

Textural Analysis of Historical Aerial Photography to Characterize Woody Plant Encroachment in South African Savanna

Andrew T. Hudak* and Carol A. Wessman*

Transitions from grassland to shrubland through woody plant encroachment result in potentially significant shifts in savanna ecosystem function. Given high resolution imagery, a textural index could prove useful for mapping woody plant densities and monitoring woody plant encroachment across savanna landscapes. Spatial heterogeneity introduced through mixtures of herbaceous and woody plants challenges quantitative assessments of changing woody plant density using remotely sensed imagery. Moreover, woody plant encroachment occurs across decadal time scales, restricting remote sensing analyses to historical aerial photograph records. Heterogeneity in vegetation structure has a significant influence on local pixel variance in high resolution images. We scanned black and white aerial photographs for 18 sites of varying woody plant density, producing images of 2-m grain size. Omnidirectional variograms derived from these images had ranges of approximately 10 m and sills highly sensitive to woody plant density, prompting us to use a textural index to indicate landscape variation in woody plant density. For validation purposes, we measured several woody overstory structural parameters in the field; a factor analysis revealed woody stem count as the best correlate with image texture. Significance of the regression of image texture on woody stem count declined as grain size of the 2-m images was coarsened to simulate that of SPOT and Landsat satellite sensors. At 10-m resolution, our textural index proved a significant indicator of woody plant density. We mosaicked sequential aerial photographs

scanned at 10-m resolution and then applied our textural filter, producing maps of historical woody plant distribution that reflected patterns in soil and vegetation type. More accurate maps of canopy structure and structural change are needed to explore potential effects of woody plant encroachment on biophysical and biogeochemical processes at large scales. ©Elsevier Science Inc., 1998

INTRODUCTION

Land use and land cover change are increasingly recognized as important drivers of global environmental change (Turner et al., 1994). Land use and land cover vary at local to regional scales, placing them firmly in the domain of landscape ecology; yet the landscape scale is the least studied scale of ecosystem dynamics (Walker, 1994). Remote sensing has emerged as the most useful data source for characterizing land use/cover across landscapes (Wessman, 1992). Strictly speaking, remote sensing cannot directly indicate land use. However, land use can oftentimes be inferred from the apparent physical state of land cover as expressed in an image, particularly if the image is at the appropriate scale. Similarly, land use change can be ascertained from apparent changes in land cover if image time series are available.

Land use/cover is typically interpreted and classified from remote sensing data and then incorporated into geographic information systems (GIS) for further spatial analysis. The integration of remotely sensed data with GIS for measuring and monitoring land use/cover change is a logical and useful synthesis that has been the focus of considerable critical review (Trotter, 1991; Dobson, 1993; Michalak, 1993; Goodchild, 1994; Hinton, 1996; Wilkinson, 1996). Forest fragmentation (Skole and Tucker, 1993), afforestation (Xu and Young, 1990), and changing settlement patterns in both urban (Lo and Shipman,

* Center for the Study of Earth from Space/Cooperative Institute for Research in Environmental Sciences, and Department of Environmental, Population, and Organismic Biology, University of Colorado at Boulder

Address correspondence to Andrew T. Hudak, CSES/CIRES, Campus Box 216, Boulder, CO 80309-0216. E-mail: hudak@cres.colorado.edu
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1990; Pathan et al., 1993) and rural (Nellis et al., 1990; Dimiyati et al., 1996) landscapes are just a sampling of the many land use change processes which have been successfully quantified by incorporating remotely sensed data into GIS.

There are two general types of land cover change: land cover conversion and land cover modification (Turner and Meyer, 1994). The distinction between land cover conversion and land cover modification has important implications for image analyses. Land cover conversion entails a shift in the relative proportions of land cover classes within a given area, such as urban expansion into formerly agricultural land, or clearcutting of forests for conversion into croplands or pastures. Land cover conversion generally attracts more attention, as it tends to be more localized and immediate in impact.

Land cover modification is more subtle and involves a shift within a particular land cover class, such as tree thinning on forested land. Land cover modification tends to occur more gradually and over a wider area, making it more difficult to perceive, but no less important over the long term or large area. An example occurring in rangelands, which is the focus of this article, is the encroachment of mostly unpalatable woody plants at the expense of desirable grasses. This "bush encroachment," as it is called in South Africa, reduces the grazing capacity of rangelands, with a consequent loss of income for ranchers. Bush encroachment may shift carbon pools and source/sink relationships, which could have large regional and global biogeochemical implications given the tremendous area of the savanna biome.

Glantz (1994) first used the term creeping environmental phenomena (CEP) to describe low-grade, long-term, cumulative environmental degradations such as desertification, pollution, etc. Incremental, almost imperceptible changes in the environment accumulate until a major degradation is realized, often well after the degradation could have been most cost-effectively halted or reversed if detected sooner. Chronic overgrazing is a global CEP; widespread bush encroachment has been observed on every continent where arid and semiarid rangelands occur (Archer, 1995), including the vast savannas of Africa, where deforestation is often assumed to be the more significant form of land cover change (Fairhead and Leach, 1996).

This article is an assessment of woody plant encroachment in South African savanna using historical aerial photography. Aerial photographs have been the traditional workhorse in terms of providing remotely sensed data for land use/cover change studies. In more recent decades, Landsat and SPOT satellite sensors have been supplanting aerial cameras. The digital availability and broader spatial extent of Landsat and SPOT images have made them increasingly attractive for landscape-scale research. However, the bush encroachment phenomenon occurs over decadal time scales, largely predating satellite data availability. Black and white aerial photographs

often constitute the only available remotely sensed data record. Although they preclude spectral analyses, black and white aerial photos possess excellent spatial detail that make them appropriate for studying bush encroachment because it is a long-term phenomenon that occurs at the small spatial scale of individual trees and shrubs.

One former study bears particular relevance for our own. Scanlan and Archer (1991) overlaid a 20 m×20 m grid onto a time series of aerial photographs of three savanna sites in southern Texas that had become encroached by woody plants. They then manually classified the vegetation in each grid cell into one of seven structural classes, representing a decadal-scale successional process typified by three major steps: 1) colonization by a pioneer woody species within a herbaceous matrix, 2) understory establishment of secondary woody species to form a woody clump, and 3) expansion and coalescence of discrete woody clumps to eventually form a continuous woodland.

The bush encroachment process in South African savannas, on the other hand, is not characterized by expanding clumps that coalesce to diameters often greater than 10 m. Typically, bush encroachment progresses as more and more individual woody stems recruit in a seemingly random pattern across the landscape. Some encroaching species coppice, yet the diameters of even the largest coppices are less than 10 m. While in a random pattern some woody stems and coppices will occur in close enough proximity to look like a large woody clump, clumps neither expand nor show evidence of coalescence by a functional mechanism, as they appear to in southern Texas (Archer et al., 1988).

Manual photointerpretation for studying bush encroachment has several formidable disadvantages. First, the cumbersome task of counting bush clumps in an aerial photograph is compounded by the number of photos needed to cover the broad spatial extent of most savannas, which is further compounded in a multitemporal analysis of a chronology of aerial photos. While the human eye may be unsurpassed for comparing spatial characteristics between two or three aerial photos, the human brain cannot efficiently process the dozens or hundreds required to cover whole landscapes at multiple points in time. Manual photointerpretation would also prove inaccurate because the sparse canopies of many savanna shrubs and small trees cannot be easily resolved. We believe that the practical difficulties of manual photointerpretation demanded an automated analysis strategy for our study.

The woody overstory produces shadows that visually distinguish it from the herbaceous understory in high resolution aerial photographs. We hypothesized that the degree of tonal variation, or texture, in aerial photographs of savanna vegetation could be related to vegetation structural parameters measured on the ground. To test our hypothesis, we used standard aerial photos and field validation data for several woody canopy parameters. Our analysis methods and results are divided into three

primary sections: 1) a preliminary geostatistical analysis to characterize the scale of canopy structural variation, 2) application and validation of a textural index to characterize bush densities, and 3) exploration of the utility of textural photomosaics for mapping bush densities across space and bush density change through time.

DATA ACQUISITION

Site Descriptions

We chose two South African savanna landscapes for this study, Ganyesa and Madikwe, each approximately 80,000 hectares (ha) in area. Ganyesa (26.5°S, 24.0°E) is situated about 300 km southeast of Madikwe (25.0°S, 26.2°E). Both occur in separate parcels of the former black homeland state of Bophuthatswana in the Republic of South Africa (RSA), just south of the Botswana border. Cattle grazing is the predominant land use in the region. Some dry cropping is practiced along shallow drainages that remain dry almost the entire year, but these crop lands amount to less than 5% of the total land area because rainfall is simply too meager, intermittent, or unreliable to support most crops. Soils at Ganyesa are very homogeneous, consisting of deep Kalahari sand. Soils at Madikwe are much more heterogeneous, varying from poorly drained clay to well drained, rocky dolomitic soils. Both landscapes are flat except for two ridges that traverse the Madikwe landscape along with some scattered rocky outcroppings. Because bush encroachment has depleted the grazing potential at Madikwe over the past several decades, the government viewed tourism as a more profitable land use and thus established Madikwe Game Reserve on a 60,000 ha portion of the Madikwe landscape in 1991 (Madikwe Development Task Team, 1994).

Both regions are sparsely populated and generally devoid of land use features besides roads, fencelines, corals, and water tanks used in cattle management. These features were digitized (Calcomp 9100 digitizing table) into vector coverages from 1:50,000 land use maps, mostly from 1984 (Surveys and Land Information, Mowbray, RSA). Digitizing accuracy was ± 13 m. These automated maps were used as base maps for rectifying the images scanned from aerial photos and for constraining subsequent spatial analyses. Soil and vegetation layers (Wildnet, Pretoria, RSA) were added to the Madikwe landscape GIS due to Madikwe's greater complexity for these two variables.

Field Data Collection

In 1996, we established 18 field transects for the purpose of measuring several woody canopy structural parameters. The transects were situated across a range of woody plant densities in four vegetation communities determined by soil type. The four communities differed in terms of physiognomy, bush density, fire frequency, and species composition of both animals and plants, with

dominant plant species often of the genus *Acacia*. Commonly encroaching woody species included *Dichrostachys cinerea* and species of the genera *Acacia* and *Grewia*. A single community comprised the Ganyesa landscape, where we located 4 transects, while three communities largely comprised the Madikwe landscape, where we located 14 transects. We used a global positioning system (GPS) (Trimble Pathfinder Basic+) to geolocate the endpoints and middle point of each transect. GPS data were differentially corrected using concurrent base station files (provided courtesy of Telkom, Inc.) and then averaged to get final position estimates, accurate to within ± 2 m. Several woody canopy structural traits were sampled within a 5-m radius of 17 points placed at 15-m intervals along each 240 m transect (Fig. 1). Field variables measured at each transect included: 1) percent woody canopy cover; 2) woody plant frequency, that is, the number of times (max=17) that a sample point along the transect occurred within the dripline of a woody plant; 3) number of woody species; 4) number of woody stems; 5) woody stem basal diameter, measured at ankle height; 6) aboveground woody biomass; and 7) woody stem height, approximated to the nearest meter.

Our intent was to compare woody overstory structural parameters between transects, not within, so we pooled data for each transect. Since Variable 1 was estimated using the plotless Bitterlich technique (Mueller-Dombois and Ellenberg, 1974; Friedel and Chewings, 1988), we averaged three measurements made at the endpoints and middle point of each transect. Variable 2 required no further preprocessing. Variable 3 was pooled by totaling the number of woody species identified along the entire transect. Variables 4 and 5 were summed for each transect. Variable 6 was allometrically estimated from Variable 5 using regression equations formulated by Tietema (1993) for the major local woody species, and then summed. From Variable 7 we calculated mean and standard deviation statistics, since we believed either might prove important.

Image Data Generation

We obtained 1:20,000 scale aerial photographs corresponding to the 18 field transect locations. Acquisition dates were 25–26 January 1995 for the Ganyesa landscape and 30 August–1 September 1994 for the Madikwe landscape (Azur Aerial Photogrammetry, Pretoria, RSA). We assumed that woody canopy structure had changed little in the intervening 1–2 year period between photo acquisition and our 1996 field campaign. An automatic brightness/contrast adjustment feature of the scanning software (Deskscan II 2.1) was employed to optimize photographic tonal variation within the 0–255 range; this helped to standardize brightness and contrast variables between photos as much as possible. Finally, we set the scanning resolution to the optical limit of the scanner (Hewlett Packard ScanJet IIc), or 300 dots per inch

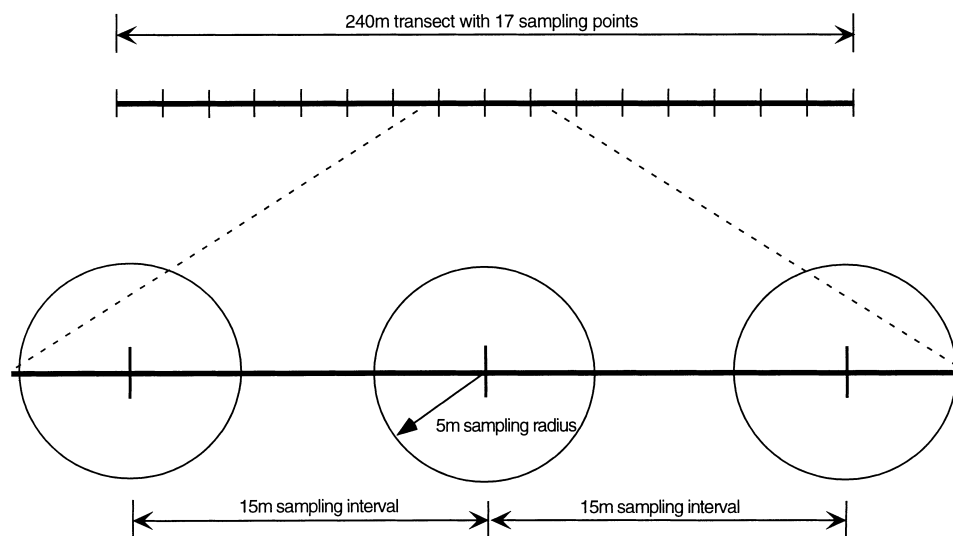


Figure 1. Schematic of the field data sampling design. Each of the 18 field transects was situated at least 100 m from any anthropogenic land use features, and within one of four major vegetation communities, to best sample the vegetation structure of each community and facilitate transect comparisons within and between the four communities.

(dpi). Output images had a grain size of approximately 1.7 m by the following formula:

$$\text{grain size (m)} = 20,000 / (300 \text{ dpi} \cdot 39.37 \text{ in/m}).$$

Using ARC/INFO software (ESRI, Redlands, CA), we georectified each image using as base maps the vector coverages from our Ganyesa and Madikwe GIS. The rectification used an affine transformation function, so no warping of the image occurred. A minimum of 10 ground control points (GCPs) were selected to rectify each image, with a maximum root mean square registration error of ± 15 m as the accuracy criterion. Grain sizes after georectification varied slightly between images (1.7–1.9 m). Therefore, we standardized image grain sizes to exactly 2 m, the nearest coarser integer value, using a nearest neighbor resampling algorithm.

DATA ANALYSIS

Preliminary Geostatistical Analysis

Each preprocessed image was much larger in extent than the 240 m field transects found within them, so we sub-setted 6–12 ha portions containing our 18 transects. Transects had been intentionally placed at least 100 m away from any anthropogenic features. Care was also taken to exclude from the image subsets any anthropogenic features or associated edge effects that can introduce anomalies into variograms (Rossi et al., 1992).

We first generated two-dimensional variograms using a routine written in Interactive Data Language (IDL Version 4.0.1b) to detect any natural sources of anisotropy in vegetation patterning, but only one of the 18 test sites exhibited anisotropic behavior (Hudak, unpublished data). Two-dimensional variograms are hard to interpret with respect to shape, range and sill values, and they are of little use when anisotropies are lacking (Woodcock et al., 1988), so we instead used an ARC/INFO GRID kriging routine to calculate matrix variograms, which assume

isotropic vegetation patterning (Cohen et al., 1990). Although generated omnidirectionally, matrix variograms can be averaged and plotted in conventional, one-dimensional form, making them more useful for depicting canopy structure than true one-dimensional variograms (Cohen et al., 1990).

At each of the 18 test sites, pixel values were converted into point values that were subsequently kriged (Isaaks and Srivastava, 1989). Visual comparison of our real variograms to ideal ones generated with spherical, exponential, Gaussian, circular, and linear models revealed our variograms to most closely resemble the spherical model, which also happens to be the conventional one (Isaaks and Srivastava, 1989). Initial variograms extended out to lag distances of several hundred meters where they became unstable because of fewer lags to control their behavior. Since we were mainly interested in the woody cover contribution to variogram behavior, we truncated the variograms at a lag distance of 100 m. By initially including an analysis area spanning several hundred meters in both the x and y directions, semivariance values at the 100-m lag distance were still constrained by a large sampling. The matrix variograms from five test sites in one of the Madikwe vegetation communities are plotted in Figure 2. Range values of approximately 5–15 m suggested this was the principal scale of spatial variation in woody cover.

Textural Analysis

The preceding geostatistical analysis implied that a statistical measure of local pixel variance, or textural index (Haralick, 1979), could prove a valuable indicator of woody canopy structure in heterogeneous savanna canopies. We calculated texture using three statistical measures of variation between neighboring pixel values: range, root mean square error, and standard deviation. The resulting textural images appeared nearly identical, so we chose the standard deviation for our textural index

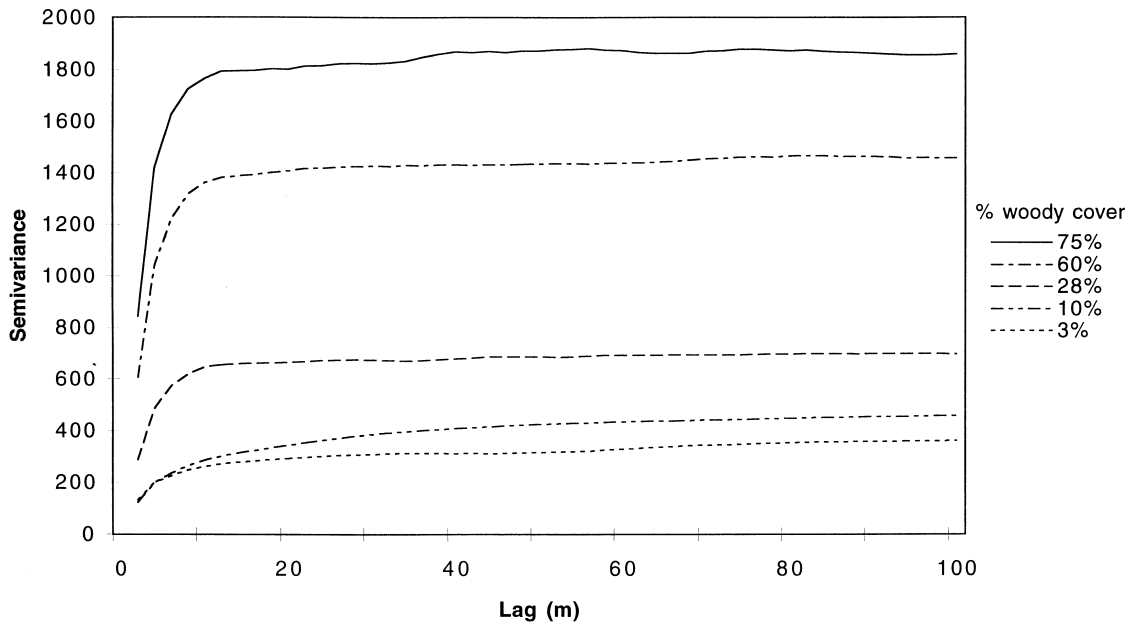


Figure 2. Typical variograms, representing five test sites situated in one vegetation community. All 18 omnidirectional variograms in this analysis were generated from 2-m image data.

because it could be most straightforwardly applied in ARC/INFO GRID. We calculated standard deviation only within a 3×3 filter window because larger filter windows had an undesirable smoothing effect on the small-scale features in canopy structure which were of primary interest to us.

We calculated mean texture for the same 18 test sites, regressed mean texture on 10-m-lag semivariance values, and obtained a very high correlation. However, while 2-m images may be obtained by scanning large-scale aerial photos, they are currently commercially unavailable from satellites. By aggregating pixels in the raw image and calculating their mean, we coarsened our original, full-extent 2-m images to 10 m, 20 m, 30 m, and 80 m—the spatial resolutions of the SPOT Panchromatic (PAN), SPOT Multispectral (XS), Landsat Thematic Mapper (TM), and MultiSpectral Scanner (MSS) sensors, respectively—and then subset the same test sites as before. By choosing these four grain sizes, we could compare the potential practical utility of these sensor resolutions for characterizing woody canopy structure with our textural index. Figure 3 shows how the relationship between mean texture and 10-m-lag semivariance steadily worsened as grain size was coarsened. Figure 4 illustrates the appearance of a typical test site sampled at all five resolutions, both before and after textural filtering.

Validation

Factor Analysis

We added two variables derived from our 18 2-m-grain test sites—10-m-lag semivariance and mean texture—to eight variables derived from our 18 field transects. Using

SPSS software (SPSS Inc., Chicago, IL), we then applied a factor analysis (Davis, 1986) to this 10×18 data matrix. Our goal was to examine the correlation structure of the variables in multivariate space to identify which variable(s) best correlate to mean texture. Table 1 shows the correlation matrix for the 10 variables along with a description of each.

By convention, we truncated the factor matrix to those eigenvectors having eigenvalues ≥ 1.0 , then rotated the factor matrix to aid identification of variable clusters (Davis, 1986). Figure 5 is a 3-D factor plot that graphically illustrates the variable loadings on the three factors. Table 2 shows the eigenvalues and rotated three-factor matrix, broken down into variable clusters.

Regression Analysis

According to the factor analysis, the lone field variable to cluster with the two image-derived variables was STEMS. Based on this result, we chose woody stem count as the best correlate to image texture. Regressions of mean texture on woody stem count again worsened as image grain size was coarsened from 2 m to 10 m, 20 m, 30 m, or 80 m (Fig. 6).

SPATIAL AND TEMPORAL EXTRAPOLATION

Image Mosaicking

We simulated three 10-m SPOT PAN images for both the Ganyesa and Madikwe study landscapes, using spatially comprehensive, historical aerial photograph coverage. Table 3 summarizes the standard, black and white photos purchased for each landscape (Surveys and Land Information, Mowbray, RSA).

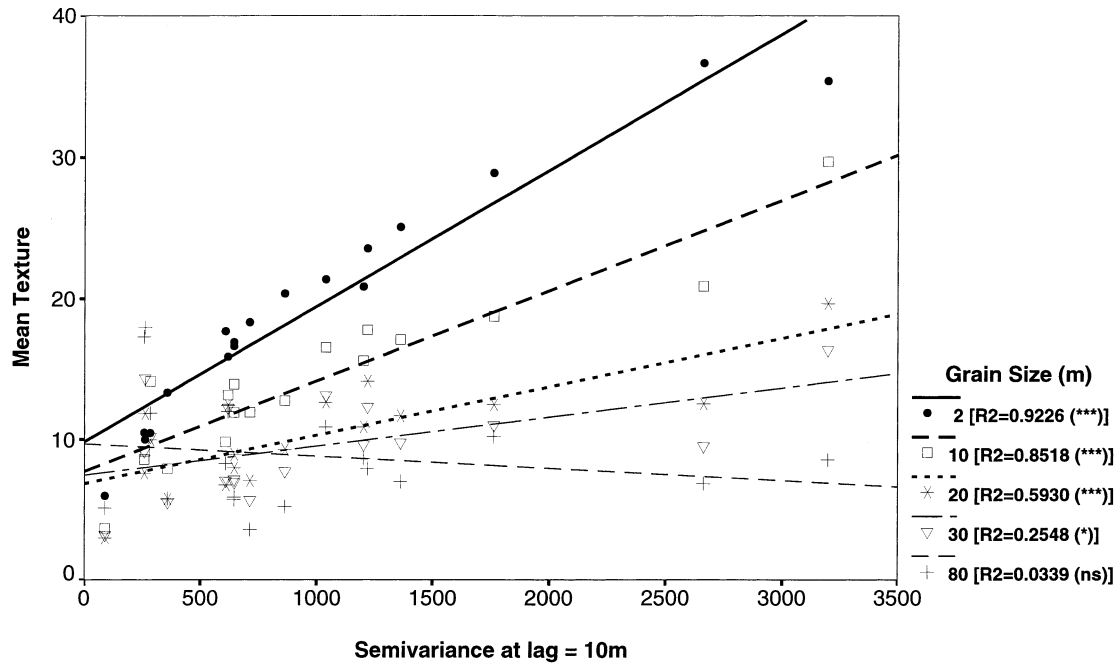


Figure 3. Linear regressions of mean texture on semivariance at a lag distance of 10 m, for the 18 test sites. Semivariances were extracted from the 2-m image data variograms. Mean texture was calculated from the same image data at grain sizes of 2 m, 10 m, 20 m, 30 m, and 80 m. Significance: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

We used the same scanning protocol as described earlier but adjusted the scanner resolution to compensate for the differential photo scales, producing output images with a consistent grain size of approximately 10 m after georectification. Georectified images were merged into three photomosaics for each study landscape: 1960, 1969, and 1982 for the Ganyesa landscape; 1955, 1970, and 1984 for the Madikwe landscape. We then resampled the photomosaics to a grain size of exactly 10 m, using a

nearest neighbor resampling algorithm as before. Next, for each study landscape, the area common to all three mosaics was subset from each. These last two operations produced, for each landscape, a composite stack of three photomosaics with the same grain size and spatial extent and, consequently, the same pixel count as well. We then applied our textural filter to each 10-m photomosaic. Finally, to remove salt and pepper effects and to ease subsequent classification, mapping, and spatial analysis, we ag-

Figure 4. Paired raw and texture images, respectively, at five spatial resolutions.

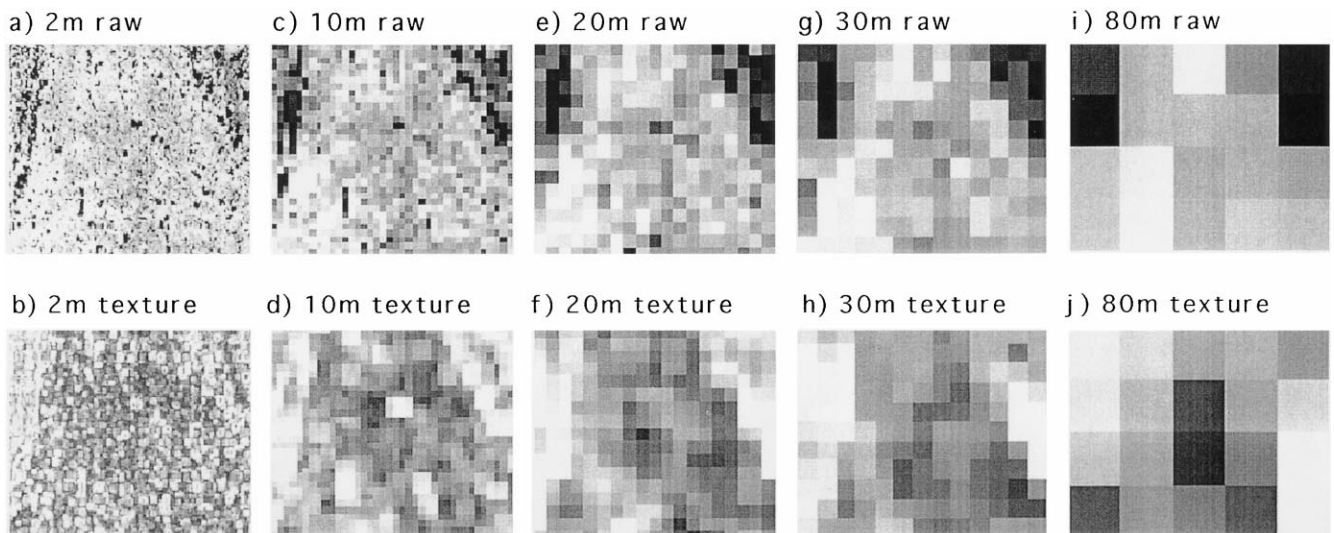


Table 1. A) Correlation Matrix for the 10 Variables Included in the Factor Analysis; B) Variable Descriptions

A. Correlation Matrix										
	biomass	cover	mnheight	sdheight	species	stemba	stems	woodfreq	grain2m	svlagten
biomass	1.00000									
cover	.83272	1.00000								
mnheight	.82750	.83892	1.00000							
sdheight	.58781	.36687	.35165	1.00000						
species	.35259	.36236	.29194	.73898	1.00000					
stemba	.95607	.92357	.86119	.60513	.45266	1.00000				
stems	.07679	.38916	-.01516	.04883	.37493	.20247	1.00000			
woodfreq	.72578	.84304	.71182	.47887	.49330	.82326	.38627	1.00000		
grain2m	.40660	.66031	.37904	.20684	.46389	.53076	.83776	.63647	1.00000	
svlagten	.28297	.53199	.23160	.10760	.36563	.38714	.81028	.53078	.96050	1.00000

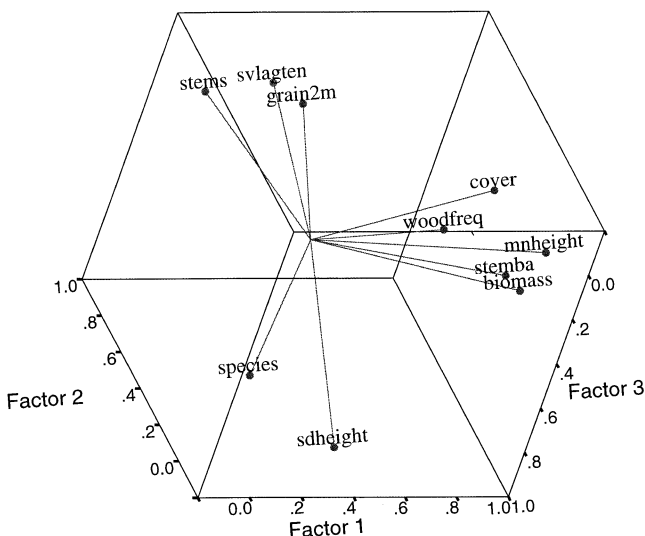
B. Variable Descriptions										
BIOMASS: total aboveground biomass										
COVER: percent woody canopy cover										
MNHEIGHT: mean of woody plant height										
SDHEIGHT: standard deviation of woody plant height										
SPECIES: total number of woody plant species										
STEMS: total number of woody plant stems										
STEMBA: total stem basal area measured at ankle height										
WOODFREQ: number of sampling points in close proximity to a woody plant										
GRAIN2M: mean canopy texture calculated from 2-m-grain images										
SVLAGTEN: 10-m-lag semivariance values, also calculated from 2-m images										

gregated the 10-m textural image pixels to a resolution of 1 ha, assigning the mean to the coarsened output pixels.

Bush Density Classification

We classified each textural mosaic using a density slice, choosing to create five bush density classes because it equally partitioned the 0–255 dynamic range of the textural data. Partitioning the mosaics in this way required that image brightness and contrast characteristics be standardized among all images comprising each mosaic.

Figure 5. Factor plot in rotated three-dimensional factor space, illustrating variable loadings upon the three factors.



This seemed a reasonable assumption for photos acquired using the same equipment, under the same conditions, at nearly the same time. However, sun-view-angle geometry created a problem with the three Ganyesa mosaics. High albedo soils caused pronounced brightness gradients across the larger-scale extent of the photos, which often overwhelmed the smaller-scale tonal contrasts indicative of canopy structure. Image contrast is subject to variations in illumination intensity and sensor response characteristics, which are difficult to eliminate (Musick and Grover, 1991). Empirical techniques have been developed to correct brightness gradients in hyperspectral imagery (Kennedy et al., 1997) but were not applied in this analysis of single-band imagery.

In contrast, such brightness gradients were not evident in the three photomosaics of the Madikwe landscape, where soils are darkly colored. The boundaries between adjacent flight strips were nearly seamless, but with one notable exception: An aberrant flight strip in the 1955 mosaic, due to “damaged film” (Surveys and Land Information, Mowbray, RSA), had a dramatically smoother texture than the other flight strips. Since the textures were incompatible, we were forced to exclude this flight strip from our 1955 bush density classification.

This problem of incongruous textural data in the 1955 mosaic served as an informative spatial analog to the problem of comparing multitemporal textural data. A visual inspection of the raw aerial photos of the same sites, but during different years, revealed that apparent canopy texture fundamentally differed as a function of photograph radiometry (contrast), not of true change in

Table 2. A) Eigenvalues of the Three Principal Factors Generated from the Factor Analysis; B) Rotated Factor Matrix, Grouped by Cluster

<i>A. Eigenvalues</i>			
<i>Factor</i>	<i>Eigenvalue</i>	<i>% of Variance</i>	<i>Cumulative %</i>
1	5.81779	58.2	58.2
2	2.12737	21.3	79.5
3	1.20584	12.1	91.5
<i>B. Rotated Factor Matrix</i>			
<i>Variable</i>	<i>Factor 1</i>	<i>Factor 2</i>	<i>Factor 3</i>
MNHEIGHT	0.94050	0.01878	0.07752
STEMBA	0.91901	0.17960	0.31279
BIOMASS	0.91199	0.04746	0.27352
COVER	0.88725	0.38816	0.09893
WOODFREQ	0.75495	0.39998	0.28514
STEMS	-0.01894	0.94465	0.10923
SVLAGTEN	0.22235	0.93119	0.06021
GRAIN2M	0.35247	0.91035	0.13742
SDHEIGHT	0.34692	-0.05218	0.89570
SPECIES	0.15554	0.31902	0.87733

canopy structure. The inability to calibrate contrast between photos precluded any absolute, quantitative comparisons. In other words, spatial frequencies in the textural data distributions from different dates were unique to each histogram. Since we wanted to compare bush density classification maps from different years, we determined it illogical to classify our textural mosaics by partitioning their histograms into five classes of equal interval. Therefore, we employed an equal area slicing algorithm to classify the textural data, which forced classes to have equal pixel counts. This was valid because pixel counts were identical between mosaics. Figures 7a–7c show the result of an equal area slicing and classification of the 1955, 1970, and 1984 textural mosaics of the Madikwe landscape. By then differencing these classification maps themselves, we did not make an absolute comparison in bush density over time, but we could at least reveal localities where relative changes in bush density might have occurred. Figure 7e is a bush encroachment map made by subtracting the 1970 from the 1984 classification map.

We noted immediately from our Madikwe classification maps that bush density patterns reflected vegetation community patterns apparent both in the field and in the Madikwe GIS. At Madikwe, soil type is the primary determinant of woody overstory structure and species composition. Therefore, we conducted a spatial analysis to quantify, beyond visual comparison (Fig. 7d), the relationship between distributions of bush density classes and soils. Soils were divided into four broad soil classes: black clay, red clay loam, dolomitic, and other, predominantly loam soils. These classes represented the four most extensive vegetation communities occurring across the landscape. Figure 8 shows that in a) 1955, b) 1970,

and c) 1984, loam soils comprise a greater proportion of the higher bush density classes, while black clay and dolomitic soils comprise a greater proportion of the lower bush density classes. These results agree with 1996 field observations of relative bush densities on these soil types.

Change Trajectories

Earlier, we referred to the difficulty in making absolute comparisons between textural data derived from images with fundamentally different contrast. We further explored this problem by comparing mean textural values between dates for the same 18 test sites used in the textural index validation. To include more data in this comparison, we added the 1994/95 images to our analysis. Since these images had a grain size of 2 m, while the historical textural mosaics had a grain size of 10 m, we aggregated 2-m pixels in the 1994/95 images to 10 m and then applied our textural filter. Because we had 1994/95 aerial photos for only our test sites, we subset areas from our historical textural mosaics that matched the extent of the 1994/95 textural images. Having standardized both the grain and extent for all textural images, we then standardized their histogram ranges to 0–255 by applying a linear stretch to each image (Haralick and Shanmugam, 1974). Finally, we clipped image subsets of all 18 test sites for all four dates. Test sites were identical in extent to the 18 test sites used in the preliminary geostatistical analysis described earlier, so any anthropogenic sources of texture in the landscape were again excluded from the subsets. Finally, mean texture was calculated for every test site in the 18×4 dataset.

Henebry and Su (1993) compared radiometries of multitemporal images by using landscape trajectories, which are simply graphs of some radiometric property of a landscape, calculated from images acquired at several points in time. We applied change trajectories to compare mean textural values between different dates. Figure 9 shows change trajectories for a) the same five Madikwe test sites as were used to exemplify typical variogram behavior in Figure 2 and b) the four Ganyesa test sites. Through time, mean texture generally increased at the Ganyesa test sites, while it generally decreased at the Madikwe test sites.

DISCUSSION

Validation

Faced with a lack of historical field data, the soil and vegetation maps from our Madikwe GIS proved instrumental in validating our historical Madikwe bush density maps. Since soils mainly determine vegetation community composition at Madikwe, and since soil patterns remain essentially static over decadal time scales, it seemed safe to assume that bush density distribution patterns should map similarly at different dates. Thus, bush den-

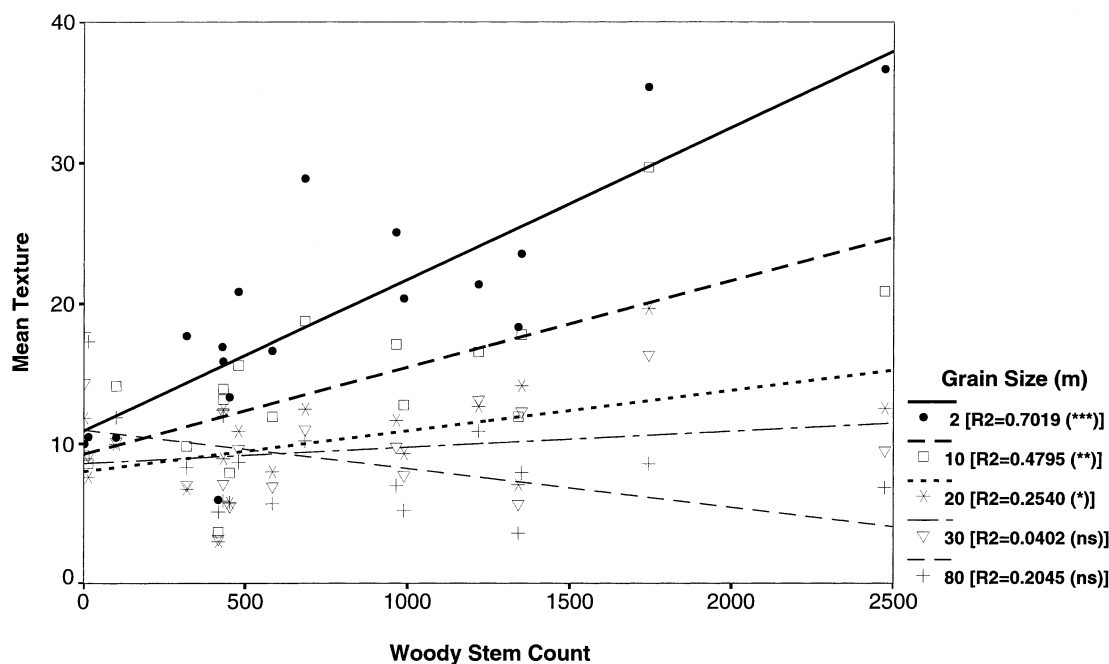


Figure 6. Regressions of mean texture on woody stem count, for the 18 test sites. Woody stem count is the total number of woody stems counted at each transect. Mean texture was calculated from the image data at grain sizes of 2 m, 10 m, 20 m, 30 m, and 80 m. Significance: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

sity distribution patterns should map similarly between different dates as long as no compositional changes have occurred. This was a reasonable expectation, as grazing has been the only land use practice throughout the aerial photo records with the exception of some dry cropping.

On the other hand, heavy grazing has increased woody plant densities throughout the region over the past several decades (Hoffman, 1997). We do not know for certain which soil types have suffered the most bush encroachment since the start of our aerial photo record. Yet, we have three lines of evidence to support the accuracy of the bush density patterns portrayed in our Madikwe bush density maps.

First, bush density patterns in Figures 7a–7c are generally consistent, and two of the local inconsistencies evident in Figure 7e can be explained by cropland clearing or abandonment. A visual inspection of the aerial photo prints confirms that the homogeneous red area in

the north central portion of Figure 7c is attributable to cropland expansion between 1970 and 1984. Further visual validation confirms that the blue areas of apparent encroachment in the south central region of Figure 7e are attributable to cropland abandonment and subsequent bush regrowth during that same period.

Second, the relationship between bush density classes and soil type has been fairly consistent over time (Fig. 8). The commonality in these graphs is for higher bush densities to occur on predominantly loam soils while lower bush densities occur on predominantly black clay or dolomitic soils. An extensive soil/vegetation survey conducted in the fledgling Madikwe Game Reserve in 1991 supports this conclusion, as do our own 1996 field observations.

Third, visual comparison of the sequential aerial photos yielded some interesting supplementary facts useful for interpreting the change trajectories (Fig. 9). First, Madikwe test sites RB and RC occur in very close proximity to each other—the same aerial photo, in fact. From the 1970 photo, it is apparent that a field containing both sites was cleared after acquisition of the 1955 photo. Moreover, the portion of the field containing test site RB was abandoned to woody plant regrowth some time prior to acquisition of the 1984 photo, while the portion of the field containing test site RC has been kept cleared. When mean textural values for test sites in the same year are ranked, the ranks do not conflict with expectations formed from a visual comparison of the photos. Also, these ranks tend to be preserved between different dates in the absence of human land cover manipulations, such

Table 3. Description of the Aerial Photographs Used in the SPOT Scene Simulations

Landscape	Photo Acquisition Date	Photo Scale
Ganyesa	May 1960	1:50,000
Ganyesa	May 1969 (northern strip)	1:60,000
	June 1969 (southern 2 strips)	
Ganyesa	May 1982	1:50,000
Madikwe	July 1955	1:30,000
Madikwe	June 1970	1:30,000
Madikwe	June 1984	1:50,000

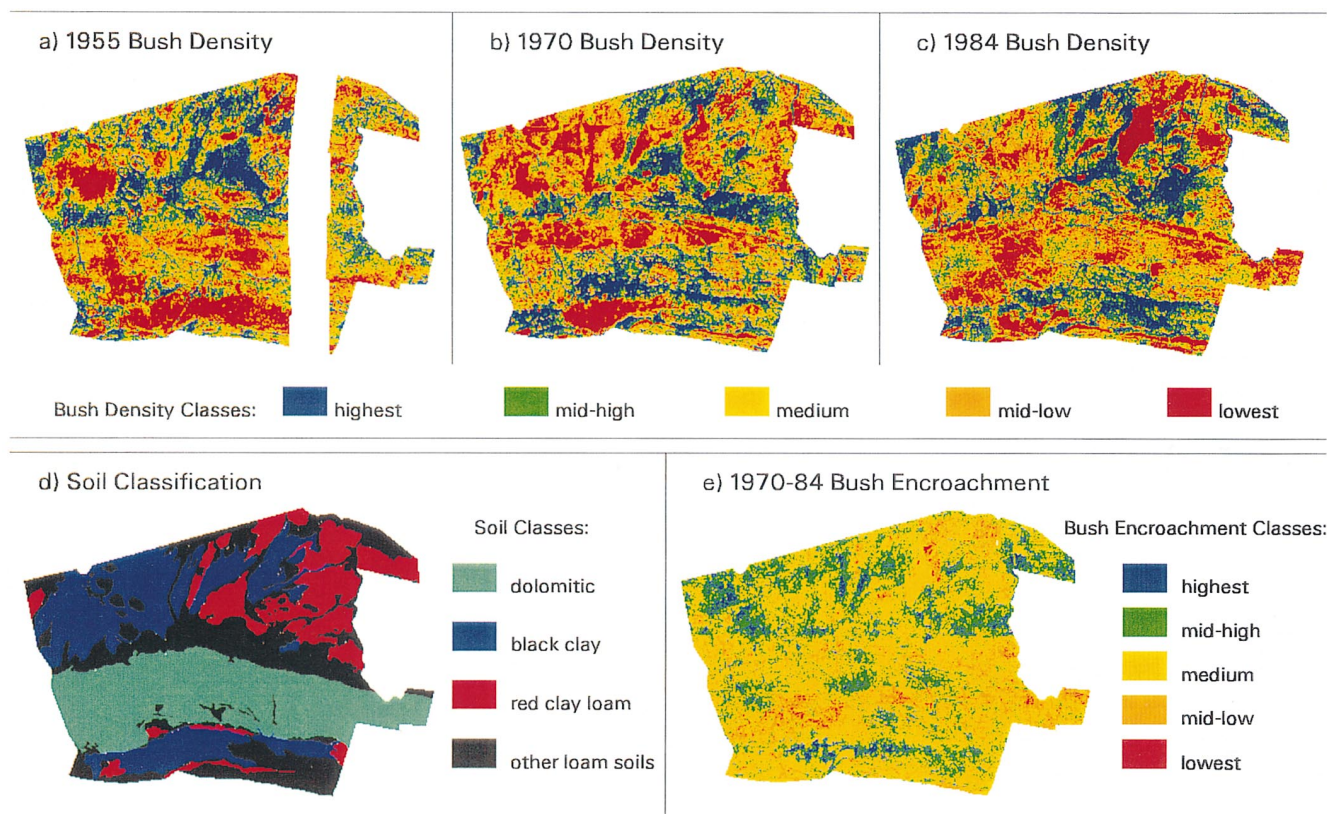


Figure 7. Historical bush density maps of the study landscape now bounded by Madikwe Game Reserve. a) 1955 bush density map (minus one flight strip with aberrant data); b) 1970 bush density map; c) 1984 bush density map; d) simplified soil map, indicative of the major vegetation communities; e) 1970–1984 bush encroachment map.

as cropland clearing or abandonment. For example, Ganyesa test site SP, which has the lowest mean texture at all four points in time, is located in a cropland that has been maintained throughout the aerial photo record.

The most plausible explanation for the discrepancy in change trajectory trends between the Madikwe and Ganyesa test sites is incongruous contrast in the source data. For example, the 1955 Madikwe photos look noticeably sharper when visually compared to the 1984 or 1970 photos. Furthermore, the 1970 photos have the same scale as the 1955 photos, indicating that this contrast discrepancy is not an artifact of dissimilar photograph scales. Thus, while our change trajectories proved useful for comparing bush densities across space, we caution that they are inappropriate for quantifying bush density change over time.

Applicability

Much previous research has promoted the use of variograms in choosing the appropriate spatial resolution for studying ecological phenomena (Curran, 1988; Woodcock et al., 1988; Oliver et al., 1989; Rossi et al., 1992; Atkinson and Curran, 1997). Despite this and the realization that ecological phenomena are scale dependent, few studies have employed variograms to determine the ap-

propriate measurement scale in studies of landscape pattern or ecosystem process (Cullinan and Thomas, 1992). Atkinson and Danson (1988) and Cohen et al. (1990) constitute noteworthy exceptions, as they used variograms to assess the spatial dependence of conifer canopy structure. Cohen et al. (1990) showed that range values derived from 1-m imagery related to mean tree canopy size, and sill values responded to vertical layering and percent canopy cover. Our own matrix variograms (Fig. 2) closely corroborate those of Cohen et al. (1990), but for a heterogeneous savanna canopy.

Most land use/cover change studies that have employed automated analyses have relied on spectral classifications that essentially consider each image pixel independent of its neighbors. Considerable land cover information is lost by ignoring the variance between neighboring pixels. In fact, it is the interpixel relationships, not the pixels themselves, that enable us to identify land cover types with our eyes. Computer pattern-recognition capabilities have far to go, however, before they can rival those of the human eye (Hay and Niemann, 1994). Thus, land use/cover classifications using aerial photos have relied on visual interpretation (Fairhead and Leach, 1996). Solely textural approaches to land cover classification have been in the still somewhat

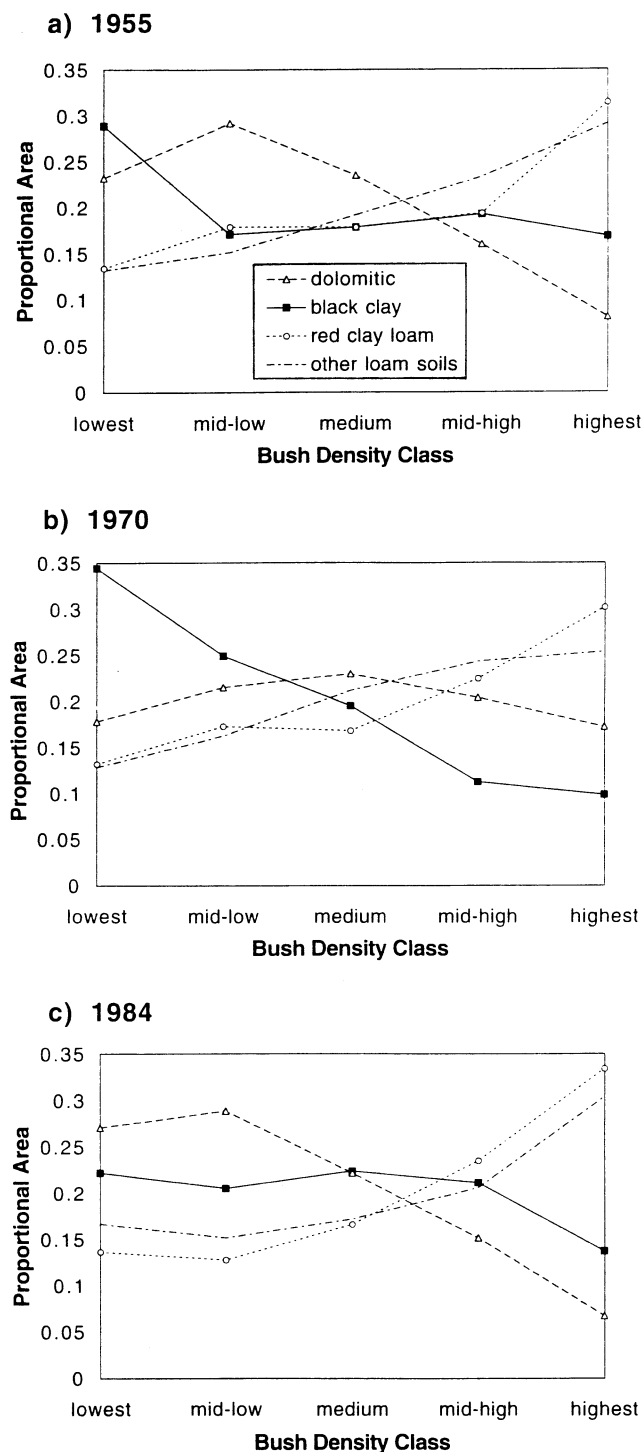


Figure 8. Proportional area of each of four soil types found within each of five bush density classes in the Madikwe landscape in a) 1955, b) 1970, and c) 1984. Before deriving these areal statistics, the area contained within an aberrant 1955 flight strip was also masked from the 1970 and 1984 photomosaics so that the equal area classification would be applied to the same area in all three years.

experimental arena of pattern recognition and knowledge-based systems. Studies have exploited image texture as an additional source of land cover type information besides spectral information (Marceau et al., 1989; Franklin and Peddle, 1989; Franklin and Peddle, 1990; Møller-Jensen, 1990; Wang and He, 1990; Agbu and Nizeyimana, 1991; Peddle and Franklin, 1991; Kushwaha et al., 1994; Hay et al., 1996; Ryherd and Woodcock, 1996). We have demonstrated a simple textural analysis that is ecologically applicable even when used alone.

Greater use of textural indices could increase our capability to measure and monitor canopy structure at landscape scales. Probably the largest constraint on using textural indices is the need for high spatial resolution (Haralick et al., 1973). Woodcock and Strahler (1987) demonstrated how local pixel variance declines as spatial resolution coarsens. Similarly, Figures 3 and 6 show how the power of our textural index declines with increasing grain size.

When the correlations between image texture and the eight field-derived woody canopy variables are ranked and considered (note the coefficients shown in boldface in Table 1), it is not surprising that image texture should correlate better with woody canopy parameters that vary principally in the horizontal plane, such as woody stem count and percent woody cover. Other woody canopy parameters vary substantially in ways not amenable to overhead measurement via remote sensing, such as canopy height (vertical variation), stem basal area or aboveground biomass (morphological variation between species). The regression of 10-m image texture on percent woody cover (not shown) was weaker than on woody stem count (Fig. 6), but still proved significant ($R^2=0.3241$; $p=0.0137$). Thus, percent woody cover estimates could also serve as useful ground truth for the textural index, especially since percent woody cover can be estimated quickly at a large sampling of points across the landscape.

The fact that our 10-m textural images significantly correlated to woody stem count suggests that not only aerial photography could be used to characterize bush densities, but also high resolution satellite data. The wider spatial extent, reduced geometric distortion, and more consistent radiometry of SPOT PAN images, for example, make them superior to our 10-m photomosaics. SPOT imagery for our study region became available in 1989 (Satellite Applications Centre, Pretoria, RSA), necessitating the use of historical aerial photography to map bush densities across our study landscapes in years prior. It would be useful to apply our textural index to a contemporary SPOT PAN image, produce a bush density map, and compare it to our historical bush density maps. To build and maintain a historical database of high resolution imagery so as to facilitate future efforts to monitor canopy structural change, it is important to maintain continuity in high spatial resolution satellite remote

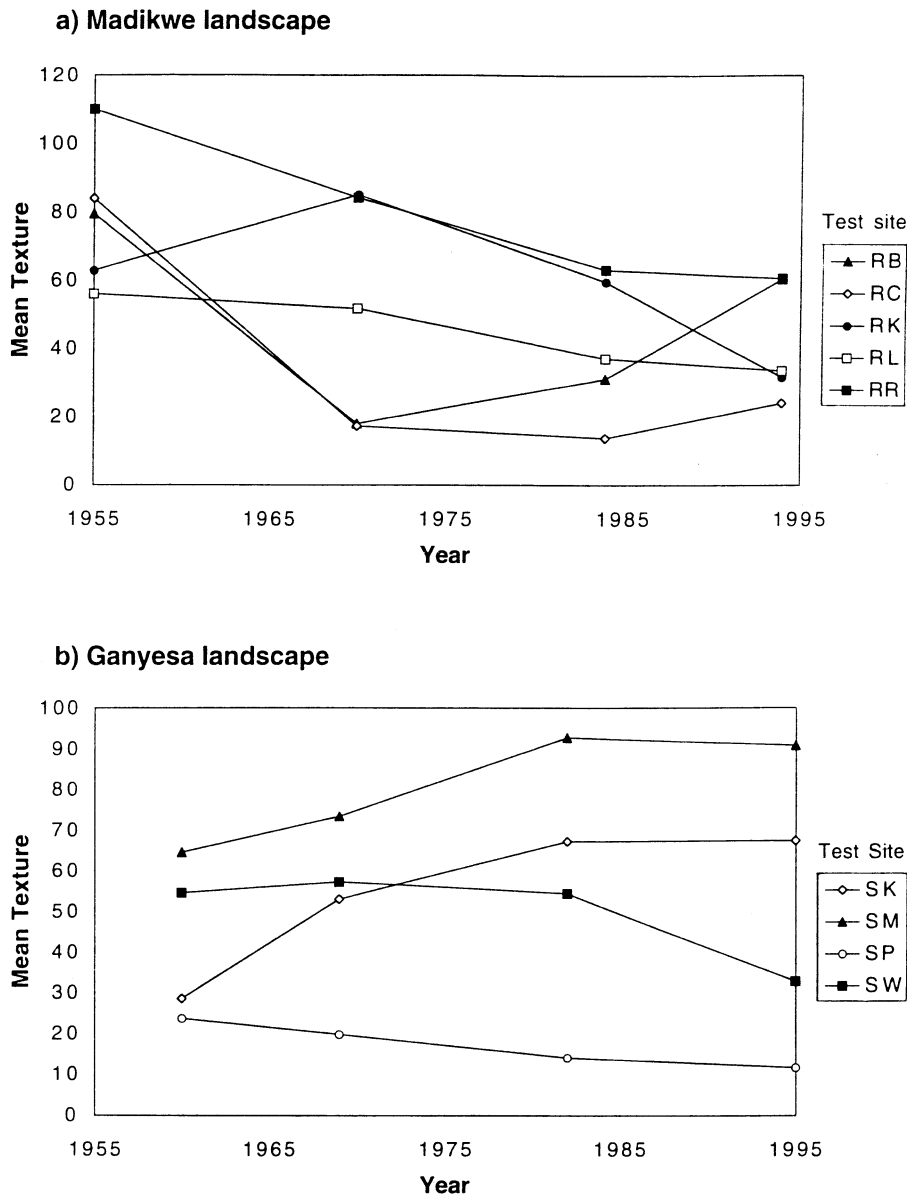


Figure 9. Change trajectories depicting mean textural values at four points in time for a) five test sites situated in one vegetation community found in the Madikwe landscape (same test sites as shown in Fig. 2) and b) four test sites situated in the single vegetation community found in the Ganyesa landscape.

sensing. There is potential to measure absolute changes in woody plant density and other types of land cover modification using our textural index and a spatial analysis procedure described in Hudak and Wessman (1997).

CONCLUSIONS

Several conclusions about the applicability of historical aerial photo records and image texture for characterizing savanna canopy structure can be drawn from the main results of this study.

1. Variograms effectively illustrated the spatial dependence of woody canopy cover in this study. Sill values proved highly sensitive to woody plant density. Range values indicated that most canopy structural variation in this heterogeneous savanna

occurs at a scale of approximately 10 m. Studies of landscape pattern or process should first employ geostatistical tools to aid in designing an analysis at the appropriate spatial scale.

2. Woody stem count was the best correlate with image texture in this study. While image texture may be a good indicator of woody plant density, it is probably a poor indicator of other canopy structural parameters of at least equal interest to ecologists, such as aboveground biomass.
3. In this analysis, the sensitivity of image texture to canopy structural variation declined sharply as image grain size was coarsened from 2 m. For satellite monitoring of vegetation cover modification across landscapes, high spatial resolution is required.

4. If the radiometric contrast within a contiguous group of aerial photos is consistent, they may be mosaicked and processed in unison to produce realistic bush density maps. However, large-scale brightness gradients induced by the bidirectional reflectance distribution function can create as yet uncorrectable artifacts in image mosaics, particularly in landscapes with high albedo.
5. The introduction of more confounding variables—different lighting, atmospheric, and surface conditions, as well as different photo equipment, acquisition, and development procedures—makes absolute texture comparisons between photos acquired in different years difficult. However, by constraining multitemporal comparisons to a common spatial extent, local areas of relative land cover modification can be mapped.
6. At three points in time, we found a consistent relationship between soil type and bush density that agrees with field observations. Thus, a GIS can prove a vital tool for validating historical vegetation maps when concurrent field data are unavailable.
7. Applying textural indices to high resolution imagery has potential for measuring and monitoring canopy structure where spectral vegetation indices fail. Improved maps of canopy structure are needed to explore the ramifications of woody plant encroachment on landscape-level carbon storage and biogeochemistry.

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