons, an analysis that is not possible with semivariance results (Deutsch and Journel 1992). Second, correlograms are standardized by definition (ranging from -1 to $+1$), and permit hypothesis testing through statistical means. A benefit of the standardized nature of correlograms is that multiple data sets, with different means and overall variances, can easily be compared. Methods are available for standardizing semivariograms by their sill variance (Rossi et al. 1992); multiple semivariograms that have been normalized in this way may then be statistically compared, giving them much of the utility of correlograms. For this study, however, we relied primarily on semivariance analysis because it remains one of the techniques most widely available for use by landscape ecologists, it is the most mathematically straighforward of the variogram family, and our study did not require the comparison of multiple variograms.

Yellowstone analysis

Yellowstone National Park (YNP) encompasses 9000 km^2 in the northwest corner of Wyoming and adjacent parts of Montana and Idaho. Our study focused on the northern 20% of the park which is primarily a lower-elevation grassland or sagebrush steppe comprising approximately 75 000 ha. The northern Yellowstone elk and bison migrate seasonally between a high-elevation summer range and this lower-elevation winter range (Craighead et al. 1972; Barmore 1980; Houston 1982). Spatial patterns of winter foraging by elk and bison in northern YNP had been mapped in 15 study areas encompassing a total of 7500 ha (~10%) of the winter range (Pearson et al. 1995) during 1991 and 1992. Individual study areas were several hundred hectares in size. Evidence of foraging activity was mapped (minimum mapping unit was 1 ha) at 2-wk intervals from mid-January through late March during 1991 and 1992, then digitized in the GRASS geographic information system (USA CERL 1991). For this analysis, we used maps of cumulative grazing intensity for each winter (Pearson et al. 1995). In addition to the ungulate foraging data, we used spatial data sets courteously provided by Yellowstone National Park, including habitat type (Despain 1991), slope, aspect, and elevation. The resolution (pixel size) of all map layers used in this analysis was 100 m $\times$ 100 m.

We constructed semivariograms for maps of habitat type, slope, aspect, and elevation, within the boundaries of the northern range. Habitat data were derived from aerial photography and comprised 33 habitat types on the northern range based on vegetation composition and structure (Despain 1991). The sill and range were identified on each variogram, indicating the predominant scale of variability of each variable. The data sets were all spatially continuous (i.e., no missing data). We also applied semivariance analysis to the ungulate foraging maps, in order to identify predominant scale of grazing variability. Because foraging patterns often reflect the quality and distribution of food resources, the spatial variability of grazing intensity may be responsive to the spatial variability of environmental factors which are linked to the quality and distribution of these food sources. Congruence between the variation of an environmental factor, such as aspect, and the variation of grazing data may constitute evidence that this environmental factor exerts a constraining influence on ungulate foraging patterns; such evidence may contribute to the understanding of how ungulates process environmental cues in order to make feeding choices.

Foraging data were not available outside of the 15 viewing areas, so approximately 90% of the landscape was assigned a value of ‘no data’. Semivariance analyses were configured to ignore missing data, a standard approach. Our initial objective was to compare the scales of variability identified by semivariograms of landscape data and foraging data, in order to elucidate the constraining relationships between environmental heterogeneity and ungulate feeding choices. The analytical difficulties described in detail below, however, limited our ability to address this objective.

Detection of known scales of variability

A series of artificial maps containing patterns at distinct scales were created to assess the effectiveness and sensitivities of semivariance analysis. All maps were raster images populated by binary data. Three different map types were evaluated, each constructed using a different technique: checkerboard maps, sprinkle maps, and hierarchical maps. We examined the role of two major variables: the size of the blocks of which the maps were composed, and the total proportion of the map occupied by blocks. Maps were created with both single and multiple scales of pattern. A summary of the properties of each class of artificial maps is presented in Table 1.

The simplest map type was the classical binary ‘checkerboard’ map, created by the TrueBasic (Kemeny and Kurtz 1993) program HierMapMaker, written specifically for this project. The map area (200 $\times$ 200 cells) is initially subdivided into blocks, whose constant size is established by the user. All blocks are initially assigned a value of zero (default habitat type). The probability of filling any block with the alternate habitat type (value $= 1$) is also set by the user. Note that any pair of numbers (other than 0 and 1) could have been used to designate the two habitat types. A random number is generated for each block, and compared to the chosen fill probability; if the random number is greater than the fill probability, the block is changed to the alternate habitat type. Thus, the total proportion of the map that is occupied by the alternate habitat type is approximately (due to the finite number of blocks) equal to the individual fill probability.

Checkerboard maps 200 $\times$ 200 cells in size were constructed using block sizes of 2, 5, 10, 20 and 50 cells. For each block size, maps were made with fill probabilities (or total proportion of map filled) equal to 0.20, 0.40, 0.60 and 0.880. Therefore, a total of 20 different maps were produced, each exhibiting a simple random pattern with a characteristic grain size. A sample checkerboard map is presented in Figure 1a. Maps were stored as text files, and analyzed using GSLIB. Agreement between the range on the semivariogram and the size of the blocks was interpreted as evidence that semivariance analysis could reliably detect the pattern in the artificial map. Although variable numbers of replicate maps were often analyzed to confirm the existence of an obvious semivariance response to pattern scale, no analysis was performed to compare the behavior of these replicate semivariograms; thus, for most analyses described in this paper, the effective sample size remained $n = 1$.

Multiple scale checkerboard maps were created simply by merging two separate maps together, a fine grain (i.e., small blocks) map and a coarse grain (i.e., larger blocks) map (Figure 1b). The maps were developed to simulate the existence of multiple scales of

Table 1. Summary of the properties of each of the map types analyzed in this study, showing the map extent (size), the pixel resolution (cell size), the size of the data blocks used to populate the artificial binary maps, and the total proportion of the artificial maps that was occupied by alternate habitat (data=1).

Map type	Map extent	Pixel resolution	Block size	Proportion of map occupied
Checkerboard (1 scale)	200 × 200	1 × 1	2, 5, 10, 20, 50	0.2, 0.4, 0.6, 0.8
Random placement	200 × 200	1 × 1	2, 5, 10, 20, 50	0.2, 0.4, 0.6, 0.8
Checkerboard (2 scales)	200 × 200	1 × 1	2, 5, 10, 20, 50	variable
Hierarchical	216 × 216	1 × 1	1, 6, 36	0.25, 0.30, 0.33, 0.42, 0.66
Yellowstone mask	200 × 500	100 × 100 m	10, 20, 100	0.2, 0.4, 0.6, 0.8
Yellowstone map layer	236 × 507	100 × 100 m	not applicable	not applicable

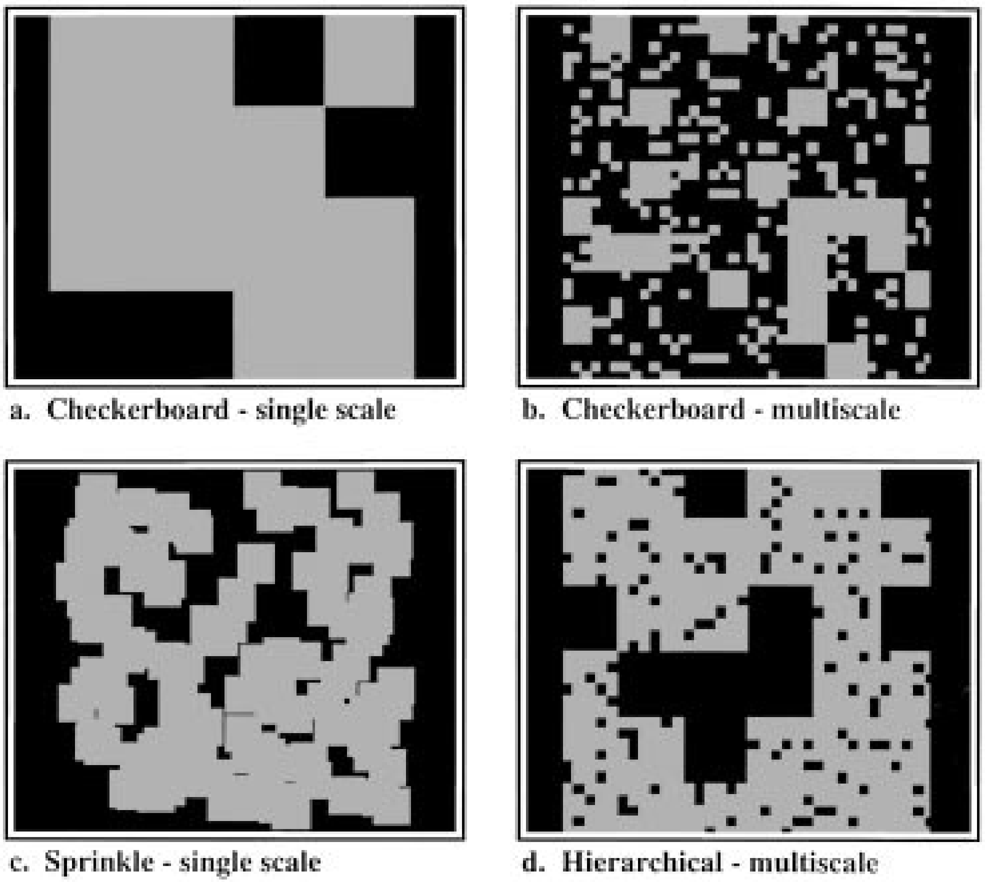

Figure 1. Sample artificial binary maps. (a) Single scale checkerboard map with 50 × 50 cell blocks. (b) Multiple scale checkerboard map with 5 × 5 and 20 × 20 cell blocks. (c) Single scale random placement (sprinkle) map with 20 × 20 cell blocks. (d) Two-level hierarchical map with 6 × 6 and 36 × 36 cell blocks.

pattern on a single landscape. An example is given by ground cover patterns, which are the combination of the pattern of tree patches (i.e., location constrained by soil type), and the pattern of shrubs found outside the tree patches (i.e., location affected by local water availability, interactions with neighboring shrubs). The total proportion of the merged map filled by the alternate habitat type (value = 1) was determined empirically, since block overlaps prevented its direct calculation. These two-scale maps were stored as text files, and analyzed using GSLIB. Appearance of two distinct peaks or inflections on the semivariogram, each with a range equal to one of the block sizes, was interpreted as evidence that semivariance analysis could reliably detect two distinct scales of pattern.

In order to more closely approximate real landscape patterns, a second class of maps was developed. All checkerboard maps have a fixed gridded structure, regardless of whether any individual block is assigned to the default or alternate habitat type. Because of this structure, it is equally likely that semivariance analysis will identify a dominant scale of variability among the default habitat blocks (data = 0) as it is that the analysis will identify a scale of variability related to the alternate habitat blocks (data = 1). In a binary system, this is equivalent to stating that either the 'on' or the 'off' blocks can contribute to the pattern. To circumvent this potential source of confusion, we created 'sprinkle' maps, in which blocks of fixed size were randomly placed on the initial map. Random placement ensures that only the 'on' blocks will have a characteristic size, and will therefore be the only blocks contributing to a spatial pattern operating at that scale, since overlapping 'on' blocks prevent 'off' areas from having a characteristic size.

Sprinkle maps were created to match the specifications of the checkerboard maps. Block sizes of 2, 5, 10, 20 and 50 cells were used; maps with each block size were created with total fill proportions of 0.20, 0.40, 0.60 and 0.80. As noted above, the proportion of the entire map filled with the alternate habitat type was calculated empirically from the final map, since randomly placed (sprinkled) blocks overlapped (Figure 1c). Therefore, the actual number of blocks to be sprinkled on each map, in order to achieve the desired total fill proportion, were derived through trial and error. Sprinkle maps of one and two scales were created, in the same manner as described for checkerboard maps.

In a further attempt to simulate more complex landscape patterns, a third class of hierarchical maps were constructed using RULE (Gardner in press). These multiple scale maps differ from those described above in one critical manner. Rather than produce multiple scales of pattern from simply merging two different maps, these hierarchical maps first create a coarse pattern, then permit the finer pattern to develop within only those areas 'turned on' at the coarser level (Figure 1d). This is akin to the soil-patch-tree hierarchy, in which broad differences in soil type exist, permitting forest patches to occur in only one type. Within a single forest patch, one of two kinds of trees can be found; however, neither tree species occurs in the non-forest patches. At any one point within the forest patch, one tree species or the other may be found: their distribution describes the finest scale pattern in the hierarchy. In this paradigm, the total proportion of the map filled by the alternate habitat type can be calculated directly as the product of the fill probabilities at each hierarchical level.

Maps of two and three hierarchical scales were created and analyzed. The variables of block size (at each hierarchical level), proportion of map filled by blocks of each size, and total proportion of map filled were varied independently. Maps were created with blocks of 1, 6 and 36 cells, and total fill proportions of 0.25, 0.30, 0.33, 0.42 and 0.66. Specifications for many of these maps were taken from Pearson et al. (1996). Semivariograms were created for each map, and were examined for the presence of multiple peaks or inflections, indicating possible detection of the multiple scales of pattern.

Effects of Proportion and Distribution of Absent Data

In order to assess the effects of broad scale deletions on semivariance analysis, we deliberately masked out portions of two northern Yellowstone continuous map layers, and created semivariograms of the resulting images. Substantial areas of absent data commonly occur in landscape ecological studies and can be due to the incomplete collection of data (e.g., our foraging viewing areas), interference by cloud cover or tree crowns which obscure photographic or satellite data, and other varied causes. Masking is a simple GIS function in which a binary map is used as a mask, or deletion template, on a second underlying map. Wherever a zero occurs in the mask layer, data is deleted from the underlying map; where a one occurs, the data is preserved. Thus, holes are punched

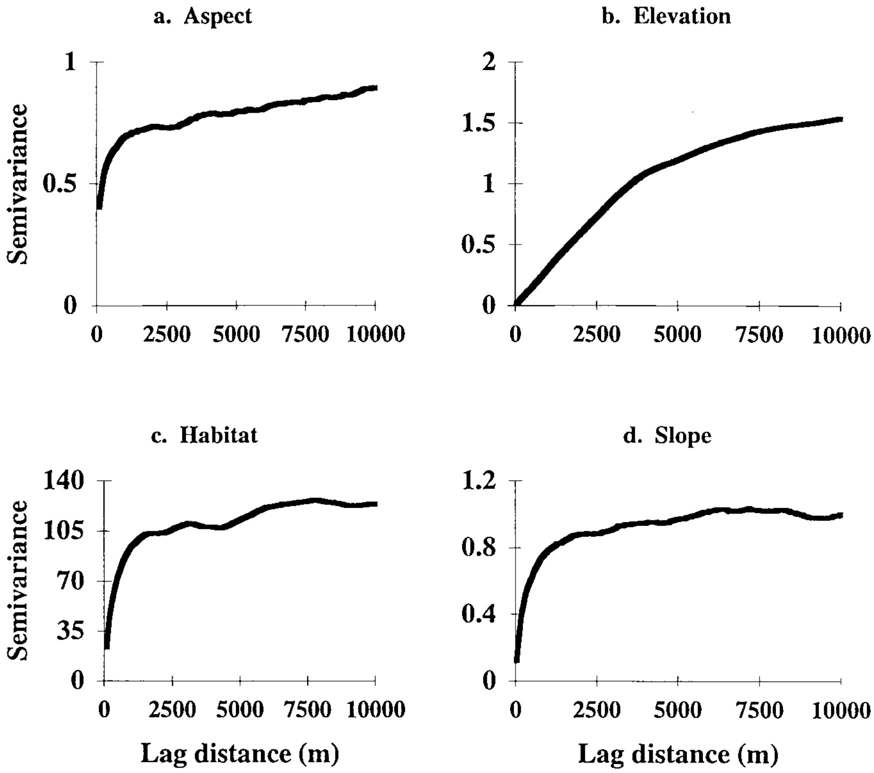

Figure 2. Semivariograms for spatially continuous data layers of (a) aspect, (b) elevation, (c) habitat type, and (d) slope in northern Yellowstone National Park (resolution is 100 × 100 m). The range for each data set was approximately 3000 m, 5000 m, 2000 m and 2000 m, respectively. This and all subsequent variogram figures display a series of overlapping discrete points, not a continuous line derived from fitting a theoretical model (e.g., spherical) to the semivariogram.

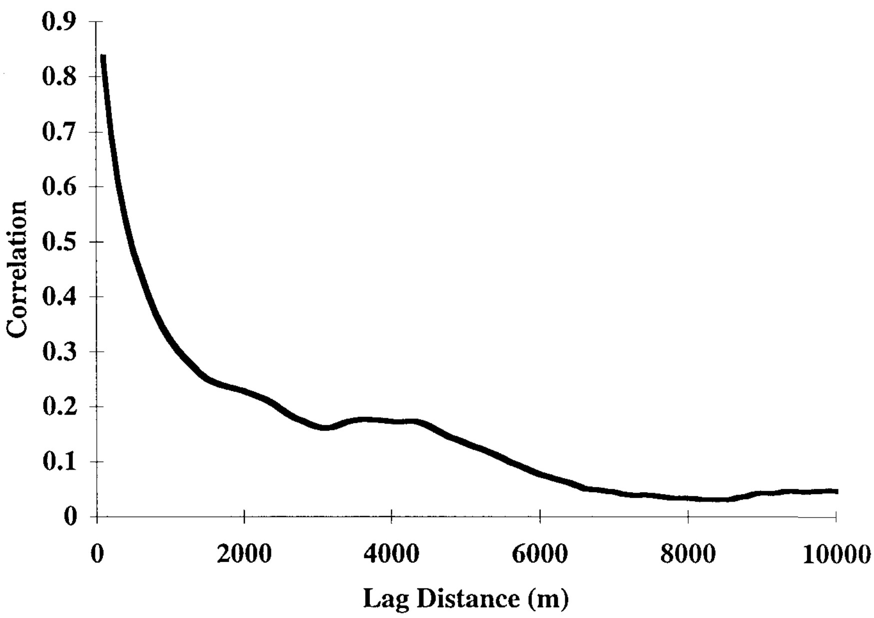

Figure 3. Sample correlogram for the habitat type data later in northern Yellowstone National Park. The shape of the correlogram is nearly identical, though inverted, to the shape of the semivariogram of the same data shown in Figure 2c. The similarity of these two plots underscores the conclusion that correlograms and semivariograms may be used interchangeably for exploratory analyses which do not require the use of statistical tests.

into the data layer according to the patterning of the mask layer. Note that the holepunched areas are classified as having no data, and subsequently are ignored by the semivariance analysis we conducted, a standard approach. This is distinct from the artificial maps discussed above which were considered to have data (either a zero or a one) at all locations.

To examine the effect of random deletions, checkerboard maps were used as the mask layers for the maps of habitat type and aspect. We used the data sets for habitat type and aspect, since we already had created semivariograms for each of the continuous maps, against which we could compare the result of the holepunch maps. Maps of a single pattern were used: block sizes were 10, 20 and 100 cells, and deleted proportions were 0.20, 0.40, 0.60 and 0.80. Semivariograms of the holepunched maps were examined to evaluate the relative effects of deleted block size and overall deletion percentage on scale detection.

To examine the effects of non-random deletions, we used the boundaries of the 15 elk viewing areas to mask the same continuous data layers, habitat type and aspect. Thus, any landscape data that fell within the boundary of any viewing area were preserved, while all data lying outside those boundaries were deleted (assigned a value of no data). The resulting maps contained approximately 10% of the data found on the original maps. Semivariograms for these holepunched maps were compared to those made from the continuous maps, to determine the effects of non-random deletions on scale detection.

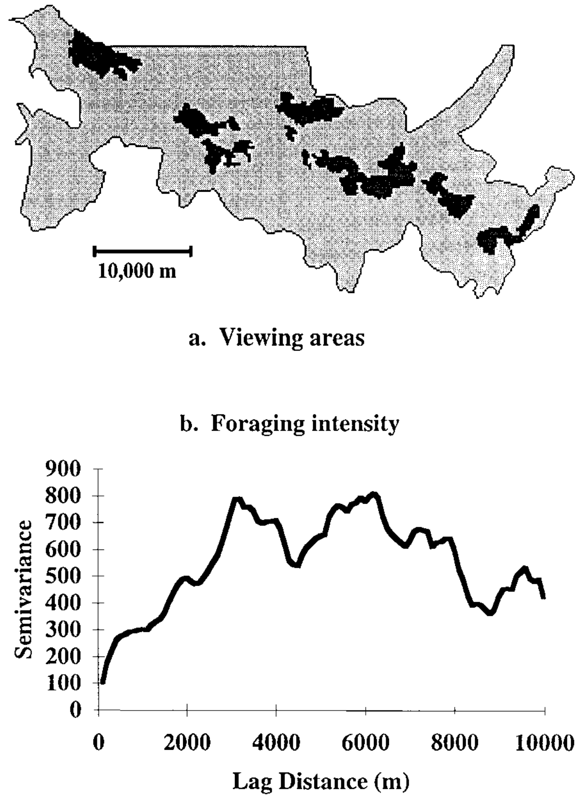

Figure 4. (a) Boundaries of 15 viewing areas within northern Yellowstone National Park, in which ungulate winter foraging was measured in 1991 and 1992 (Pearson et al. 1996). (b) Semivariogram of foraging intensity data from these 15 study sites.

Results

Yellowstone analysis

Semivariograms of the continuous environmental data sets for Northern Yellowstone clearly identified the dominant scale of variability in each map layer. These semivariograms fit the standard stair-step pattern, with range and sill relatively easy to identify (Figure 2). The plot in Figure 2, and all subsequent variogram figures, displays a series of overlapping discrete points; we elected not to fit a continuous model to the semivariogram. A correlogram for the habitat type map layer is shown in Figure 3, which demonstrates that both techniques give similar results when applied to the same data set. The ranges for aspect, elevation, habitat type and slope, respectively, were approximately 3000 m, 5000 m, 2000 m and 2000 m.

Semivariograms of the ungulate foraging data for the 15 discontinuous study areas were more troublesome to interpret (Figure 4). The multiple peaks and valleys of the sample variogram presented in Figure 4b illustrate the difficulty of identifying a single range and sill on such plots, which exhibit erratic behavior that is likely due to the rapidly declining sample sizes of data available for analysis of longer lags. Extracting the underlying spatial pattern of foraging intensity from these erratic semivariograms proved impossible, and voided our initial objective of relating the process of ungulate grazing to underlying biotic and abiotic patterns on the landscape.

Detection of known scales of variability

Single scale maps

Semivariograms of artificial maps with a single scale of pattern showed clear and interpretable results. For both checkerboard and sprinkle type maps, the range on the semivariogram accurately reflected the size of the blocks of which the map was constructed (Figures 4a and 4c). The block size was identified regardless of the total proportion of the map that was filled (see Methods for discussion of map construction). The range for the 50 × 50 cell checkerboard map (Figure 5a) was indicated by an inflection at a lag distance of 50 grid cells; the range for the 20 × 20 cell sprinkle map (Figure 5c) occurred at a lag distance of 20 grid cells.

Multiple scale maps

The results of our analysis of multiple scale maps were less encouraging than those of single scale maps. Semivariograms of checkerboard maps with two distinct block sizes did indeed show detectable inflections that correctly identify each block size. The semivariogram ($n = 1$ replicate) in Figure 5b shows distinguishable inflections at lag distances of 5 and 20 grid cells, for a map composed of 5 × 5 and 20 × 20 cell blocks. Note that the larger scale pattern still exhibits a higher semivariance. The behavior of the semivariograms around such inflections was often unpredictable, however, making unambiguous interpretation of the plots problematic. We did not conduct significance testing of the individual peaks and valleys.

Semivariograms of two-level and three-level hierarchical (RULE) maps also showed adequate identification of the multiple block size. Figure 5d exhibits inflections at lag distance of 6 and 36 grid cells, corresponding to the 6 × 6 and 36 × 36 cell blocks of the two-level map (see Figure 1d). As before, the coarsest pattern produced the greatest semivariance, while the finer patterns were indicated by inflections in the semivariogram prior to the actual sill. As indicated for multiple scale checkerboard maps, behavior of the semivariance at known pattern scales was ambiguous, rendering proper interpretation of similar results unlikely in the case of actual data.

Effects of proportion and distribution of absent data

The sensitivity of semivariance analysis to random deletions from the data was related to both the size of the blocks that were deleted, and the total proportion of the original data set that remained. Small blocks, up to approximately 3% of the total map area, could be deleted in very high proportions without degrading the semivariogram results. Range and sill could still be identified clearly in maps from which approximately 90% of all the data had been deleted, in small random blocks. A sample semivariogram for a map of habitat type from which 80% of the data was deleted in 100 × 100 m blocks is presented in Figure 6a.

As the size of the deleted blocks increased relative to the scale of the total map, the variogram became more sensitive to the total deletion percentage. Blocks of intermediate size, defined loosely as larger than 3% and smaller than 25% of the map size, could be deleted with little effect on the semivariogram, so long as approximately 50% or more of the original map data remained. The semivariogram for the map of habitat type from which 80% of the data was deleted in 1000 × 1000 m blocks is presented in Figure 6b. When more than half of the total map layer was deleted by random blocks of this size, interpretation of the resulting variograms became difficult, due to the presence of sharp dips that obscured the sill.

When the deleted blocks were larger than 25% of the map size (up to the maximum lag distance of 50% of map size), variograms became problematic, and the range and sill were often effectively obscured. Figure 6c presents a semivariogram for the habitat map from which 80% of the data was deleted in 5000 × 5000 m blocks. Although the sill is retained in this figure, note the marked peak at a lag distance of 5000 m, which clouds interpretation of the plot.

Scale detection by semivariance analysis was found to be more sensitive to non-random deletions than to random deletions. When continuous Northern Yellowstone map layers were masked (i.e., deleted) with the boundaries of the 15 viewing areas (see Figure 4a), the resulting semivariograms were nearly impossible to interpret (Figure 7). This difficulty may be illustrated by comparing the semivariogram of the masked habitat data to the semivariogram of the continuous data (Figure 1c). Although the size of each viewing area was small (i.e., less than 1% of the total map area), the semivariograms showed deep dips, which appeared to reflect the scale and relative location of the viewing area boundaries as much if not more than the scale of variability of the data contained within those boundaries. Because nearly 90% of the spatial extent of the data set is occupied by missing data (all points outside the viewing areas), semivariance calculations for many lag distances, and particularly long lags, were hindered by small sample sizes. Small samples of point pairs likely were responsible for erratic semivariance results, as presented in Figure 7. If a more continuous data set had been analyzed, the dips in the semivariogram might have

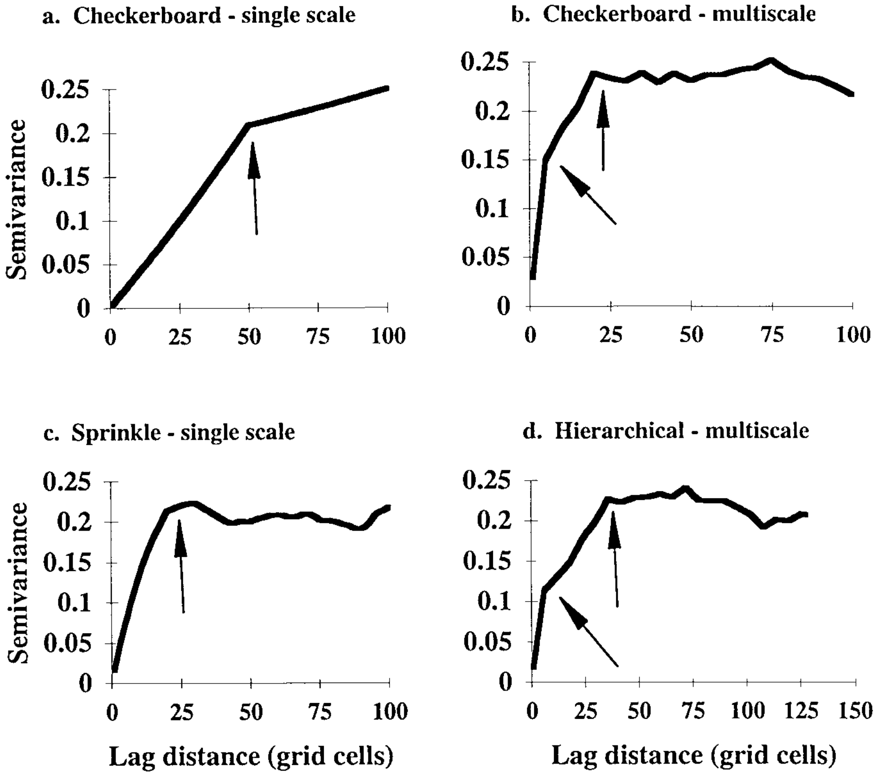

Figure 5. Semivariograms for artificial maps shown in Figure 1. Arrows indicate inflections in the semivariance that identify pattern scales on each map. (a) Single scale checkerboard map with 50 × 50 cell blocks, showing inflection at a lag of 50 grid cells. (b) Multiple scale checkerboard map with 5 × 5 and 20 × 20 cell blocks, showing inflections at lags of 5 and 20 grid cells. (c) Single scale random placement (sprinkle) map with 20 × 20 cell blocks, showing inflection at a lag of 20 grid cells. (d) Two-level hierarchical map with 6 × 6 and 36 × 36 cell blocks, showing inflections at lags of 6 and 36 grid cells.

been interpreted to reflect multiple scales of variation in foraging intensity, produced by the response of foragers to multiple scales in landscape heterogeneity. Based on our evaluation of the sensitivity of semivariograms to missing data, however, we feel that the dips in the foraging semivariograms unfortunately reflect the discontinuous nature of the data, rather than an underlying ecological pattern.

Discussion

Yellowstone analysis

Although semivariograms for the continuous Yellowstone environmental data sets were easily interpreted, the irregular condition of the variograms for the discontinuous ungulate foraging data rendered comparison of these sets of variograms impossible. Range and sill could be easily identified in the former (Figure 2), but were difficult or impossible to identify in the latter (Figure 4b). The spatially discontinuous nature of the foraging data, collected in discrete sampling locations (i.e., viewing areas), was primarily responsible for the irregularity of the corresponding semivariograms, due to small and unstable sample sizes (see discussion above). It has been noted previously (Webster and Oliver 1992) that semivariograms generated from environmental data sets containing fewer than 50 or 100 data points may be of little analytical value.

Because of the extensive missing data outside the boundaries of the 15 viewing areas (nearly 90% of the total map area), a variety of local dips and spikes appeared in the semivariograms for the foraging data. These irregularities reflect effects of small sample size, as follows. Pairs of sample points separated by lag distances that are approximately equal to the size of the foraging areas are more likely to straddle a border of the area than are pairs separated by shorter or longer lag distances. Data points (i.e., locations) outside the foraging areas were classified as no-data; therefore, when one of the straddling points fell in a

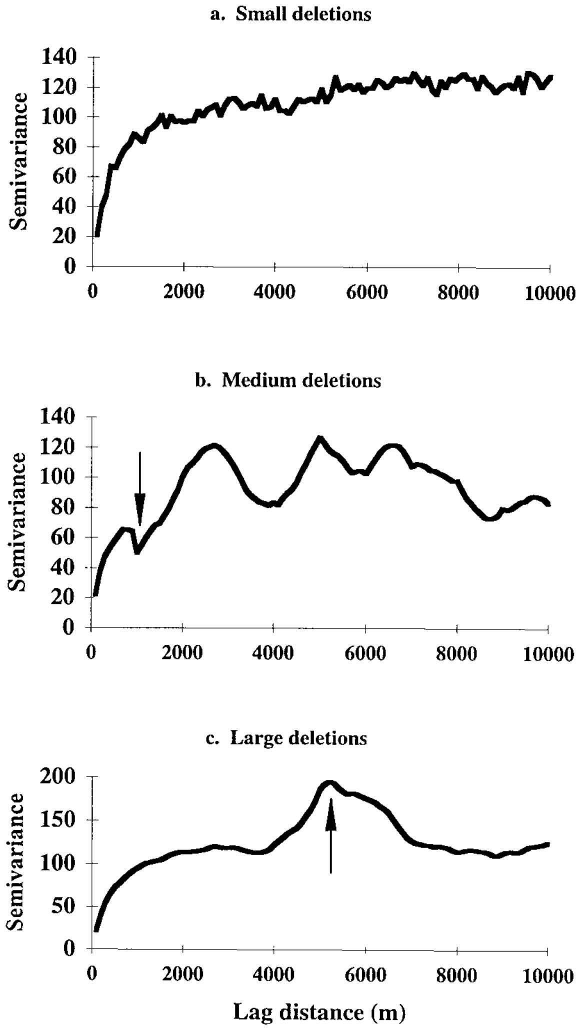

Figure 6. Semivariogram of habitat data of northern Yellowstone National Park, masked by single scale checkerboard maps. In all cases, 80% of the total area of the original map was deleted. Arrows indicate problematic areas on each variogram. (a) Small deletions of 100 × 100 m blocks. (b) Medium sized deletions, of 1000 × 1000 m blocks. (c) Large deletions of 5000 × 5000 m blocks.

no-data area, that pair of points was ignored in the semivariance calculation. Thus, the semivariance at lags near the average foraging area size was derived from a markedly smaller sample of points than the semivariance at smaller or larger lags. Smaller sample sizes resulted in a less confident, or more variable, calculated semivariance for large lags. The semivariogram may exhibit localized peaks or dips at those lag distances, since they represent the variance between only a small number of paired points. Note that these irregularities also can be found at multiples of the orig-

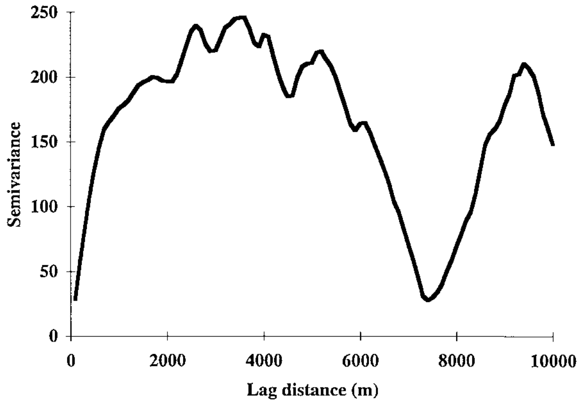

Figure 7. Semivariogram for habitat map of northern Yellowstone National Park, masked by the boundaries of the 15 ungulate forage viewing areas (see Figure 4a). Habitat data falling within the boundary of any viewing area were included in the analysis; data falling outside the boundaries were ignored. Compare plot to semivariogram of spatially continuous data (Figure 1c).

inal (i.e., smallest) lag distance, further complicating interpretation of the plot.

It therefore proved impossible to decipher the semivariograms and determine the dominant scale of variability (i.e., the range) for the ungulate foraging data. The semivariograms were strongly dominated by peaks and dips that appeared to reflect the average size of the viewing areas, as well as larger multiples of that average size. Because the specific behavior (peak or dip) of the variogram at those lag distances is unpredictable, due to the small sample size, conclusions were difficult to extract from the analysis. Since we were prevented from adequately characterizing the dominant scale(s) of the foraging pattern, we were unable to relate foraging scales to the characteristic scales of the environmental variables of habitat type, slope, aspect, and elevation. Future research into this relationship is strongly suggested, however, and might profitably be conducted by collecting spatially continuous foraging data over a smaller study area; continuous grazing data might yield insight into the relationship between the process of grazing and existing landscape patterns.

Detection of known scales of variability

Single scale maps

It is clear that semivariograms were capable of accurately identifying the dominant scale of pattern in each of the artificial maps created for this analysis. The semivariogram range consistently reflected the size of the blocks populating the map, displaying a distinct inflection at a lag distance equal to the block size. The cause of the inflection is easily understood. At lags smaller than the block size, a greater than average number of pairs of points will fall entirely within either a block (habitat type = 1), or entirely outside a block (habitat type = 0). In both cases, the variance between the pair of points is zero, and the total semivariance at that lag consequently is reduced. As the lag distance increases, the number of pairs of points that straddle the edge of a block (and exhibit maximum variance) increases, while the number of pairs within a single habitat type declines. Thus the semivariance increases, reaching a clear inflection point at a lag distance equal to the block size. The behavior of the semivariance at lags beyond the inflection point is unpredictable: it may continue to rise with a noticeably reduced slope, or decline slightly. The exact behavior of the semivariance, unique to each map analyzed, is related to the specific arrangement of the blocks (see discussion of effects of sample size, above), and may be stabilized by analyzing larger maps (e.g., 1000×1000 cells). At larger lag distances, an harmonic effect can be noted, in which the variogram exhibits peaks or dips at lag distances that are multiples of the block size. Despite these variations, the initial inflection point is easily recognized.

Semivariance analysis therefore is capable of detecting the dominant patch size in single scale maps, and thus may be used reliably to identify, for example, the size of shrubby vegetation patches on an otherwise grassy landscape. Many other applications of semivariograms exist, although it should be noted that average and maximum patch sizes can be calculated by most geographic information systems (GIS) packages. Semivariance analysis, however, is capable of distinguishing patterns which may result from the arrangement of the patches, as well as their size. Note that the shrub and grassland example clearly represents a binary system which closely resembles the artificial maps examined above. In real landscapes, however, more than two cover types are likely to occur, which can be expected to produce more complicated spatial patterns. Each cover type may have its own particular dominant scale of variability; therefore such maps potentially may exhibit multiple scales of pattern.

Multiple scale maps

The results of the analyses of multiple scale artificial maps suggest that the identification of the broad scale patterns will be easier, as a rule, than the identification of the fine scale patterns, when relying on semivariance analysis. The analysis detected multiple scales of pattern, appearing as distinct inflections of the semivariogram at lag distances less than the range; however, broader scale patterns (i.e., larger blocks) always exhibited greater semivariance, so that the range consistently corresponded to the scale of the coarsest map pattern. Although these findings were initially encouraging, it seems unlikely that semivariance analysis would be as successful at distinguishing multiple scales of pattern in real data sets. The severe regularity of the overlaid patterns on the artificial maps here analyzed is likely responsible for the ability of semivariograms to distinguish individual pattern scales. The noise associated with real-world patterns (e.g., variation in patch sizes, or patch shapes) should make detection of a fine scale pattern that is otherwise subsumed by a coarser pattern extremely difficult, since the inflections that otherwise identify the fine scale pattern will likely be lost in the normal meandering nature of many semivariograms of real data.

Our results indicated that identification of fine scale patterns in data sets which also exhibit coarse scale patterns may not be possible with semivariance analysis. Conversely, practitioners of this analysis can feel comfortable that fine patterns should not, in most cases, inhibit the identification of the pattern associated with coarse scale landscape objects. In this sense, semivariance analysis acts like a high pass filter: the analysis principally detects the broadest scale of spatial variations (the sill), while indicating finer scale variations in data to a lesser degree (inflections prior to the sill). Attempting to use semivariance analysis to quantify multiple scales of environmental pattern is not recommended. Fourier analysis (Korner 1989) may be more suited to this application, although it is too highly sensitive to the variability found in the scales of real world patterns, and is hampered further by its requirement of very large sample sizes. Additional potential techniques have already been noted (see Gardner 1998).

It is worth noting, however, that the analysis of hierarchical maps did adequately distinguish up to three distinct scales of pattern. Since these maps may mimic natural patterns more closely than the checkerboard and sprinkle maps, accurate identification of their multiple scales of pattern may be seen as evidence that techniques related to semivariance analysis may have some success with natural data sets. Such techniques certainly would have to account for the

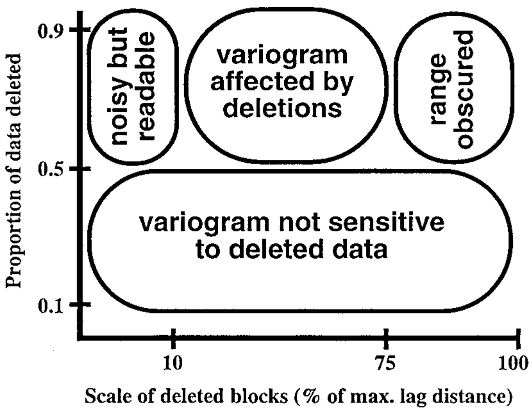

Figure 8. Summary of semivariogram sensitivity to deletion scale and deletion percentage. Scale of deleted blocks is defined as the proportional length of one side of a block relative to the maximum lag distance. Maximum lag distance for semivariance analysis is normally set to one half the length of the shortest side of a data set or map. Proportion of data deleted is defined as the proportion of the total area of the data (or map) deleted.

often broad variation in characteristic patch sizes, in order to isolate overlapping scales of pattern.

Effects of Proportion and Distribution of Absent Data

The sensitivity of semivariograms to random deletions of varying scale and intensity are summarized in Figure 8. Semivariograms were found to be insensitive to missing or deleted data, when the size of the deleted blocks of data was small (i.e., less than 10% of the maximum lag distance, or less than 0.25% of the map area). Small random deletions from the data set did not substantially hinder semivariance analysis, which produced results identical to those derived from the full data set. This result is encouraging, since it identifies semivariograms as a relatively robust tool for landscape ecology. Absent data is a problem common to most studies, resulting from such diverse causes as collection error, loss of data sheets, misrecording of data followed by subsequent removal of outliers, interference by clouds in aerial and satellite imagery, and non-systematic data collection procedures in general (such as random-walk GPS methods). In several of these cases, it is likely that absent data will occupy a relatively small spatial area, and their effect on the corresponding semivariogram will likely be minimal.

Semivariograms of data sets with moderately large (i.e., between 10% and 75% of the maximum lag distance, or 0.25% and 14% of map area) blocks of absent data displayed irregular results, characterized by abrupt local peaks and valleys that obscured the true range and sill in many cases. The influence of the scale of the deleted blocks of data appears to overwhelm the influence of the underlying data patterns. Missing data in this scale range therefore can seriously affect the results of semivariance analysis, and should be avoided. Deletions at these scales potentially may result from cloud obstructions of aerial or satellite imagery. Therefore, a deletion scale of approximately 25% of map area is suggested as a criterion that may be employed to distinguish usable from unusable data sources. Note that the criterion of 25% is not a quantitatively derived limit, but rather an estimate based on our limited empirical trials.

When deleted blocks were larger, (e.g., > 75% of maximum lag distance, or 14% of map area), semivariograms became effectively unreadable in all cases examined. There simply is not enough data left in such partial maps to be analyzed, and the results that are obtained are likely to be meaningless. Clearly, data sets characterized by such large absences should not be candidates for semivariance analysis.

One common approach to incomplete data sets, or data sets comprised of samples sparsely distributed in space, is to interpolate the existing data to create a continuous map. Kriging (Burrough 1986) is one of the most widely used and powerful interpolation techniques, and is a common feature of many spatial analysis packages. This technique should be used cautiously, however, on data sets for which the semivariogram is likely to give poor results; kriging relies directly on a semivariogram of the sampled data to derive the model for interpolation, a model which may give spurious results if the semivariogram itself is problematic. Other interpolation techniques, such as moving window averaging, Thiessen polygons or triangulation (Burrough 1986) may be employed in circumstances where large blocks of missing data may adversely affect semivariogram behavior.

Semivariograms of landscape data layers masked by the limits of the foraging viewing areas (i.e., nonrandom deletions) compared poorly to those derived from the continuous data. The masking operation eliminated approximately 90% of the landscape data, while retaining only 15 small patches (data points located within the boundaries of the viewing areas). Semivariograms of the masked data layers were irregular and difficult to interpret: it appears that the quantity of landscape data that remained was insufficient to provide clear results. Although a moderate amount of data were available for calculation of semivariance at short lag distances (i.e., less than half the average length of a viewing area), estimates of the semivariance at larger lag distances proved more difficult. Short lags could be fit within single viewing areas, and a substantial number of point pairs then could be identified for analysis. At lag distances larger than the largest viewing area, however, lagged pairs of points for which data was available could only be obtained by locating one point in one viewing area, and the second in a different viewing area. Naturally, these occurrences were rare on a map with 90% absent data, so semivariances for larger lag distances was based on increasingly small sample sizes. The behavior of semivariogram at those lag distances was chaotic, and the results unlikely to be meaningful.

Since it was demonstrated that semivariograms of previously continuous, but masked, data were not reliable, it became clear that interpretation of the semivariograms for the actual foraging intensity data collected within the viewing areas would be suspect. Indeed, the hoped-for comparison between scales of landscape patterns and scales of foraging intensity went unrealized, owing to the uncertain and often spurious behavior of the foraging semivariograms.

This finding indicates that care should be taken when designing sampling schemes of spatial data which will later be subjected to comparison. The size and distribution of sampled areas must be taken into account, and ideally should be closely matched. It is likely that randomly located sampling points will provide better results than non-randomly located points, since the distribution of the latter may be reflecting an underlying (but unsampled) spatial pattern. In the present case, this underlying pattern might have been the topology of the study area, since viewing areas were explicitly selected that they might afford unobstructed sight lines over foraging areas. Clearly, with this criterion, the location of the viewing areas on the landscape was non-random.

If the cost of data collection is high, transects will provide better information for semivariogram analysis than will study plots, which cannot encompass an equivalent range of lag distances. Transects should ideally be traced in at least two perpendicular directions, if not more, in order to permit analysis of patterns in more than a single compass direction, and to evaluate the assumption of anisotropy (Isaaks and Srivastava 1989). Similarly, if survey plots must be used, their orientation should be arranged to provide maximum information about spatial variance in all directions: the long axes of rectangular plots can be oriented to a variety of compass directions, serving in a limited way as transects. Circular plots will give the least useful information for semivariance analysis, compared to rectangular plots and transect lines.

Application of semivariance analysis to landscape ecology

Our evaluation of the sensitivity of semivariograms to various data set manipulations revealed semivariance analysis to be a relatively robust procedure that may profitably be applied to ecological data at landscape scales. Semivariograms are effective at determining scales of pattern forged into artificial maps, and proved capable of identifying the scale of the coarsest spatial pattern in several types of Yellowstone environmental data. Although multiple scales of pattern were identified in artificial maps with some success, results suggested that similar success will be difficult to attain with noisy, real world data. The examination of the effect of deletions on semivariance results showed that small scale deletions do not strongly affect the performance of semivariogram analysis, while larger scale deletions, and deletions of larger areas, increasingly degrade the interpretability and reliability of the resulting semivariograms (Figure 8).

Semivariograms should be used for preliminary analysis of the spatial behavior of many landscape data sets. Ideal data sets will be completely and regularly sampled. Data sets with either missing or irregularly sampled data may also be candidates for the analysis, so long as the proportion and scale of missing data blocks is not overly large (see discussion of criteria above). This is a promising conclusion for landscape ecologists, who are familiar with the difficulties of obtaining continuous and error-free data, even for small study areas. Satellite and aerial imagery which is partially obscured by cloud cover, transmission errors, and other impairments may be analyzed with semivariance analysis, if the affected errors are not overly large.

Semivariance analysis therefore is recommended as an effective technique for characterizing some elements of the spatial behavior of landscape data sets, and can serve as an excellent data exploration tool. Semivariograms can provide insight into the scale of spatial patterning of ecological data, which may reflect the scale of landscape structuring forces. Unfortunately, standard semivariance analysis does not appear to lend itself well to the study of multiple scales of pattern. Its applicability to research into hierarchical spatial patterns and structuring forces is therefore limited. While semivariograms are capable of identifying the single coarsest scale of pattern on landscapes, and are relatively insensitive to problematic data distributions, the elucidation of multiple pattern scales currently remains out of reach. One alternative approach may be based on an analysis of the residual errors obtained by fitting a semivariogram model (Isaaks and Srivastava 1989) to actual semivariogram data: patterns observed in the residual plot may provide clues to the existence of multiple pattern scales underlying the dominant (coarsest) pattern. Nonetheless it is clear that if characterization of the scales of landscape patterns, and the search for the processes that underlay those patterns, will continue to be a focus of the field of landscape ecology, additional techniques will need either to be adapted for the task or developed outright.

Acknowledgments

We thank Dr. Robert H. Gardner for his many insightful comments, and for graciously providing his computer program for the generation of hierarchical landscape maps (RULE). We also thank Dr. Scott M. Pearson for kindly sharing UNIX scripts that simplified greatly the use of GSLIB. The manuscript was improved by comments and suggestions from Dr. Robert V. O'Neill, Mark Dixon and Sarah Gergel. We are grateful to Drs. John Pastor and Serge Rambal for their helpful review comments. Funding was provided by an award from the Graduate School Research Committee, University of Wisconsin-Madison.

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