Measuring Landscape Structure Using Geographic and Geometric Windows

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Abstract

Characterization of spatial structure in the landscape is important for many types of landscape analyses. The Spatial Measurements Package has been developed to facilitate spatial analysis of spectrally classified digital images. The software is unique in that it is designed to operate on neighborhoods of "patches" instead of individual pixels. Patches are defined as areas of contiguous pixels assigned to the same class. A patch and its neighbors comprise a "geographic window," the size and shape of which depend upon local landscape characteristics. The software permits computation of (1) average patch size, (2) standard deviation of patch sizes, (3) patch diversity, and (4) patch interspersion. This research presents the measurement of landscape structure using both the conventional rectangular geometric window and the proposed geographic window on a classified image of northeastern Colorado. For most measures the geographic window seems to provide a better characterization of landscape structure than the geometric window.

Introduction

Windows (also called kernals or masks) are used in many sciences to define a sub-area of interest from a larger geographic region. For example, computer scientists and computer cartographers use windowing transformations to focus-in on, and to rotate, parts of graphic displays (Newman and Sproull, 1979; Monmonier, 1982). The window concept is also applied in the field of geographic information systems (GIS), where "neighborhood functions" are used to characterize parameters within a certain distance or direction from a point (Tomlin, 1990). Of interest here is the use of windows in digital image analysis to define the area within which neighborhood calculations are made.

Traditionally, windows have been defined as rectangles (*n*- by *n*-pixel arrays), the dimensions of which are specified by the image analyst (e.g., Newman and Sproull, 1979; Monmonier, 1982; Jensen, 1986). Rectangular windows are commonly used on unclassified satellite data to compute the local variance of brightness values, co-occurrence matrices, and other measures of image texture, and to carry out operations such as edge detection and filtering (Gurney and Townshend, 1983; Jensen, 1986; Hodgson, 1991).

Windows are also applied to nominally classified data for a variety of purposes (Gurney, 1981; Gurney and Townshend, 1983; Fosnight, 1987). For example, windows are employed in post-classification analysis of spatial patterns to "improve" spectrally-based classifications using procedures such as minimum-area filtering or proximity analyses (e.g., Fosnight, 1987; Hodgson, 1991). Windows are also used to reclassify land cover to land use by means of contextual analysis (e.g., Wharton, 1982; Merchant, 1985).

In addition, windows are used to evaluate environmental phenomena (e.g., wildlife habitat) by characterizing landscape structure through measurements of spatial characteristics such as land-cover diversity or interspersion (Murphy, 1985; Robinove, 1986; Lyon *et al.*, 1987). Such applications are more common as interest in the spatial structure of landscapes increases (e.g., Addicott *et al.*, 1987; Turner, 1990; Musick and Grover, 1991; Briggs and Nellis, 1991).

This paper focuses upon the application of windows in spatial and contextual image analysis to assess *landscape structure* (the spatial characteristics and organization of the landscape). Characterization of the spatial patterns and structures in landscapes ordinarily focuses on a patch of land cover and its neighborhood, an area that may vary in size and shape depending upon the application and the study area characteristics (Merchant, 1984; Merchant, 1985; Addicott *et al.*, 1987; Hodgson, 1991). Merchant (1984) observed that the conventional "geometric" window (usually rectangular) may have some shortcomings when used to assess spatial characteristics of nominally scaled (e.g., spectrally classified) data. He proposed the "geographic window" as an alternative (Figure 1c). Merchant defined a "geographic window" as one that changes in size and shape *in response to changes in local landscape characteristics*, so that any patch within the original window dimensions is *completely* included in the dynamically changing geographic window (Figure 2). The geographic window focuses on a patch and its neighboring patches, rather than on a pixel and its neighboring pixels (the conventional approach in image analysis). "Patches" (analogous to "objects" in GIS) are defined as groups of spatially contiguous pixels assigned to the same class. Few experiments to evaluate the geographic window concept have been conducted to date.

In this paper we compare the measurement of landscape

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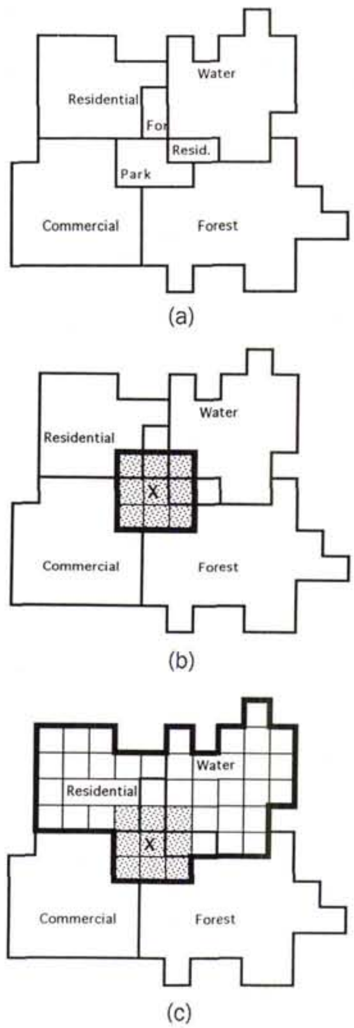

Figure 1. A 3 by 3 geometric window versus a geographic window. (a) A theoretical landscape containing seven patches and five land-cover types; (b) The extent of the geometric window centered over pixel X; (c) The geographic window has expanded beyond the original 3 by 3 geometric size (shaded) to incorporate entire patches. The value computed for the window will be assigned to pixel X.

structure, using geometric and geographic windows, for a test site in northeastern Colorado. We also report on the development of a set of software—The Spatial Measurements Package—designed to enable image analysts to test and evaluate the geographic window as an alternative for characterizing landscape structure.

Background

Geometric windows appear to perform well when the pixel is the basic unit of analysis, as in operations involving high-pass and low-pass filters, edge detection, or textural measures applied to unclassified digital imagery. Because the shape, size, and orientation of a geometric window are normally fixed, such parameters must be carefully chosen. Chavez and Bauer (1982, p. 23) suggest a method for determining the appropriate window size, stressing that "... there is no constant rectangle or kernal size that provides the best results for every image because the optimum kernal size is dependent on the 'busyness' of the individual image ... ."

In studies involving nominally classified data, the definitions of geometric window characteristics (e.g., size) and implementation strategies (e.g., sequential or simultaneous) have been shown to influence the mapped results (Davis and Peet, 1977; Townshend, 1986; Hodgson, 1991). Hodgson (1991) developed a strategy for simultaneously using multiple geometric windows (varying in size, shape, and orientation) for mapping land cover, suggesting that a primary weakness of a single geometric window for such purposes has been that such a window typically fails to simulate visual interpretation strategies (i.e., window size, shape, and orientation are static, and multiple landscape characteristics cannot be considered simultaneously).

Merchant (1985) tested his geographic window concept on a subset of a Landsat Thematic Mapper image of the Topeka, Kansas area. Initially, the data were stratified into water, vegetated, and non-vegetated pixels. Then a "region-growing" algorithm was used to identify patches of similar land-cover composition. By analyzing patch size and neighborhood statistics (e.g., regional diversity and interspersion) a land-use classification was produced. Using such spectral/spatial logic, certain spectrally inseparable land-use classes were successfully discriminated.

Merchant's research defined the concept of the geographic window and established its value in land-use mapping. That early implementation of the geographic window, however, was very analyst-intensive, and resulted in tabular, as opposed to mapped, output of landscape structure. Recently, an automated geographic window was successfully developed (Whistler, 1989) and used for measuring and mapping landscape structure (Dillworth, 1990).

The configuration of a geographic window is defined by the local size and shape of landscape patches (Figures 1 and 2). Patches are never truncated by the boundaries of the geographic window. Where patches fall entirely within the constraints of an analyst-defined window size, window dimensions remain unchanged. However, where a patch extends beyond the analyst-specified window, the geographic window expands to incorporate the entire patch in computations. In all cases, the calculated window value is placed into the central pixel of the original analyst-defined window.

Study Area

A portion of a Landsat-5 multispectral scanner (MSS) image of the Colorado High Plains (2 August 1987) was selected in order to demonstrate the differences between the geometric and geographic windows. The study area is located in northeastern Colorado and was selected because of its diverse landscape, influenced by variations in physiography, vegetation distribution, and human impacts. The land cover of the study area includes irrigated and non-irrigated croplands,

Figure 2. The size and shape of the geographic window vary depending on landscape characteristics. The shaded area represents the original 3 by 3 geometric window location.

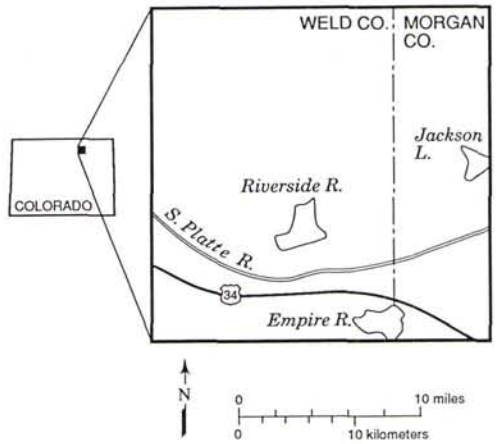

Figure 3. Location of study area in the Colorado High Plains.

grasslands, the South Platte River and its floodplain, and several large reservoirs (Figure 3 and Plate 1).

Methodology

The Spatial Measurements Package was developed to measure the spatial characteristics of classified data using both a geographic (STRUCTUR program) and a rectangular geometric (GEOMET program) window (Whistler, 1989). These programs were developed using RM/FORTRAN and the ERDAS Toolkit Module, and require a classified image as input. Therefore, the study area subscene was spectrally classified into eight land-cover classes (water, wetland, bare soil, sparse grassland, dense grassland, irrigated cropland, unirrigated cropland, and mixed vegetation) prior to beginning the spatial analysis (Plate 2). This classification scheme represents land-use/land-cover classes spectrally separable on Landsat MSS data[1].

Landscapes can be characterized in many ways. Potentially valuable landscape descriptors include grain size (average and standard deviation), diversity, interspersion, association, isolation, pattern (random, regular, or clustered), connectivity, and shape (Merchant, 1984; Forman and Godron, 1981). The programs in the Spatial Measurements Package measure four aspects of spatial structure[2]: average patch size, standard deviation of patch sizes, patch diversity, and patch interspersion. For the theoretical landscape shown in Figure 1, Table 1 demonstrates the calculation of each of the measures discussed below using both the 3- by 3-pixel geometric window and the geographic window. Although these attributes can be measured in a variety of ways, the formulae used below were selected because of previous successes documented in the literature and because of their appropriateness to raster data. (For a more thorough discussion of alternative methods of measuring landscape structure, see Dillworth (1990).)

Ecologically, patch size affects species diversity, productivity, and nutrient exchanges (Forman and Godron, 1981). Visual analysis of the unclassified and classified satellite data reveals that patch size varies throughout the study area, both in terms of average patch size and standard deviation of patch sizes. While this research looks at overall patch size (regardless of cover type), an alternative strategy would be to examine the patch size distributions of individual land-cover types. Average patch size (AVG) refers to the average number of pixels that constitute individual patches within a window, and is calculated as

$$\text{AVG} = \text{Sum of the Patch Sizes/Number of Patches} \quad (1)$$

[1] Although there are certainly roads and scattered buildings in the study area, they could not be mapped consistently as separate classes, and, therefore, are not included in subsequent analyses.

[2] These measures are spatial in that the adjacency and arrangement of patches defines the size and shape of the window.

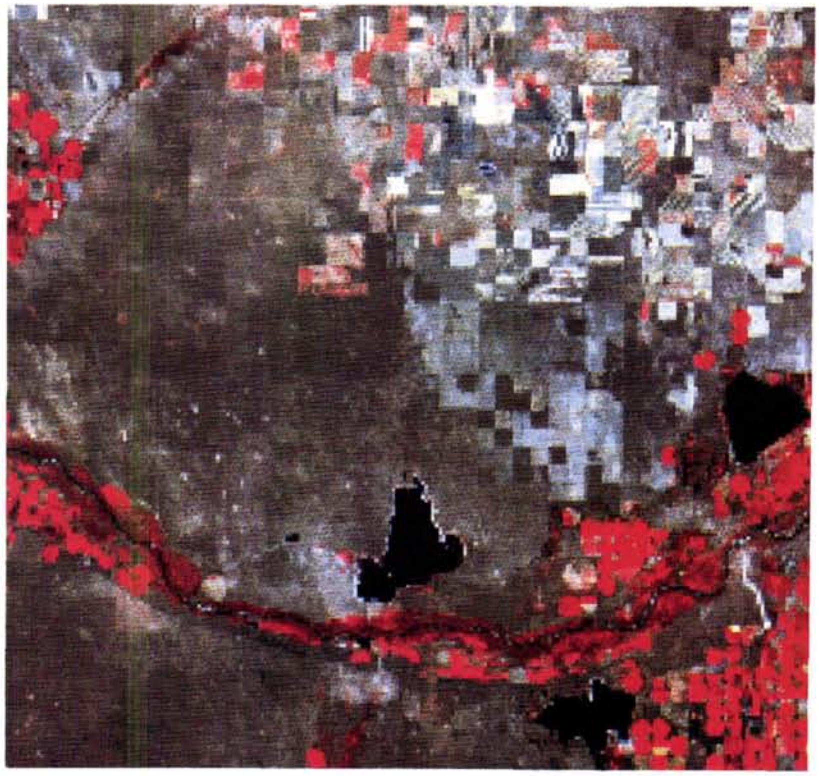

Plate 1. Landsat MSS image of the study area (Colorado High Plains, 2 August 1987, scene ID # 85124917025 ×0, EOSAT image Copyright, 1987).

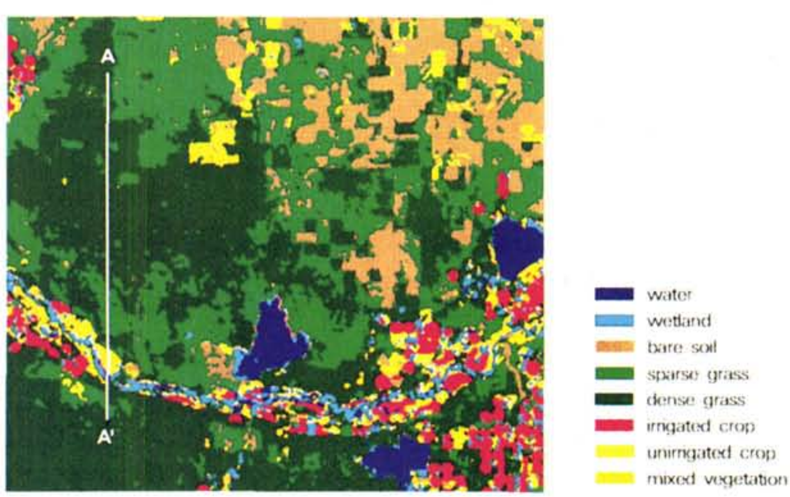

Plate 2. Land cover classification based on spectral information. Transect A-A' defines the geographic location of the values graphed in Figure 8.

TABLE 1. COMPUTATION OF SPATIAL STRUCTURE OF FIGURE 1 LANDSCAPE

Attribute	Calculation	Result
AVG (Geom.)	(1 + 1 + 1 + 1 + 5)/5 = 9/ 5 =	1.80
AVG (Geog.)	(16 + 2 + 21 + 2 + 5)/5 = 46/5 =	9.20
STD (Geom.)	SQRT[((1-1.8)^2 + (1-1.8)^2 + (1-1.8)^2 + (1-1.8)^2 + (5-1.8)^2)/5] = SQRT[12.8/5] =	1.60
STD (Geog.)	SQRT[((16-9.2)^2 + (2-9.2)^2 + (21-9.2)^2 + (2-9.2)^2 + (5-9.2)^2)/5] = SQRT[306.8/5] =	7.83
DIV (Geom.)	(4/5)*SF = 0.8*SF = 0.8*255 =	204.00
DIV (Geog.)	(4/5)*SF = 0.8*SF = 0.8*255 =	204.00
INT (Geom.)	(5/9)*SF = 0.56*SF = 0.56*32500 =	18200.00
INT (Geog.)	(5/46)*SF = 0.11*SF = 0.11*32500 =	3575.00

Standard deviation of patch sizes (STD) refers to the dispersion of patch sizes from the calculated average patch size within a window, and is computed as

$$\text{STD} = \text{Sqrt}[\text{Sum}(\text{PatchSize}_i - \text{AVG})^2/\text{Number of Patches}] \quad (2)$$

where PatchSize_i is the size of each individual patch in the window, and AVG is the value computed in Equation 1.

Diversity describes the types and variety of features (in this case, types of land cover) that make up a landscape. In the region studied here, the upland areas tend to have a smaller variety of land cover (primarily grassland and non-irrigated cropland) than the South Platte floodplain (a mixture of water, wetland, irrigated crop, bare soil, and mixed vegetation). Patch diversity (DIV) measures the number of different types of patches within a window. The formula used here is a standardization of the Species Variety Measure (Auclair and Goff, 1971). It is calculated as

$$\text{DIV} = (\text{Number of Classes Present}/\text{Number of Possible Classes})*\text{SF} \quad (3)$$

where the number of possible classes is a function of the number of patch types mapped by the analyst, and SF is a scaling factor[3].

Interspersion (INT) is a measure of how many patches occur within a window. In this High Plains study area, interspersion varies from quite low in the grassland sites to higher in the dryland farming landscapes. The formula for interspersion used in this study is based on the Spatial Complexity Index (Monmonier, 1974). Interspersion is calculated as

$$\text{INT} = (\text{Number of Patches}/\text{Window Size})*\text{SF}. \quad (4)$$

[3] Because calculated values for diversity an d interspersion fall between 0 and 1, scaling factors (SF) are used in their computation in order to maintain the dynamic range between the fractional values. Data values are then truncated to integers for display and further analysis. (Diversity SF = 255; Interspersion SF = 32500.)

The spatial data resulting from these computations are output as individual 16-bit image files (except diversity, which is an 8-bit file). As image files, they can be subjected to further image processing and analysis. In this research the output from these spatial measurements was used to assess the differences between the geographic and geometric window strategies.

Implementing the Window Programs

Both the geographic and the geometric window programs initially require the analyst to specify the field-of-view for computations by entering geometric dimensions for the window. In both cases, statistical results are output to the center pixel of the original geometric field-of-view. The geographic window, however, uses the geometric dimensions as a starting point, expanding when necessary to include whole patches; the geographic window never shrinks to a size smaller than specified. Thus, in areas dominated by small patches (e.g., urban landscapes), the geographic window remains close to its original dimensions. In a landscape made up of large patches (e.g., rangeland), the size and shape of the geographic window may change dramatically.

In this study the initial field-of-view was established as a 5- by 5-pixel window. The small window size was chosen so that the detail of finely textured landscapes could be discerned. The spatial measures were originally computed on an image made up of 451 rows and 451 columns. Following computation, the first and last three rows and columns of the output data were deleted in order to remove the effect of image edge on computations[4].

Geographic versus Geometric Window Results

The landscape structure revealed by the geographic and the geometric windows varies for several of the spatial measures (Table 2 and Figures 4 to 8). Large differences occur among the values computed by the geographic and geometric windows in all of the spatial measures except diversity. This was expected because diversity is the only measure that does not incorporate the *size* of patches within a window in its computation.

Values for average patch size are obviously limited by window size when computed with the geometric window. For example, the largest patch revealed by the geometric window is 25 pixels (the size of the window). The geographic window, however, identified a patch made up of over 32,000 pixels in the same landscape. The smallest patch identified by the geographic window covers four pixels; because that patch apparently was cut off by the geometric window, a minimum patch size of 2 was detected.

[4] In the STRUCTUR and GEOMET programs, pixels outside the image are initialized to 0 in order to fill the window and allow calculations to begin at row 1, column 1. The 0's outside the image are NOT included in any calculations; they simply serve as place-holders.

TABLE 2. STATISTICS FOR GEOGRAPHIC AND GEOMETRIC WINDOWS

	Geographic				Geometric			
	AVG	STD	DIV	INT	AVG	STD	DIV	INT
Minimum	4	1	31	1	2	1	31	1300
Maximum	32236	16117	223	6802	25	11	223	13000
Mean	9698	2704	59	73	16	4	59	2578
Std. Dev.	10724	4690	31	229	8	3	31	1479

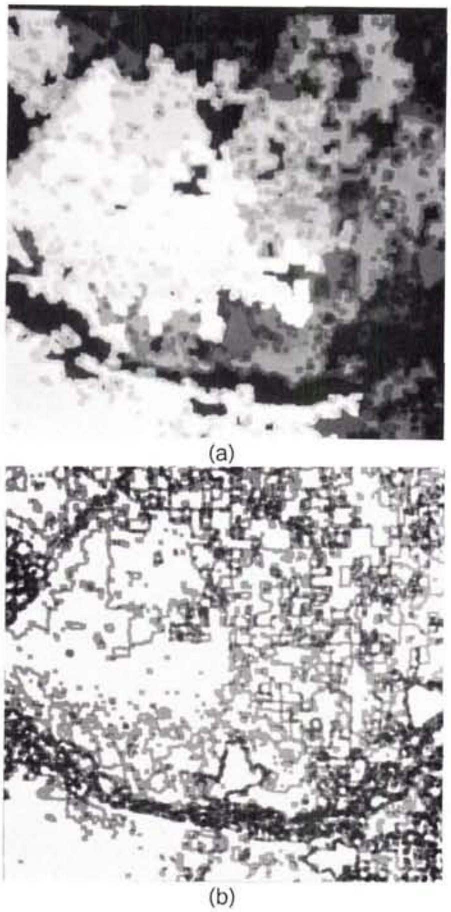

Figure 4. Average patch size measured with (a) the geographic window, and (b) the geometric window. Brighter tones indicate larger patches.

When comparing the two average patch size maps (Figure 4) the effect of constraining measurement within a geometric window becomes clear. The geometric window map has the appearance of an edge map. From the geometric window results, one might assume that patch size was relatively consistent from the upland down into the floodplain. The geographic window reveals a distinctly regional variation in average patch size, with patch size decreasing from large grassland patches, to moderately sized upland agricultural patches, to small patches in the irrigated lowlands. Transect A-A' (Figure 8a and 8b), established from grassland in the north through the floodplain of the South Platte River in the south, further clarifies differences between the average patch size results achieved with the two window types. As the transect data demonstrate, the geometric window misses the presence of some very large patches in the grassland areas (especially in comparison with the small patches found in the floodplain of the South Platte River).

Standard deviation of patch sizes is similarly constrained by the size of the geometric window. While both strategies identify edge locations as areas of highly variable patch size, the geometric window reveals much less variability in patch size than does the geographic window. Patch size standard deviations range from 1 to 11 pixels when computed with the geometric window, but range from 1 to 16,117 pixels when the geographic window is used (Table 2). Regions of similar patch size are clearly visible on the geographic window map (Figure 5a), with patches of similar size occurring in the eastern part of the image (heavily cultivated), and more variable patch sizes in the west (dominated by grassland). It is impossible to delineate similar regions on the geometric window map (Figure 5b). The transect (Figure 8c and 8d) shows similar patterns, except that the abrupt changes in patch size identified by the geographic window are "smoothed" by the geometric window, creating a stair-step appearance as the 5- by 5-pixel window progresses in and out of patches.

As discussed earlier, diversity is a function of the number of cover types present compared to the number of cover types possible. Because window size is not a variable in the diversity calculation, the results achieved using the geo-

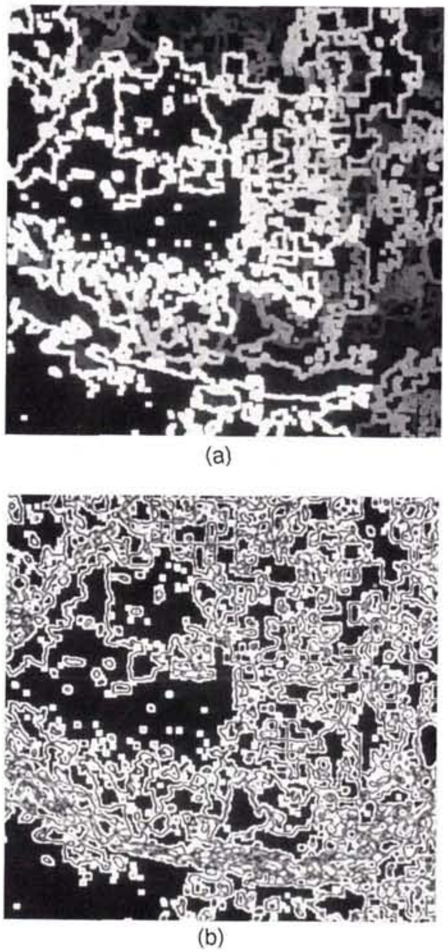

Figure 5. Standard deviation of patch sizes measured with (a) the geographic window, and (b) the geometric window. Brighter tones indicate higher standard deviations.

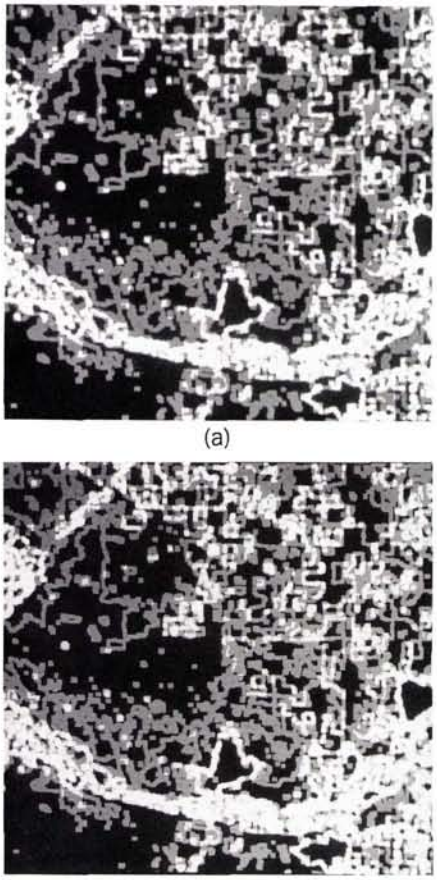
(a)
(b)

Figure 6. Patch diversity measured with (a) the geographic window, and (b) the geometric window. Brighter tones indicate higher diversity levels.

graphic and geometric windows are identical (Table 2, Figures 6, 8e, and 8f). As the measure reveals, diversity is highest near patch edges, with concentrations of high diversity occurring in localities characterized by many small patches of variable cover type (e.g., the irrigated lowlands and the reservoir edges). The lowest diversity values occur within patch interiors, where only one type of cover is present.

Because interspersion is a function of window size, it too is affected by the fact that the geometric window fails to change in response to landscape characteristics. Interspersion values, measured as the ratio of the number of patches compared to the window size, are larger in the case of the geometric window, where the window size is always 25 pixels (Table 2). An important difference in the results of the two types of interspersion measurements is in the magnitude of values calculated by the geographic and geometric windows. The highest level of interspersion measured by the geographic window is 6802 times higher than the lowest level of interspersion, while the highest level of interspersion calculated by the geometric window is only 10 times greater than the lowest value. These differences are apparent in the transect data also (Figures 8g and 8h). The geographic window histogram reveals very high interspersion near the river compared to interspersion levels in the uplands. This is confirmed by visual analysis of the land cover map (Plate 2). While the geometric window identifies high levels of interspersion in the floodplain, it also identifies moderate levels of interspersion throughout the upland grasslands. All patch edges (including those in the floodplain) are identified as areas of high or moderate interspersion by the geometric window. Regions of high interspersion (irrigated agriculture), medium interspersion (upland bare soil and unirrigated cropland), and low interspersion (grasslands) are more distinct on the map produced using the geographic window (Figures 7a and 7b). The geometric window does identify the high interspersion levels in the irrigated agriculture localities, but the values throughout the remainder of the landscape do not form visually distinct regions.

It is interesting to note the similarities between the diversity map and the geometric interspersion map. The calculated range of values differs between the measures (Table 2).

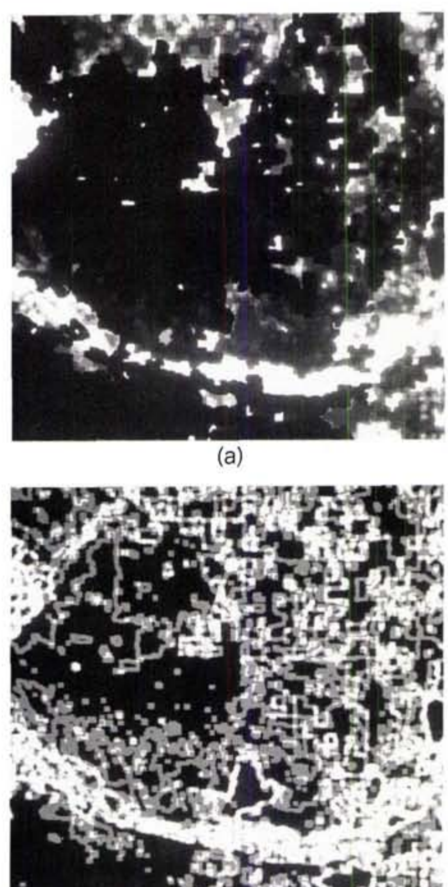
(a)
(b)

Figure 7. Patch interspersion measured with (a) the geographic window, and (b) the geometric window. Brighter tones indicate higher levels of interspersion.

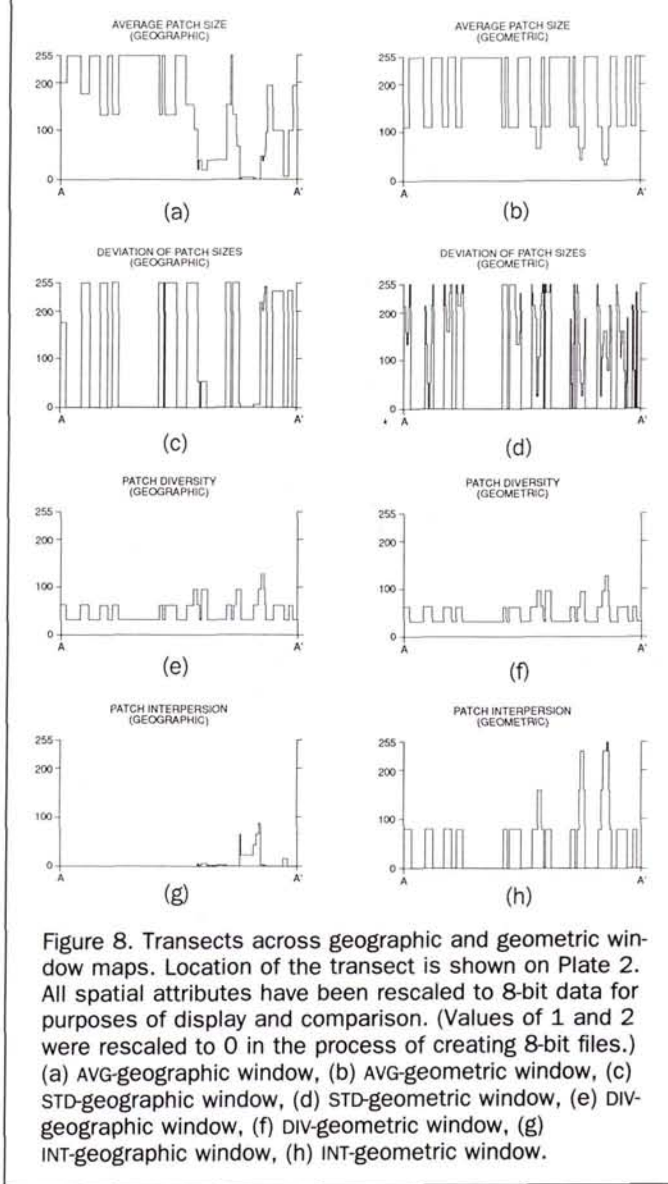

Figure 8. Transects across geographic and geometric window maps. Location of the transect is shown on Plate 2. All spatial attributes have been rescaled to 8-bit data for purposes of display and comparison. (Values of 1 and 2 were rescaled to 0 in the process of creating 8-bit files.) (a) AVG-geographic window, (b) AVG-geometric window, (c) STD-geographic window, (d) STD-geometric window, (e) DIV-geographic window, (f) DIV-geometric window, (g) INT-geographic window, (h) INT-geometric window.

However, once the interspersion values are rescaled to 8-bit data for display, the landscape patterns are quite similar, with only subtle differences apparent at the pixel scale. Recall that diversity maps the number of cover types within a window; geometric interspersion maps the number of patches within a window. When cover type changes, a new patch must be present. Conversely, when a new patch is present, cover type must have varied. The subtle differences between diversity and geometric interspersion occur where several patches are present (high interspersion), but these patches represent only a small variety of cover (low diversity). For example, a window might contain only two types of land cover, but it might be split among four patches. Clearly, diversity and geometric interspersion are strongly related.

The geographic interspersion measure differs from diversity (and geometric interspersion) in that it is not as sensitive to patch edges. In a broad sense, the geographic interspersion measure identifies similar landscapes (e.g., the South Platte floodplain). On the other hand, it does not map the grasslands as a highly (or even moderately) variable landscape. Thus, geographic interspersion offers information not available with the diversity measure.

Summary of Spatial Measures

With the exception of diversity, differences in mapped landscape structure occur between the geographic and geometric window strategies. Average patch size and standard deviation of patch sizes seem to be mapped more realistically with the geographic window, where whole patches are included in such computations. In both instances regional patterns present in the geographic window maps are absent from the geometric window maps. When calculated with the geographic window, the interspersion measure also seems to reflect the land-cover patterns present in the landscape. The geometric interspersion measure identifies patch edges as areas of high interspersion, duplicating information provided through the diversity calculation.

Absolute versus Relative Information

Another important difference between the geographic and geometric windows is in the significance that can be attributed to the spatial values output for each pixel. With the geographic window it is possible to obtain absolute, as opposed to relative, information about landscape structure. For example, an average patch size computed as 7500 pixels, where each pixel represents 0.6241 hectares, equals 46 hectares. On the other hand, for the same measurement made with a 5- by 5-pixel geometric window, the largest average patch size possible would be 15.6 hectares, regardless of the true landscape characteristics. Given adequate familiarity with a landscape, one might be able to use a geometric window to make relative judgments about whether the average patch size in one area is smaller or larger than average patch size in another location. The magnitude of that difference, however, cannot be quantified. The capability of making accurate measurements of spatial structure has important implications for ecological studies, for instance, where knowledge of landscape characteristics, such as patch size and patch interspersion, is important in modeling wildlife habitat and understanding ecological dynamics at a landscape scale (Forman and Godron, 1981; Lyon *et al.*, 1987).

Conclusions

The geographic window represents a new approach to extracting spatial information from classified data. The advantage of the geographic window is that entire patches are included in calculations. This allows for production of maps of landscape structure where each value is meaningful in terms of the landscape, instead of simply being a function of the geometric window dimensions chosen by the analyst. Of the spatial measures examined here, only patch diversity was unaffected by the type of window employed. This occurred because window size was not a factor in the patch diversity formula used here.

In a landscape where all patches are approximately the same size (e.g., a densely developed urban center), it might be possible to define a geometric window larger than most patches and then obtain a reasonable assessment of the landscape's spatial structure. However, where spatial structure is being measured across a variable landscape (e.g., mixed urban and cropland, or mixed cropland and grassland), a geographic window will reveal patterns in spatial structure missed by a geometric window.

To date, the geographic window has been employed for spatial post-processing of image classifications (Merchant, 1985) and for landscape regionalization (Dillworth, 1990). The Spatial Measurements Package has also been expanded recently to include additional measures of patch dominance, patch shape, and patch interspersion (Whistler and Dillworth, 1991).

Appropriate uses of both geographic and geometric window types require further research. Some differences between a 5 by 5 rectangular geometric window and a geographic window have been demonstrated here. It is possible that some of the differences detected between the two window types were a function of the shape and/or size of the geometric window, and that other shapes or sizes of *geometric* windows would reveal additional unique landscape information.

Because the geographic window described here is designed to work on classified data, the results of measuring landscape structure are obviously related to the process of image segmentation. Research related to the effects of classification on landscape structure measurement is currently underway. Continuing efforts should also be directed at implementing additional measures of landscape structure (e.g., isolation, association, connectivity, and pattern).

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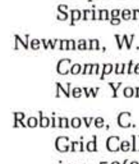

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