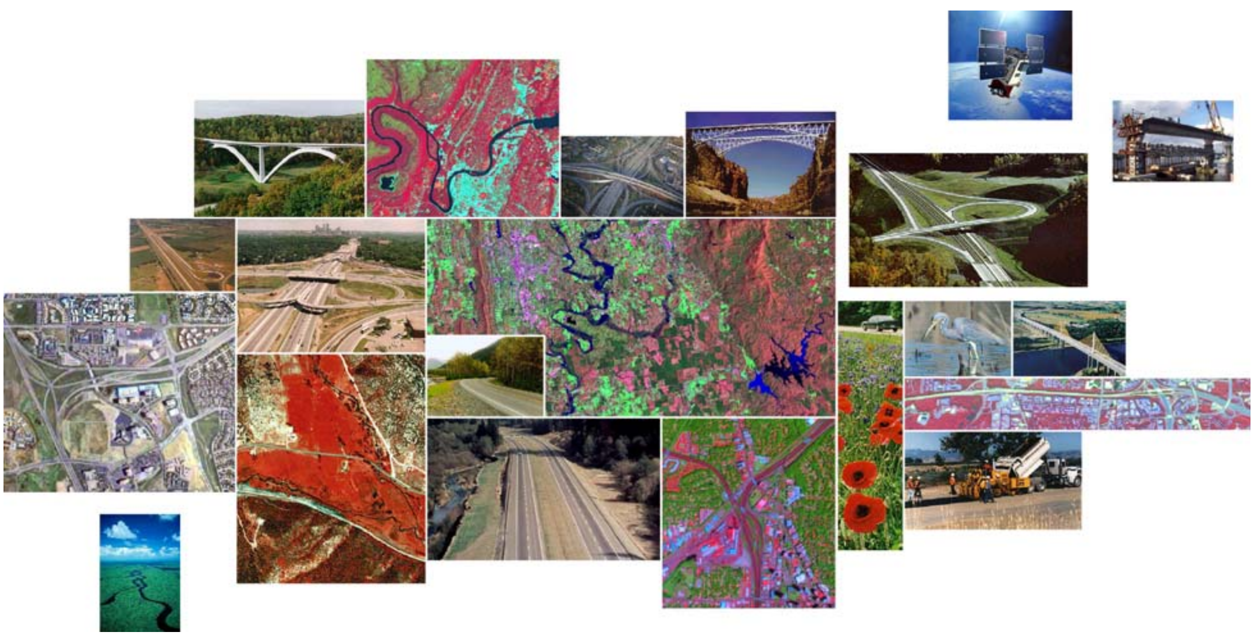
NCRST-E National Consortium for Remote Sensing in Transportation - Environmental Assessment

TECHNOLOGY GUIDE: NCRSTE_TG009

Information Extraction from Remote Sensing Imagery Using Textural Analysis



December 2005

Prepared by
C. Laymon and M. Al-Hamdan
National Space Science and Technology Center
Global Hydrology and Climate Center
Huntsville, Alabama

TABLE OF CONTENTS

Page

1. Introduction …………………………………………………………………….... 3
2. Techniques……………………………………………………………………. 4
2.1. Statistical Methods ……………………………………………………… 4
2.2. Geometrical Methods …………………………………………….......... 5
2.3. Model-based Methods …………………………………………………... 6
2.4. Signal Processing Methods ……………………………………………... 8
3. Case Study ……………………………………………………………………. 11
4. References ……………………………………………………………………. 23

1. INTRODUCTION

Classification of remote sensing imagery is a means of compressing much spectral data into more readily understandable and interpretable information. In so doing, much of the noise in data is eliminated resulting in a signal that is relatively course. Detecting landscape change via image classification is limited by the high degree of generalization intrinsic to classification systems that stems from a) conventional dependence on a limited number of spectral bands, b) aggregation of information inherent in statistical approaches to classification and c) dependence on a single sensing system with a fixed spatial scale. The combined effect is that change is not detected until gross changes have occurred that are discernable within the generalization framework.

Transformations in the form of ratios and indices (i.e. NDVI, EVI, polarization index) derived from multispectral data generally provide higher fidelity than classification, but are limited to the spatial resolution of the original data. Assessment of change detection via indices offers increased sensitivity to change, but interpretation of the meaning of the change is often less intuitive.

Texture analysis refers to a class of mathematical procedures and models that characterize the spatial variations within imagery as a means of extracting information. Texture is an areal construct that defines local spatial organization of spatially varying spectral values that is repeated in a region of larger spatial scale. Thus, the perception of texture is a function of spatial and radiometric scales. Mathematical procedures to characterize texture fall into four general categories, statistical, geometrical, model-based methods and signal processing methods and include Fourier transforms, convolution filters, co-occurrence matrix, spatial autocorrelation, fractals, etc. (Tuceryan and Jain, 1998; Zhao, 2001).

Because texture has so many different dimensions, there is no single method of texture representation that is adequate for a variety of textures. Here, we provide a brief description of a number of texture analysis techniques and some examples. Many terms will be unfamiliar to the reader and one is encouraged to seek other sources for more in depth discussion. Most image processing software packages that are commercially available today include several texture analysis tools. Few, however, make full use of these tools because of the difficulty interpreting results.

Despite their potential value, textural measures have not been exploited in any formal way for routine monitoring of landscape change. Although, texture analysis has been used to *classify* remotely sensed images, its value is restricted within the limitations afforded by classification. The spatial variations in image values that constitute texture are generally due to some underlying physical variation in the landscape that alters the reflectivity or emissivity. Textural analysis techniques can be used to provide quantitative metrics that are highly sensitive to the underlying processes of change. For example, Lam et al. (2002) showed that a quantitative description of landscape complexity could aid in the interpretation of landscape processes. Lam et al. (1998) showed the value of spatial metrics, such as fractal dimension, in revealing the spatial characteristics of images.

Fractals and spatial autocorrelation are two spatial analytical techniques used to measure geometric complexity (Lam et al., 2002) and conveniently describe many irregular, fragmented patterns found in nature (Mandelbrot, 1983). One of the advantages of fractal and spatial autocorrelation techniques over other spatial indices used in landscape ecology, such as contagion, dominance, and interspersion is that it can be applied directly to unclassified images (Lam et al., 2002). Also, in contrast to autoregressive and Markov models, fractals have high power in low frequencies, which enables them to model processes with long periodicities (Ojala and Pietikyinen, 2004). Although the fractal technique has been applied extensively in a variety of disciplines (e.g., Krummel et al., 1987; MacLennan and Howarth, 1987; Lovejoy and Schertzer, 1985; Barbanis et al., 1999; Lu and Hellawell, 1995), its use as a spatial technique for characterizing remote sensing images is limited and needs to be evaluated more thoroughly (Lam et al., 2002). Emerson et al. (1999) concluded that more research is needed to link textural analysis of remotely sensed images with the complexity of geographical processes. Quattrochi et al. (2001) examined the relationship between fractal dimensions and spectral resolution of imagery. Likewise, Lam et al. (2002) concluded that further research on fractal and related textural analysis methods applied to multi-resolution imagery would afford a better understanding of the impact of scale on the analysis of environmental phenomena. Quattrochi et al. (2002) measured the fractal dimensions of different environmental and ecological landscapes to determine if they had characteristic fractal dimensions that could be used to identify regions of varying degrees of complexity and used for change detection without the need to classify images beforehand. Al-Hamdan (2004) showed that important forest-related measures could be effectively estimated from remotely sensed radiometric data using textural analysis techniques. Textural metrics were related to landscape characteristics. The study also revealed optimal radiometric and spatial resolutions among various remote sensors for detecting differences in surface characteristics.

These and other studies provide a foundation for using textural analysis models to characterize landscape change. These techniques rely explicitly on data from a single sensing system and none exploit the information that is available from other sensing systems at contrasting but complementary spatial scales and frequencies. Textural and adaptive filters provide various metrics regarding heterogeneity at the scale of multiple pixels. Because texture has so many different dimensions, there is no single method of texture representation that is adequate for a variety of textures.

2. TECHNIQUES

A wide variety of techniques for describing image texture have been proposed in the research literature. Tuceryan and Jain (1998) defined four major categories for analysis techniques: statistical, geometrical, model-based and signal processing.

2.1. Statistical Methods

Statistical methods analyze the spatial distribution of gray values by computing local features at each point in the image and deriving a set of statistics from the distributions of the local features (Ojala and Pietikyinen, 2004). The use of statistical features is one of the early methods proposed in the research literature (Tuceryan and Jain, 1998). The reason behind that is the fact that the spatial distribution of gray values is one of the defining qualities of texture. Statistical methods can be classified into first-order (one pixel), second-order (two pixels) and higher-order (three or more pixels) statistics based on the number of pixels defining the local feature (Ojala and Pietikyinen, 2004). The first-order statistics estimate properties like the average and variance of individual pixel values, ignoring the spatial interaction between image pixels, second- and higher-order statistics on the other hand estimate properties of two or more pixel values occurring at specific locations relative to each other. Co-occurrence features and gray level differences (Weszka et al., 1976) are the most widely used statistical methods, which inspired a variety of modifications later on (Ojala and Pietikyinen, 2004) including signed differences (Ojala et al., 2001) and the Local Binary Pattern (LBP) operator (Ojala et al., 1996). LBP operator combines statistical and structural approaches to texture analysis by incorporating occurrence statistics of simple local microstructures. Autocorrelation function, which has been used for analyzing the regularity and coarseness of texture (Kaizer, 1955; Emerson et al., 1999; Lam et al., 2002; Al-Hamdan, 2004), and gray level run lengths (Galloway, 1975) are examples of other statistical approaches (Ojala and Pietikyinen, 2004).

2.2. Geometrical Methods

Geometrical methods try to describe the primitives and the rules governing their spatial organization by considering texture to be composed of texture primitives. The structure and organization of the primitives can be presented using Voronoi tessellations (Tuceryan and Jain, 1990). An example of often-used primitive elements would be image edges (Ojala and Pietikyinen, 2004). The desirable properties in defining local spatial neighborhoods and because the local spatial distributions of tokens are reflected in the shapes of the tessellations are some of the advantages of this method. Segmentation of textured images is one example of texture features based on Voronoi polygons (Tuceryan and Jain, 1998) (Figure 1). Gray level texture images and a number of synthetic textures have been successfully segmented with identical second-order statistics by this algorithm (Ojala and Pietikyinen, 2004).

Edge detection with a Laplacian-of-Gaussian or a difference-of-Gaussian filter (Marr 1982, Voorhees & Poggio 1987, Tuceryan and Jain 1990); adaptive region extraction (Tomita and Tsuji 1990); or mathematical morphology (Matheron, 1967; Serra, 1982) are some techniques used for extracting the primitives (Ojala and Pietikyinen, 2004). Once the primitives have been identified, the analysis is completed either by computing statistics of the primitives (e.g. intensity, area, elongation, and orientation) or by deciphering the placement rule of the elements (Zucker 1976, Fu 1982).

A method in which the observable textures are considered as distorted versions of ideal textures has been proposed by Zucker (1976). The placement rule is defined for the ideal texture by a graph that is isomorphic to a regular or semiregular tessellation. These graphs are then transformed to generate the observable texture, which is used to determine which of the regular tessellations should be used as the placement rule (Ojala and Pietikyinen, 2004). In another approach, Fu (1982) proposed to regard the texture image as texture primitives arranged according to a placement rule (Ojala and Pietikyinen, 2004). The primitive is usually a collection of pixels, but it can be as simple as a single pixel that can take a gray value. The placement rule is defined by tree grammar and a texture is then viewed as a string in the language defined by the grammar whose terminal symbols are the texture primitives. This method can be used for texture generation as well as texture analysis, which is an advantage (Ojala and Pietikyinen, 2004).

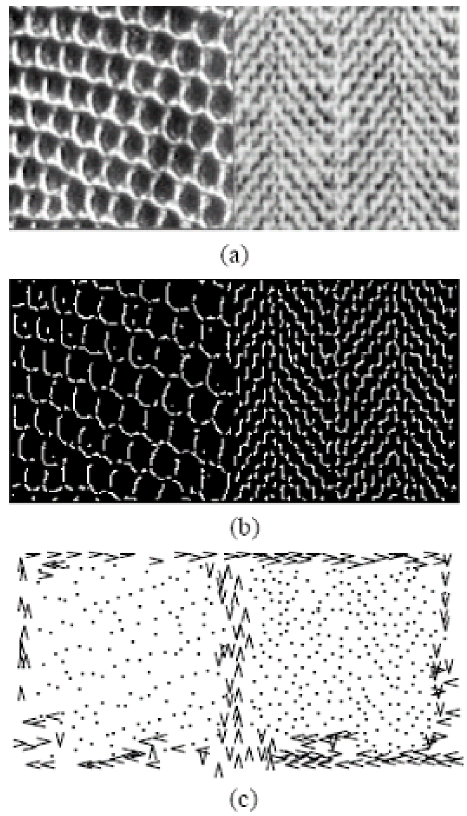
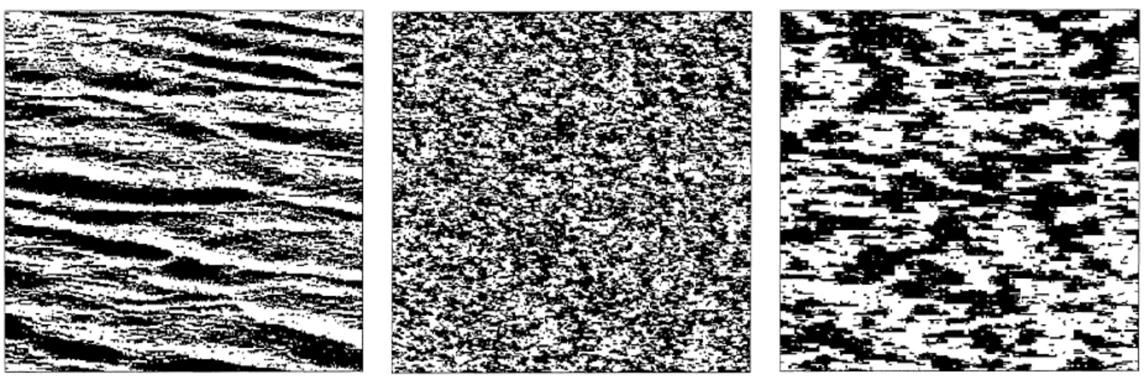


Figure 1. Texture segmentation using the Voronoi tessellation. (a) An example texture pair from Brodatz's album (Bajcsy and Lieberman, 1976), (b) the peaks detected in the filtered image, and (c) the segmentation using the texture features obtained from Voronoi polygons (Tuceryan and Jain, 1990). The arrows indicate the border direction. The interior is on the right when looking in the direction of the arrow (Tuceryan and Jain, 1998).

2.3. Model-based Methods

Model based texture analysis methods are based on the construction of an image model that can be used not only to describe texture, but also to synthesize it (Ojala and Pietikyinen, 2004). The model parameters capture the essential perceived qualities of texture. These methods hypothesize the underlying texture process, constructing a parametric generative model, which could have created the observed intensity distribution (Ojala and Pietikyinen, 2004). The intensity function is considered to be a combination of a function representing the known structural information on the image surface and an additive random noise sequence. Pixel-based models view an image as a collection of pixels, whereas region-based models regard an image as a set of subpatterns placed according to given rules (Ojala and Pietikyinen, 2004). Region-based models are an example of random mosaic models, which tessellate the image into regions and assign gray levels to the regions according to a specified probability density function (Schachter et al. 1978). The facet model is a pixel-based model, which assumes no spatial interaction between neighboring pixels, and the observed intensity function is assumed to be the sum of a deterministic polynomial and additive noise (Haralick & Watson 1981) (Ojala and Pietikyinen, 2004). Random field models analyze spatial variations in two dimensions. Global random field models treat the entire image as a realization of a random field (Frieden 1980, Hunt 1980), whereas local random field models assume relationships of intensities in small neighborhoods (Ojala and Pietikyinen, 2004). A Gibbs random field is a global model, where using cliques of neighboring pixels as the neighborhood system, a probability density function is assigned to the entire image (Besag, 1974; Hassner and Sklansky, 1980; Geman & Geman 1984; Ojala and Pietikyinen, 2004). Markov random fields (MRFs) have been popular for modeling images because they are able to capture the local (spatial) contextual information in an image. These models assume that the intensity at each pixel in the image depends on the intensities of only the neighboring pixels. MRF models have been applied to various image processing applications, such as texture synthesis (Cross and Jain, 1983; Wang and Liu, 1999), texture classification (Chellappa and Chatterjee, 1985; Khotanzad and Kashyap, 1987), image segmentation (Therrien, 1983; Cohen and Cooper, 1987), image restoration (Geman and Geman, 1984), and image compression (Ojala and Pietikyinen, 2004) (Figure 2).



(a) (b) (c)

Figure 2. Example of water texture synthesis. (a) Original water texture, (b) The synthesized water texture with MRF modeling, (c) The synthesized water texture with multiresolution MRF modeling (Wang and Liu, 1999).

Mandelbrot (1983) proposed describing images with fractals, a set of self-similar functions characterized by so-called fractal dimensions (FD), which is correlated to the perceived roughness of image texture (Pentland 1984). In contrast to autoregressive and Markov models, fractals have high power in low frequencies, which enables them to model processes with long periodicities (Ojala and Pietikyinen, 2004). For a surface, such as remotely sensed images, FD can be estimated using the isarithm method (Lam et al., 2002) (Figure 3). The isarithm method computes a mean fractal dimension from individual FD values of gray-scale contours. For each isarithm (contour) value and each step size, the algorithm classifies each pixel below the isarithm value as white and each pixel above this value as black (Quattrochi et al., 2001). It then compares each neighboring pixel along the rows or columns and determines whether the pairs are both black or both white. If they are dissimilar, then an isarithm lies between the two neighboring pixels. The length of each isarithm line is approximated by the total number of boundary pixels (Quattrochi et al., 2001). A linear regression is performed using the logarithms of the total length of the boundary and the step size. The regression slope is used determine the fractal dimension FD of the isarithm line. The final fractal dimension FD of the surface is the average of the FD values for those isarithms having a coefficient of determination greater than or equal to 0.9 (Jaggi et al., 1993; Emerson et al., 1999; Quattrochi et al., 2001; Lam et al., 2002).

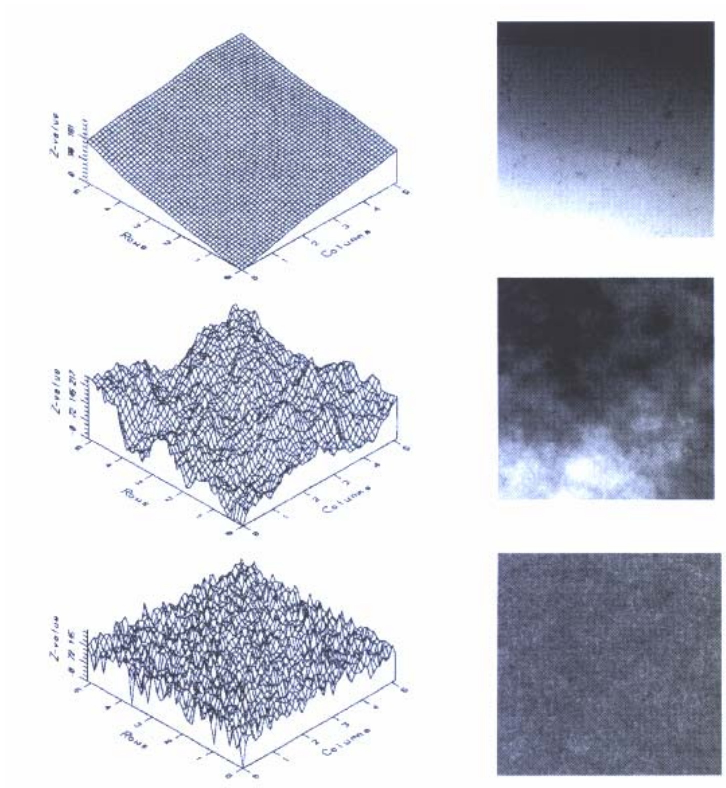


Figure 3. Three simulated surfaces and corresponding images from top to bottom, Fractal Dimension (FD) = 2.1, 2.5, 2.9. (Lam et al, 2002).

Many natural surfaces have a statistical quality of roughness and self-similarity at different scales. Fractals are very useful and have become popular in modeling these properties in image processing (Tuceryan & Jain 1998). Quattrochi et al. (2002) measured the fractal dimensions of different environmental and ecological landscapes to determine if they had characteristic fractal dimensions that could be used to identify regions of varying degrees of complexity and used for change detection without the need to classify images beforehand. Al-Hamdan (2004) showed that important forest-related measures could be effectively estimated from remotely sensed radiometric data using textural analysis techniques. Textural metrics were related to landscape characteristics. The study also revealed optimal radiometric and spatial resolutions among various remote sensors for detecting differences in surface characteristics.

2.4. Signal Processing Methods

Signal processing methods analyze the frequency content of the image. Spatial domain filters, such as Law's (1980) masks, local linear transforms proposed by Unser and Eden (1989), and various masks designed for edge detection (e.g. Roberts' and Sobel's operators (Rosenfeld and Kak, 1976)) are the most direct approach for capturing frequency information (Ojala and

Pietikyinen, 2004). Rosenfeld and Thurston (1971) introduced the concept of edge density per unit area: fine textures tend to have a higher density of edges than coarse textures.

Another class of spatial filters are moments (Laws, 1980), which correspond to filtering the image with a set of spatial masks. The resulting images are then used as texture features (Ojala and Pietikyinen, 2004). Tuceryan (1992) used moment-based features successfully in texture segmentation. 'True' frequency analysis is done in the Fourier domain. The Fourier transform describes the global frequency content of an image, without any reference to localization in the spatial domain, which results in poor performance. Spatial dependency is incorporated into the presentation with a window function, resulting in a so-called short-time Fourier transform (Ojala and Pietikyinen, 2004). The squared magnitude of the two-dimensional version of the short-time Fourier transform is called a spectrogram, which Bajcsy and Lieberman (1976) used in analyzing shape from texture.

Multiresolution analysis, the so-called wavelet transform, is achieved by using a window function, whose width changes as the frequency changes (Mallat, 1989). If the window function is Gaussian, the obtained transform is called the Gabor transform (Turner, 1986; Clark and Bovik, 1987). A two-dimensional Gabor filter is sensitive to a particular frequency and orientation (Ojala and Pietikyinen, 2004). Other spatial/spatial-frequency methods include the difference-of-Gaussians (Marr 1982) and the pseudo-Wigner distribution (Jacobson & Wechsler 1982). Texture description with these methods is done by filtering the image with a bank of filters, each filter having a specific frequency. Texture features are then extracted from the filtered images. Often many scales and orientations are needed, which results in texture features with very large dimensions (Ojala and Pietikyinen, 2004). Dimensionality can be reduced by considering only those bands, which have high energy (Reed & Wechsler 1988, Jain & Farrokhnia 1991). Alternatively, redundancy can be reduced by optimizing filter design so that the frequency space is covered in a desired manner (Manjunath & Ma 1996) (Ojala and Pietikyinen, 2004).

Lucieer (2004) presented a supervised texture-based image segmentation technique that identifies objects from fine spatial resolution Light detection And Ranging (LiDAR) imagery and from multi-spectral Compact Airborne Spectral Imager (CASI) imagery (Figures 4 and 5). The proposed algorithm provided good segmentation results for a test case study with a composite image of five different textures. The study provided a texture-based supervised segmentation algorithm that derived labeled objects from remotely sensed imagery. Texture was modeled with the joint distribution of Local Binary Patterns (LBP) and local variance. The segmentation algorithm was a hierarchical splitting technique, based on reducing uncertainty at the level of the image blocks that are obtained. This technique provides not only a texture-based image segmentation, but also an indication of uncertainty for all object building blocks (Lucieer, 2004). The spatial distribution of uncertainty values provided information about the location and width of transition zones. The study showed that object uncertainty values provide important information to identify transition zones between fuzzy objects (Lucieer, 2004).

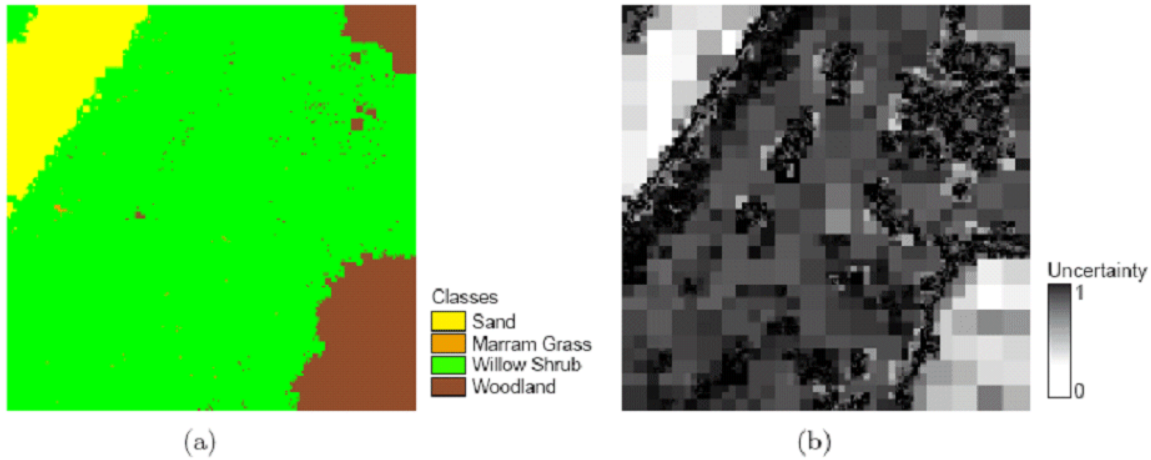


Figure 4. Segmentation result band 12 CASI image: (a) Supervised texture-based segmentation of band 12 of a CASI image with four reference land cover classes; (b) Related uncertainty for all object building blocks (Lucieer, 2004).

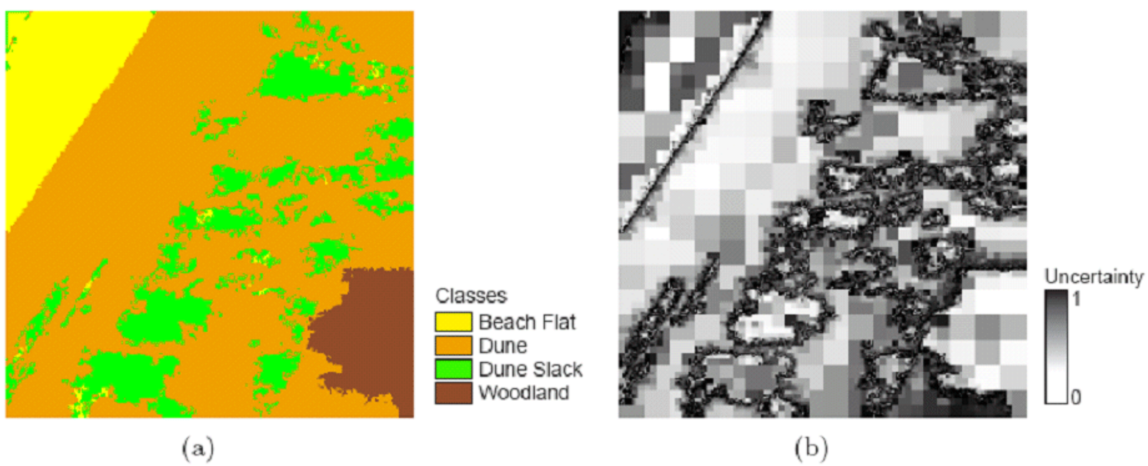


Figure 5. Segmentation result LiDAR DSM: (a) Supervised texture-based segmentation of the LiDAR DSM with four reference land form classes; (b) Related uncertainty for all object building blocks (Lucieer, 2004).

Ohanian and Dubes (1992) have studied the performance of various texture features. They compared four fractal features, sixteen co-occurrence features, four Markov random field features, and Gabor features (Tuceryan and Jain, 1998). The evaluation was done on four classes of images: Gauss Markov random field images, fractal images, leather images, and painted surfaces. The co-occurrence features generally outperformed other features (88% correct classification) followed by fractal features (84% classification). Using both fractal and co-occurrence features improved the classification rate to 91% (Tuceryan and Jain, 1998). It also used the energy from the raw Gabor filtered images instead of using the empirical nonlinear transformation needed to obtain the texture features as suggested in (Jain and Farrokhnia, 1991 cited in Tuceryan and Jain, 1998). Their study did not compare the texture features in segmentation tasks.

Kim et al. (2004) presented an efficient method of detecting ridges and ravines in gray scale images by using local min and max operations (Figure 6). This method comes from the idea that, of the gray scale morphological operations, the opening operation tends to remove small bright details and the closing operation removes dark details from the gray scale image (Kim et al., 2004). In this method, the properties of opening and closing are implemented by combining the fuzzy logic operations (local min and max operations). This method needs no information of ridge or ravine direction, and has been shown to be capable of detecting ridges and ravines of various pixel widths (Kim et al, 2004).

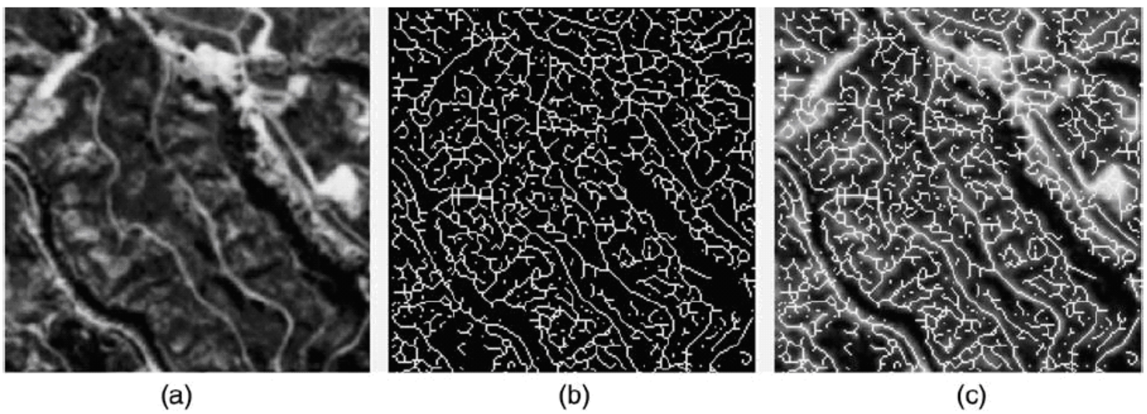


Figure 6. Detecting ridges in a gray-scale airphoto: (a) original image, (b) ridges derived from (a), and (c) ridges overlaid on original image (Kim et al., 2004).

3. CASE STUDY

We provide a case study in more detail that illustrates how some of the information extraction techniques described above can be utilized in processing remotely sensed images. Environmental protection is accomplished through Environmental Assessments and Environmental Impact Statements (EIS) that seek to prevent adverse environmental effects from taking place rather than mitigating problems caused by past activities or practices. Characterization of floodplains is a necessary component of EISs associated with proposed transportation corridors that cross or encroach upon floodplains. A study was conducted to examine the utility of remotely sensed data in characterizing the water resistance characteristics of forested flood plain areas that might lie in highway corridors or be subject to highway crossings (Al-Hamdan, 2004). One objective of this study was to use remotely sensed data and GIS to characterize vegetated landscapes based on their complexity and roughness associated with forests. We show demonstrated that important forest-related measures could be effectively estimated from remotely sensed radiometric data using textural analysis techniques. This characterization facilitates hydraulic and hydrologic modeling because surface roughness is required to compute the flow information needed by engineers in the design of highways that cross flood plains in forested areas, especially in large areas where human access is very difficult. More specifically, the research objective was to determine whether or not important measures of forest-related surface roughness could be effectively estimated from remotely sensed data using the textural analysis techniques. Several remotely sensed images of different spatial and spectral resolution were obtained for several forested regions (Figure 7).

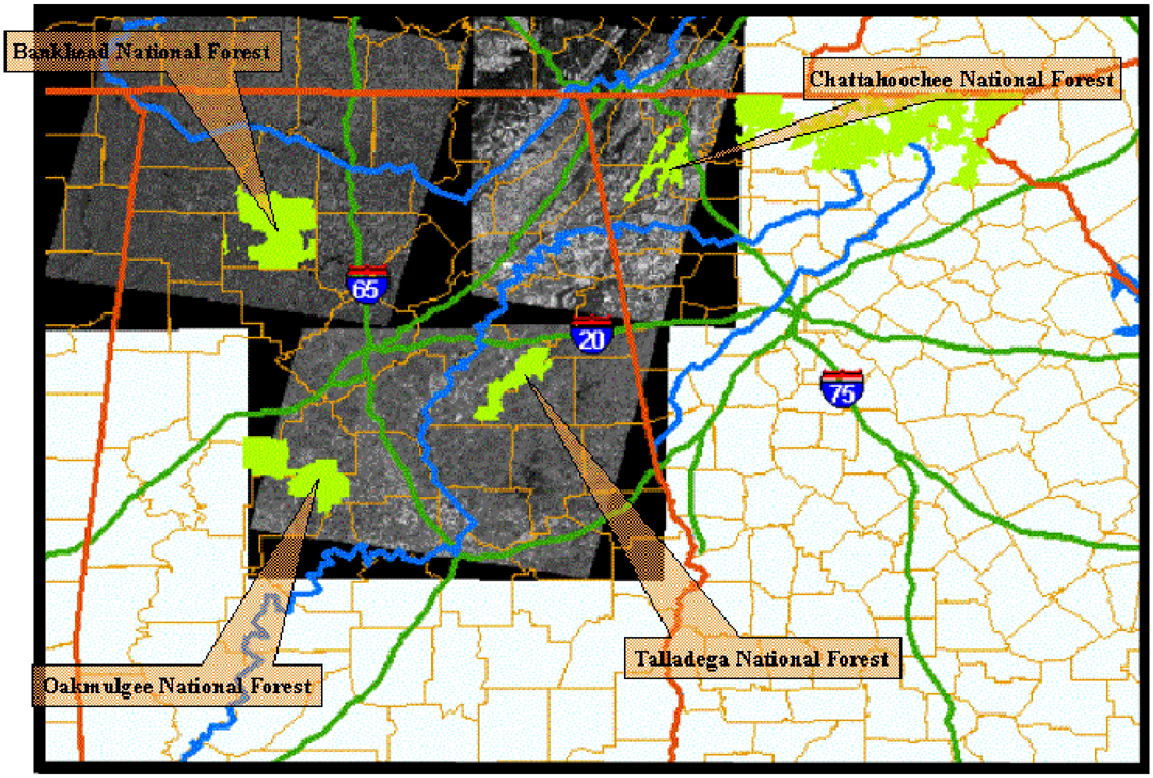


Figure 7. Forest sites used in Al-Hamdan's case study.

Textural analysis techniques, namely fractals and spatial autocorrelation methods, were used to characterize these images in terms of image complexity and roughness associated with forests. The effects of spatial and spectral characteristics of the data on the estimates of the textural indices were also examined. For a given tree species, the reflectance values recorded by remote sensors are a function of the size and continuity of the forest canopy. Thus, for hydraulic and hydrological purposes, such as overland flow modeling in forests, there is a need to define the relationship between satellite information (digital numbers) and canopy closure, as well as the relationship crown width and diameter at breast height (DBH). These relationships are then used to estimate the flow roughness coefficient Manning's *n* using models like the one developed by Musleh (2003) in an experimental study.

The textural analysis techniques applied in the case study include fractals and spatial autocorrelation methods. Fractals are measures of the self-similarity and thus ultimately measure the degree of complexity of the imaged land surface. The fractal dimension (FD) can be visualized as related to the relationship between the total length of a surface feature and the step size used to measure that length. For a landscape surface, FD can be estimated using a method that is called the isarithm method (Lam et al., 2002). The isarithm method computes a mean FD from individual FD values of gray-scale contours (isarithms). For each isarithm value and each step size, the algorithm classifies each pixel below the isarithm value as white and each pixel above this value as black (Quattrochi et al., 2001). It then compares each neighboring pixel along the rows or columns and determines whether the pairs are either both black or both white. If they are dissimilar, then an isarithm lies between the two neighboring pixels. The length of each isarithm line is approximated by the total number of boundary pixels (Quattrochi et al., 2001). A linear regression is performed using the logarithms of the total length of the boundary and the step size. The regression slope B is used determine the fractal dimension of the isarithm line, where $\mathrm{FD} = 2 - B$. As a flat surface grows more complex, FD increases from a value of 2.0 to nearly 3.0 as the surface begins to fill a volume. The final fractal dimension FD of the surface is the average of the FD values for those isarithms having a coefficient of determination greater than or equal to 0.9 (Quatrochi et al., 2001; Lam et al., 2002; Emerson et al., 1999; Jaggi et al., 1993).

Spatial autocorrelation is an assessment of the correlation of a variable in reference to spatial location of the variable. Spatial autocorrelation measures the level of interdependence between the variables, the nature and strength of the interdependence. Moran’s I is one of the oldest measures of spatial correlation. It compares the value of a variable at any one location with the value at all other locations and can be applied to zones or points with continuous variables associated with them. Computation of Moran's I is achieved by division of the spatial covariation by the total variation.

Landsat TM images were acquired covering four National Forests areas wherein the forest stand characteristics (such as trunk size, distribution, species, etc) are well known. Topographic data in the form of digital elevation model (DEM) data sets were also obtained from the U.S. Geological Survey. The four National Forests for which data were obtained include Chattahoochee National Forest (GA), Talladega National Forest (AL), Oakmulgee National Forest (AL), Bankhead National Forest (AL) (Figure 7). A data set was constructed in Arc-View that consisted of the spatial distribution of species attributes, digital elevation files and the Landsat scenes. Leaf-on satellite images were used because forest canopies reflect more energy than do bare trees. A review of the forestry literature revealed that the relationship between tree canopy characteristics and trunk size has been extensively studied and quantified. Not surprisingly, these studies have shown that canopy size and trunk diameter are strongly related and thus it should be possible to indirectly estimate trunk diameters from observations of the canopies. Small subsets of each image (samples) were collected from each forest area making sure to obtain equal coverage of all parts of the forest (Figures 8 and 9). A total of at least 150 samples were collected from the forests for statistical analysis. The FD and Moran’s I values were found for all bands of the Landsat TM coverage and for all samples. The averages of FD and Moran’s I for each sample were calculated using the results of all Landsat TM bands except the thermal band, which has a different spatial resolution.

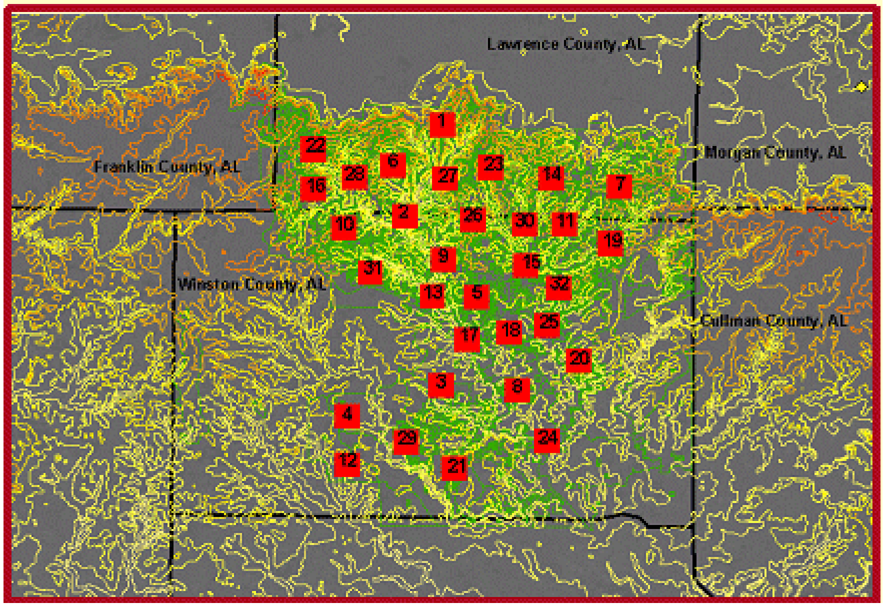


Figure 8. Location of sampling sites in Bankhead National Forest.

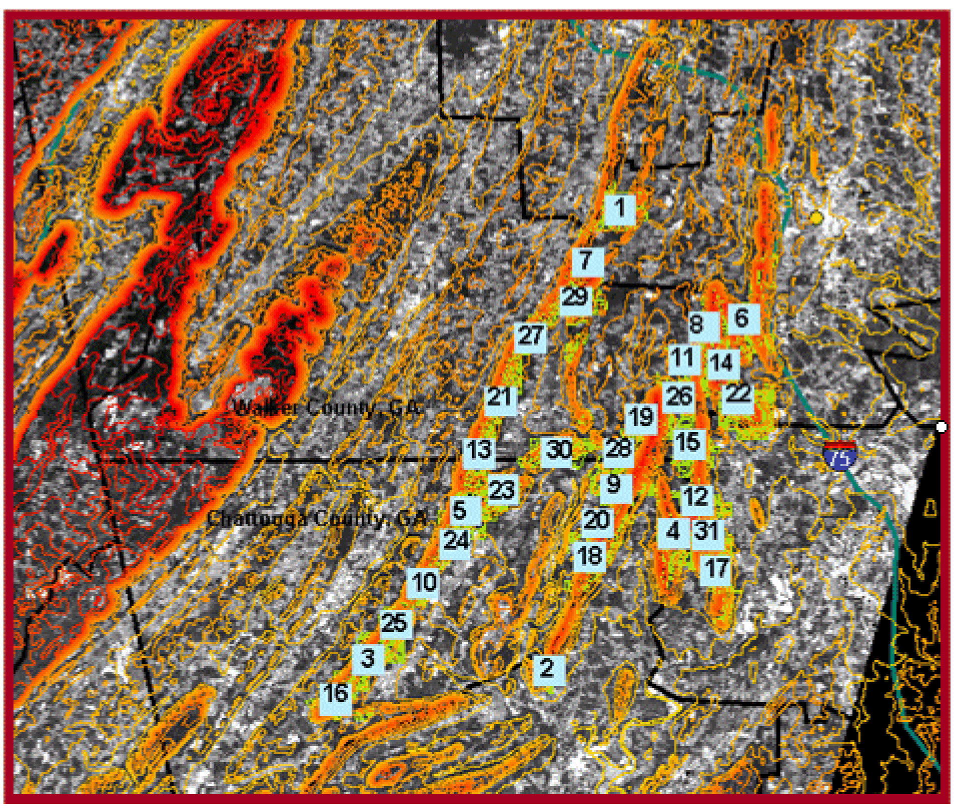


Figure 9. Location of sampling sites in Chattahoochee National Forest.

Overall, this study demonstrates that important measures of forest-related surface roughness including average stand thickness can be effectively estimated from remotely sensed data using the textural analytical techniques. Regression models to predict stand size classes from fractal dimensions and Moran's I calculated from Landsat TM data were developed (Figures 10 and 11). The image is represented and displayed in a digital format by subdividing the image into small equal-sized and shaped areas, called picture elements or pixels, and representing the brightness of each area with a numeric value or digital number which is the integration of the brightness levels within that pixel. If the two adjacent pixels with a same area are covered with continuous small crown trees as in Figure 12(a), this results in two homogenous surfaces, and so the integration result in both pixels will be close, and thus the two pixel values will be similar in magnitude. If the pixel values do not vary significantly, there is less complexity in terms of fractals and more homogeneity in terms of autocorrelation, thus a smaller FD and higher Moran's I. On the other hand, if the pixels are covered with large crown trees as in 12(b), adjacent pixels are inhomogeneous so the integration results in both pixels will be dissimilar and the two pixel values will not be close in magnitude. If the pixel values vary significantly, there is more complexity in terms of fractals, less homogeneity in terms of autocorrelation, and results in higher FD and lower Moran's I. That explains why the regressions showed that FD increased (positive slopes) and the Moran's I decreased (negative slopes) as the sawtimber (Diameter at Breast Height > 9.0 inches) percentage increased, whereas FD decreased (negative slopes) and Moran's I increased (positive slopes) as the saplings (DBH = 1.0-4.9 inches) percentage increased. The study also demonstrates that rough terrain significantly masks the effect of the differences in stand characteristics on the spatial indices (Figure 13).

Three out of four data sets were selected for model development and the fourth one was utilized for technique validation. Verification of stand size predictions showed that the developed models, especially the fractal dimension models, gave accurate estimates (Table 1). The results also revealed those textural metrics were sensitive to changes in hydraulic roughness and that the sensitivity increases as the vegetation thickness increases (Figures 14-17). Thus, they were capable of capturing hydraulically significant surface roughness indicating that it can be an effective measure of flow resistance in forested flood plain areas. The study also revealed optimal radiometric and spatial resolutions among various remote sensors for detecting differences in surface characteristics.

This case study showed that "complexity" is more evident in Landsat TM visible bands than in infrared bands. The same textural analyses were performed with image data at higher and lower resolutions than Landsat TM data. Results indicated that Landsat 30-meter resolution is better than IKONOS 4-meter and MODIS 250-meter resolutions in detecting potential differences in surface characteristics using the textural analytical techniques of fractals and autocorrelations. This result, of course, is directly due to the similarity of image resolution and tree canopy scale.

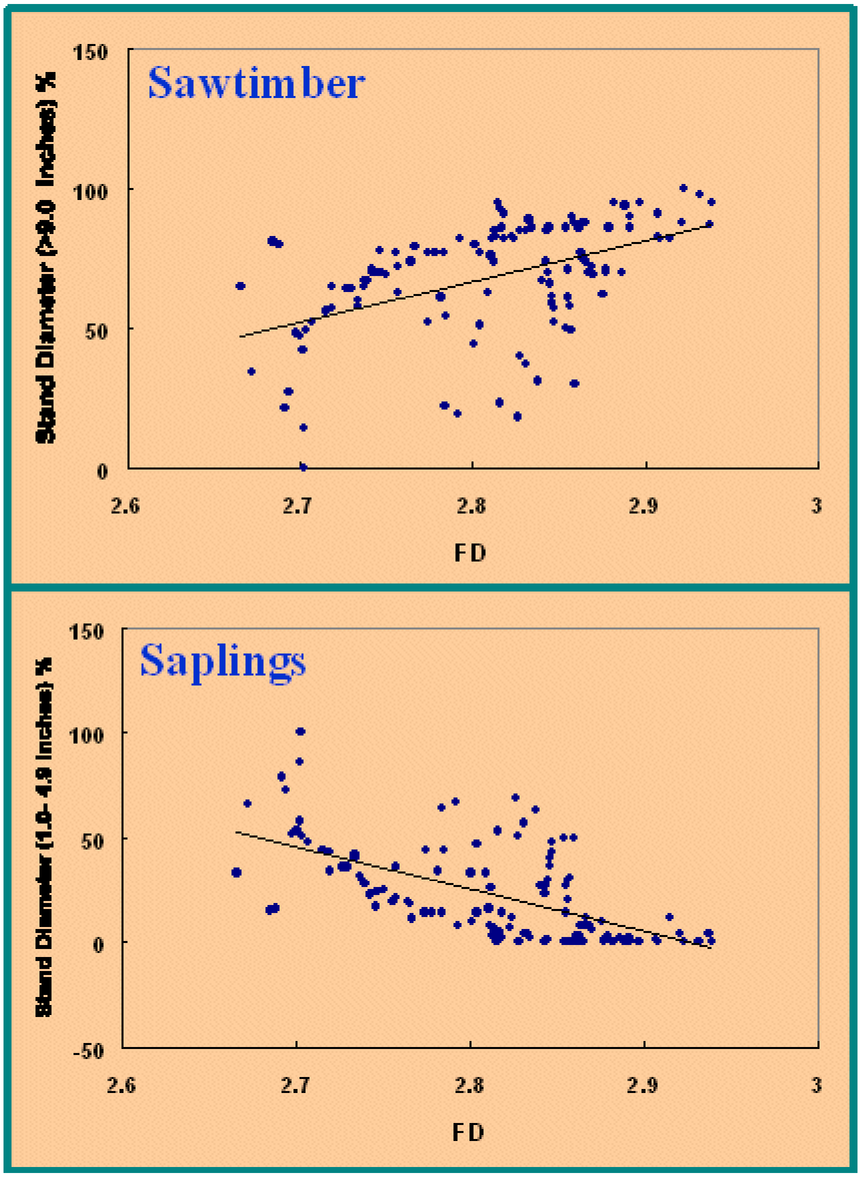


Figure 10. Linear regression prediction models using fractal dimension.

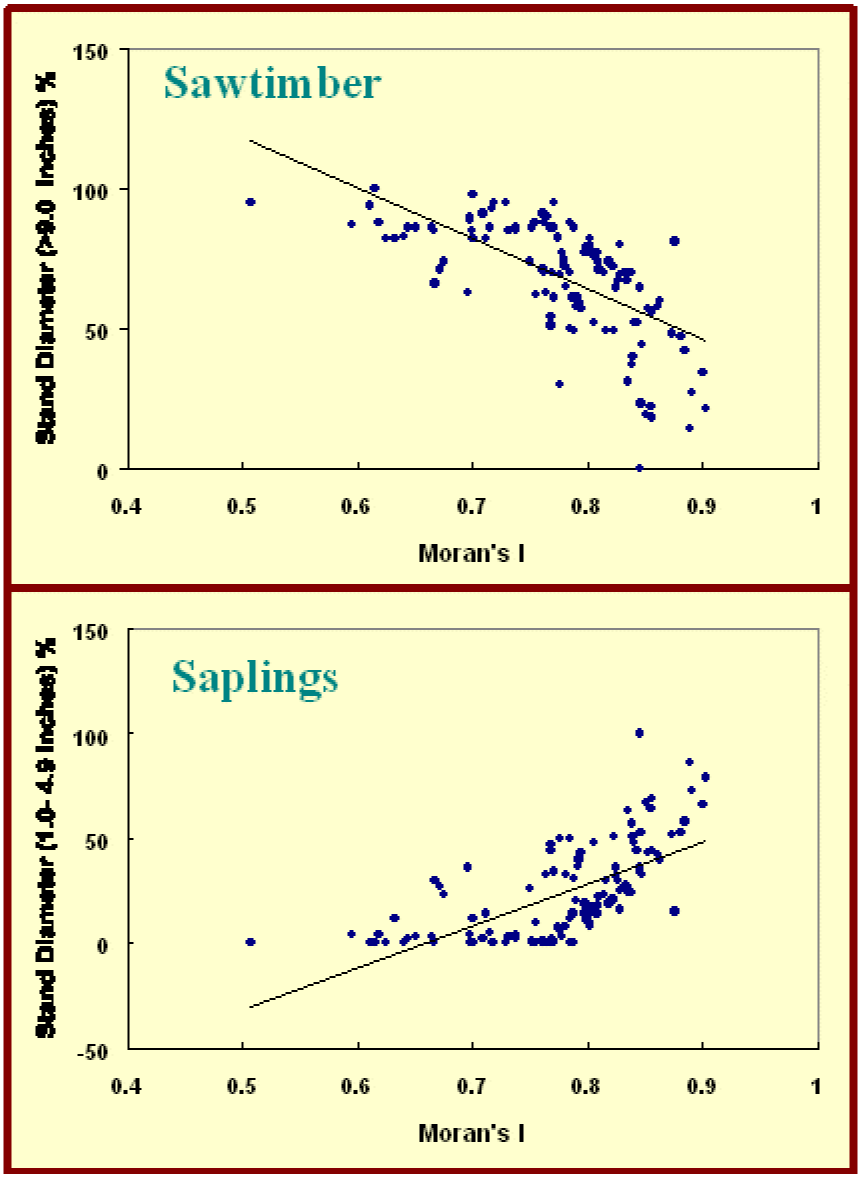


Figure 11. Linear regression prediction models using Moran's I.

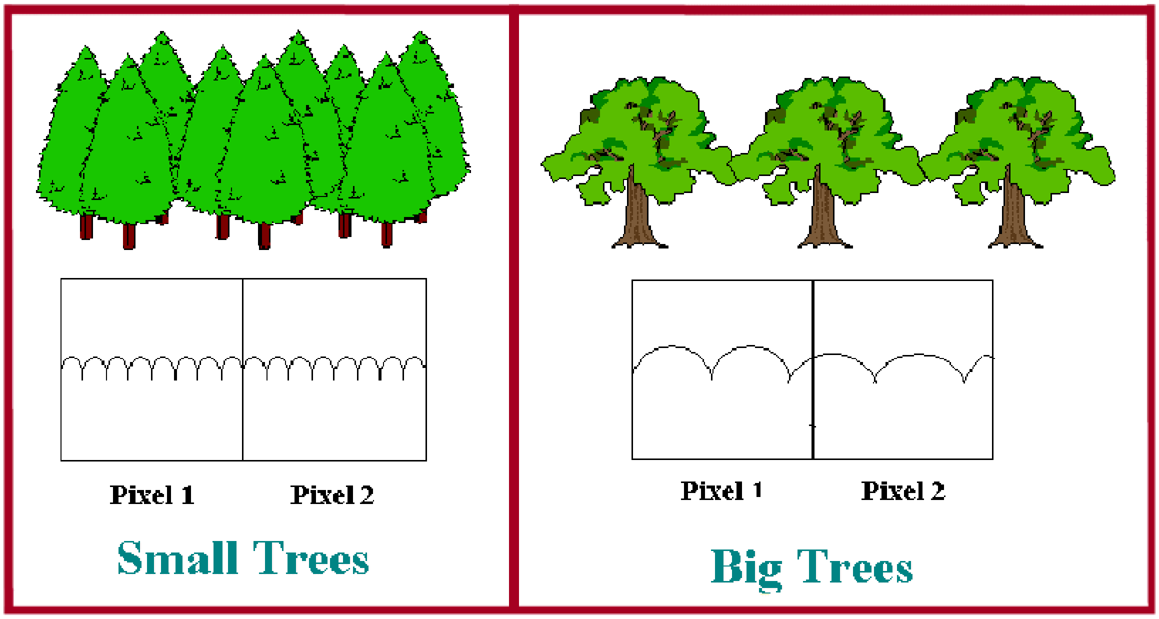


Figure 12. Size class effect on remotely sensed data.

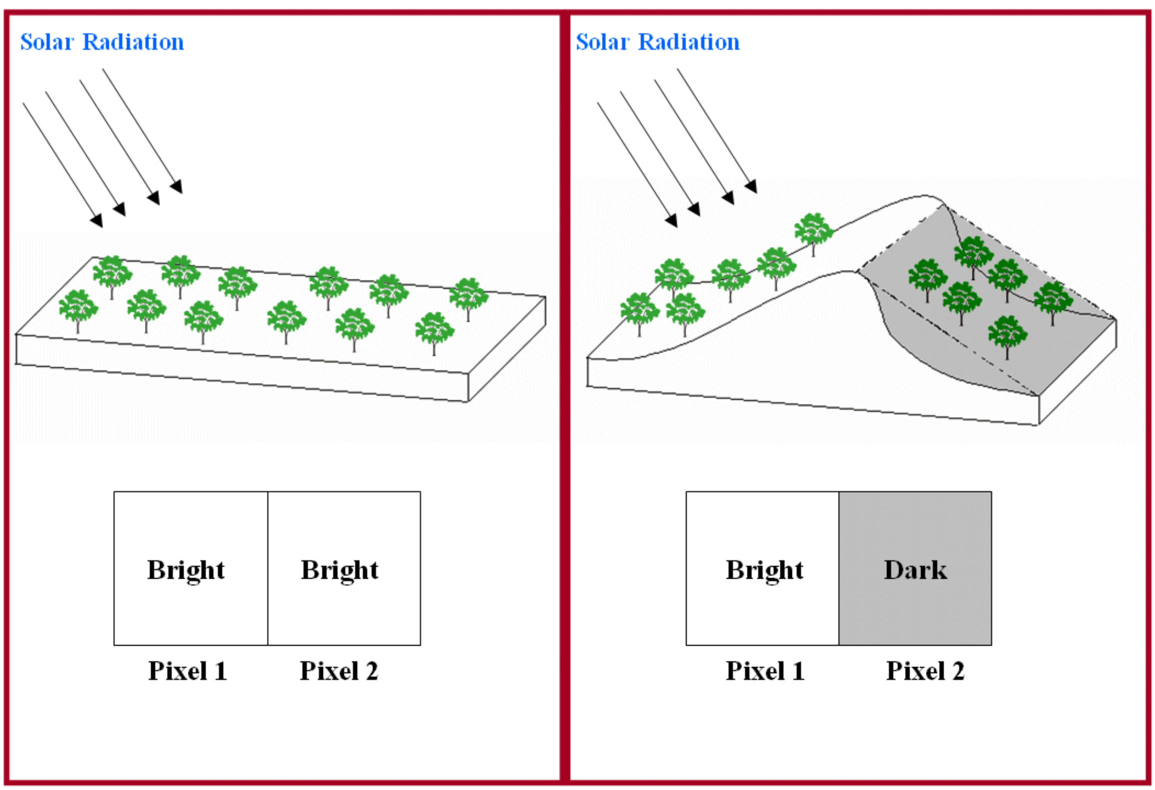


Figure 13. Terrain effect on remotely sensed data.

Table 1. Performace evaluation measures of the developed stand size prediction models.

Stand Size Prediction Model*	Mean Error (%)	*MAE* (%)	*RMSE* (%)	r	Nash-Sutcliffe Efficiency Statistic
$Sawtimber(\%) = -340.51 + 145.45 * FD$	4	9	11	0.75	0.48
$Sawtimber(\%) = -352.01 + 149.97 * FD - 0.0054 * Elevation$	3	8	10	0.75	0.50
$Saplings(\%) = 593.02 - 202.73 * FD$	-7	9	12	0.80	0.45
$Saplings(\%) = 635.34 - 219.37 * FD + 0.02 * Elevation$	-4	8	11	0.79	0.55
$Sawtimber(\%) = 209.48 - 181.88 * I$	10	12	15	0.74	0.09
$Sawtimber(\%) = 297.75 - 270.35 * I - 0.0886 * Elevation$	2	11	13	0.67	0.22
$Saplings(\%) = -131.6696 + 199.51 * I$	-13	14	17	0.79	0.01
$Saplings(\%) = -219.08 + 287.13 * I + 0.0878 * Elevation$	-5	11	14	0.74	0.32

* Sawtimber: diameter at breast height (DBH) > 9 inch, Poletimber: DBH = 5-8.9 inch, and Saplings: DBH = 1-4.9 inch

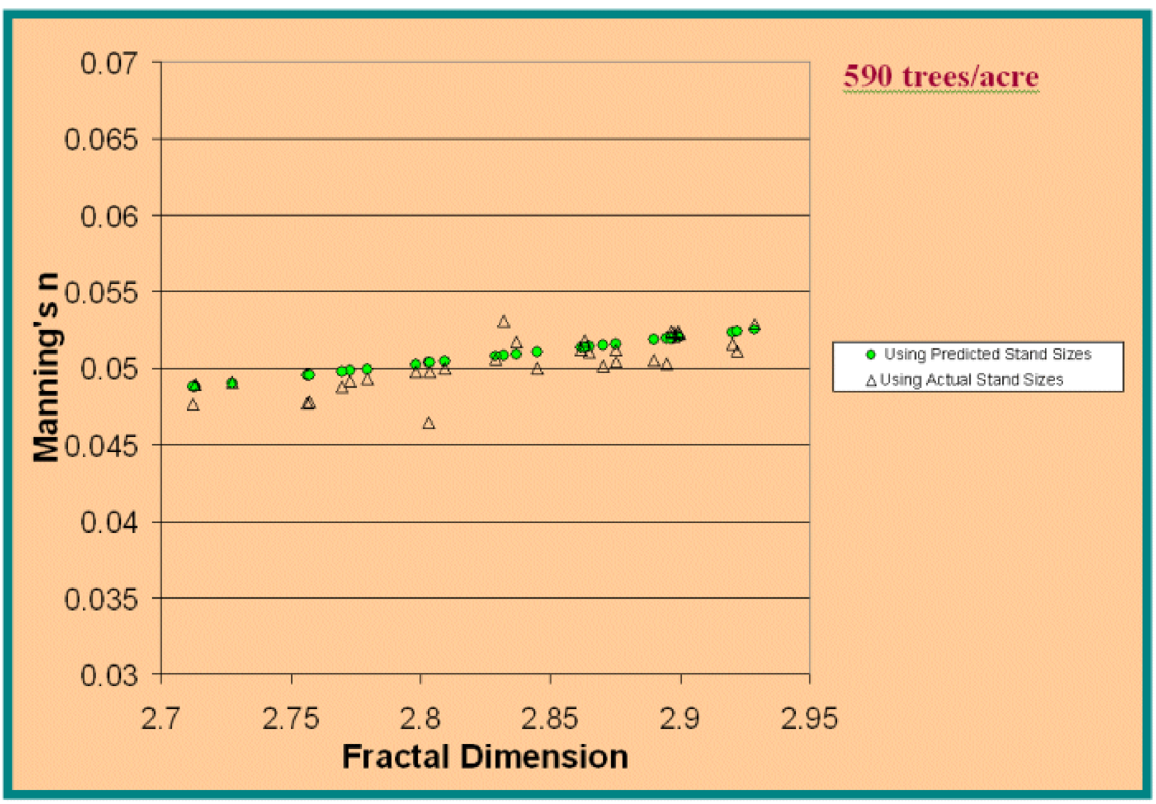


Figure 14. The roughness coefficient Manning's n for Chattahoochee National Forest using the Fractal Dimension.

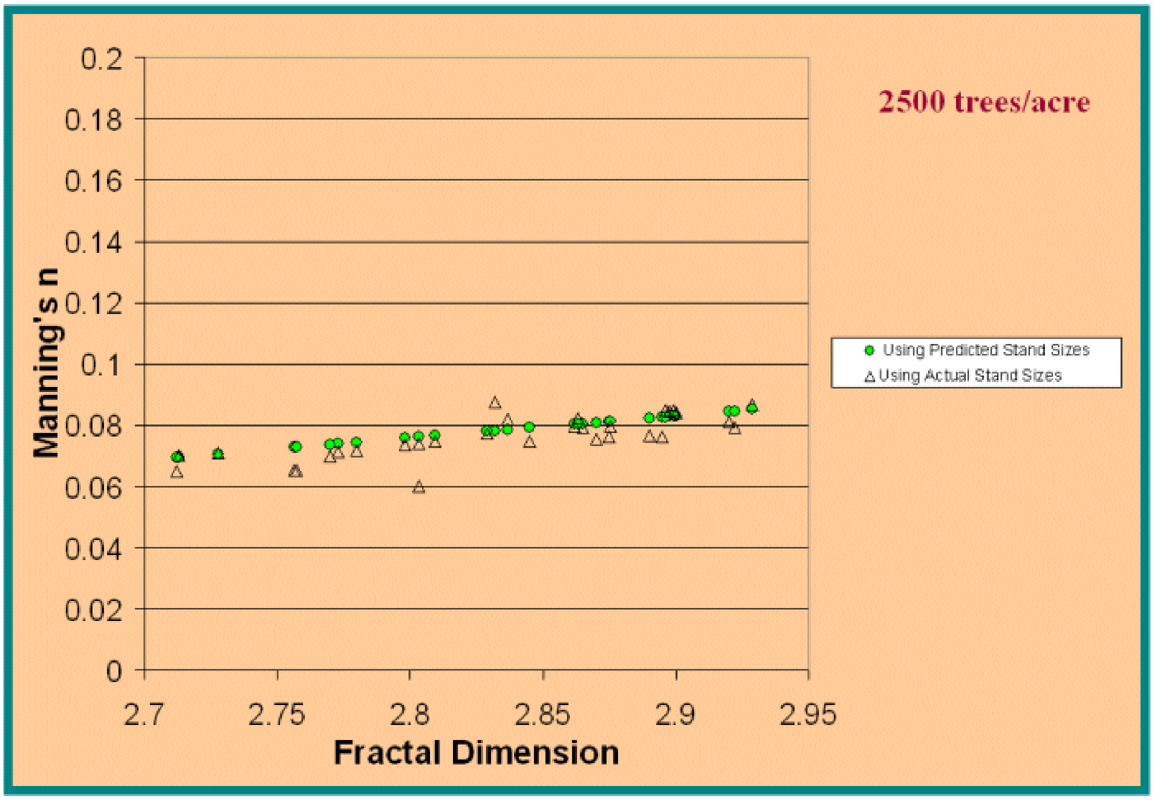


Figure 15. The roughness coefficient Manning's n using the Fractal Dimension for a large number of trees per acre (2500 trees/acre).

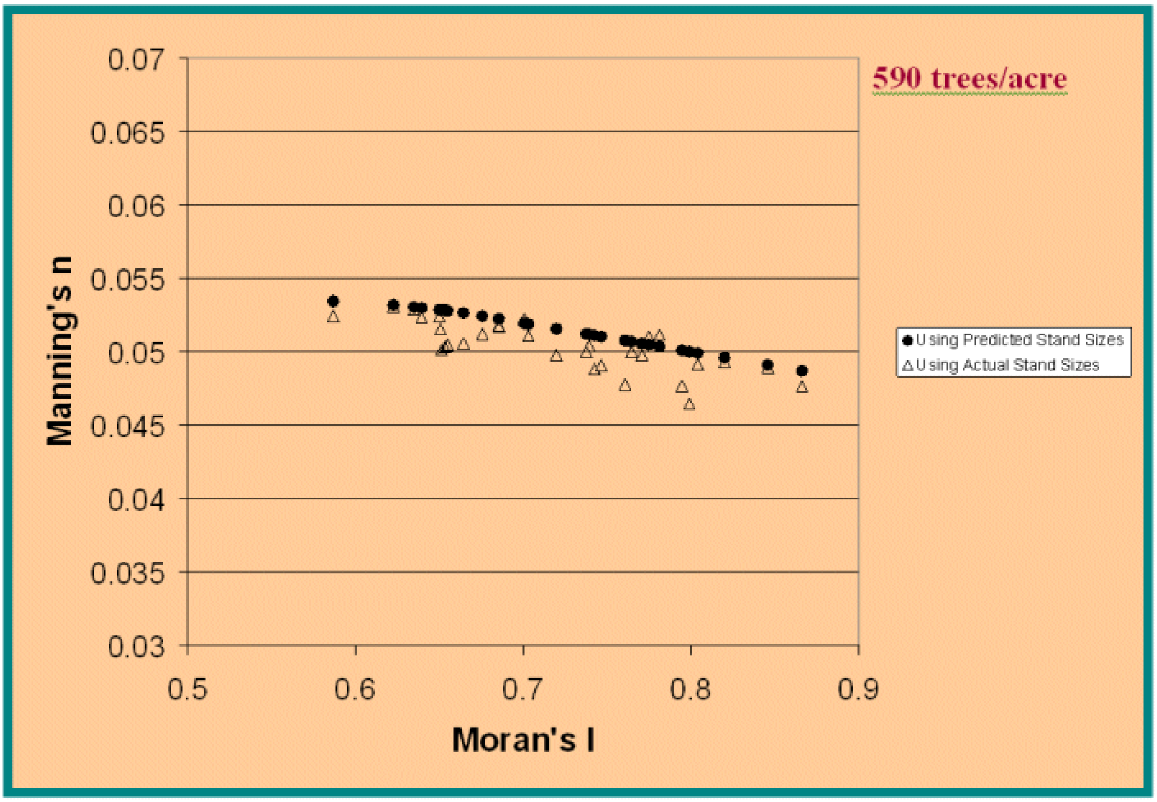


Figure 16. The roughness coefficient Manning's n for Chattahoochee National Forest using Moran's I.

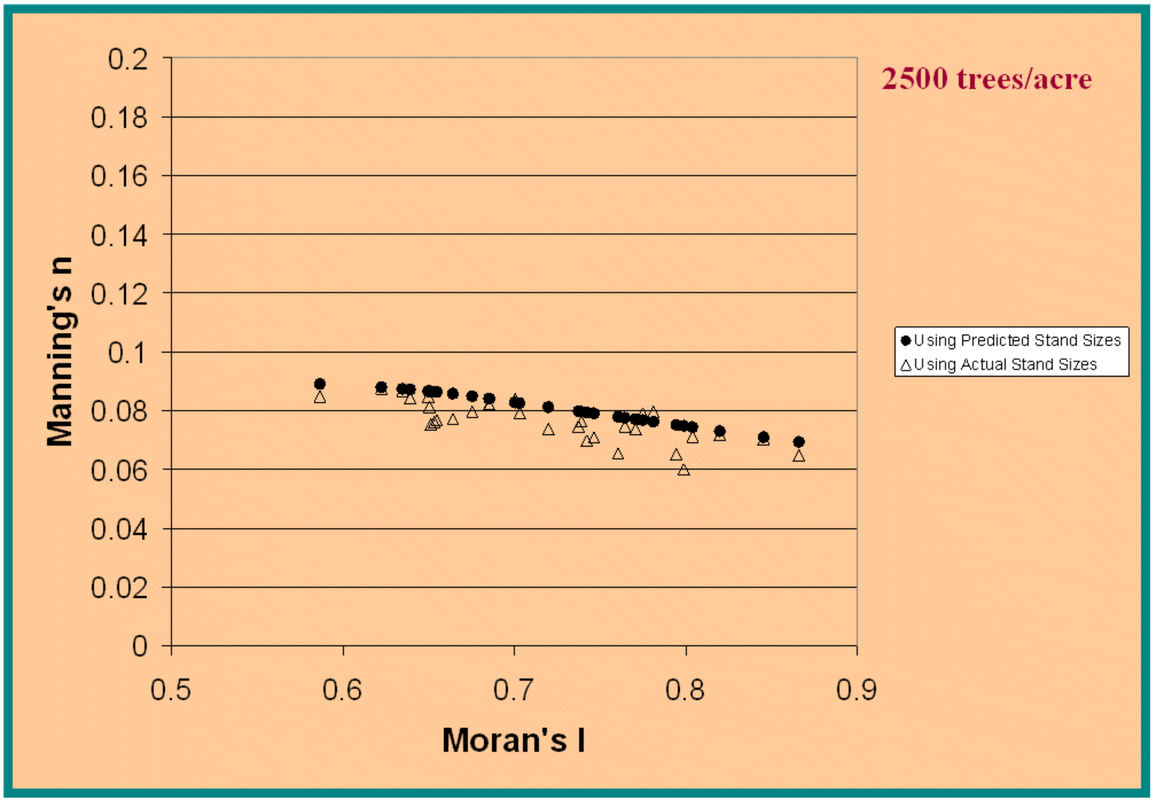


Figure 17. The roughness coefficient Manning's n using Moran's I for a large number of trees per acre (2500 trees/acre).

4. REFERENCES

Al-Hamdan, M. Z.: Flow Resistance Characterization of Forested Flood Plains Using Spatial Analysis of Remotely Sensed Data and GIS. Ph.D. Dissertation. University of Alabama in Huntsville. Huntsville, AL, 2004.

Bajcsy, R. and L. Lieberman, "Texture Gradient as a Depth Cue," *Computer Graphics and Image Processing*, 5, pp. 52-67, 1976.

Barbanis, B., Varvoglis, H., and Vozikis C. L.: Imperfect Fractal Repellers and Irregular Families of Periodic Obits in a 3-D Model Potential. Astronomy and Astrophysics, 344: 879-90, 1999.

Besag, J.: Spatial interaction and the statistical analysis of lattice systems. Journal of the Royal Statistical Society B, 36(2), 192--225, 1974.

Chellappa, R. and Chatterjee, S.: Classification of textures using Gaussian Markov random fields. IEEE Transactions on Acoustics, Speech, and Signal Processing, 33(4), pp. 959--963, 1985.

Clark, M. and Bovik, A. C.: Texture segmentation using Pattern Recognition Letters, 6, pp. 261-267, 1987.

Cross, G. and Jain, A.K.: Measures of Homogeneity in Texture. 211 - 216, 1983.

Emerson, C. W., Lam N. S.-N., and Quattrochi D. A.: Multiscale Fractal Analysis of Image Texture and Pattern. Photogrammetric Engineering and Remote Sensing, 65: 51-61, 1999.

Frieden, B.R.: Statistical models for the image restoration problem. Comput. Gr. Image Process. 12, 40- 59. 1980.

Fu, K.S.: Syntactic Pattern Recognition and Applications. Prentice Hall, Englewood Cliffs, N.J., 1982.

Galloway, M. M.: Texture Analysis Using Gray Level Run Lengths. Computer Graphics and Image Processing, 4, 172-179, 1975.

Geman S. and Geman D.: Stochastic relaxation, Gibbs distributions, and the Bayesian restoration of images. IEEE Trans. Pattern Anal. Machine Intell., 6, pp. 721-741, 1984.

Haralick, R.M., Watson, L.: A facet model for image data. Comput. Vision Graphics Image Process 15, 113–129, 1981

Hassner M. and Sklansky, J. The use of Markov random fields as models of texture. Computer Graphics and Image Processing, 12:357--370, 1980.

Hunt, G.R.: Electromagnetic radiation: the communication link in remote sensing. In: Siegel, B.S, Gillespie, A.R. (Eds.), Remote Sensing in Geology. Wiley, New York, pp. 5 – 45, 1980.

Jacobson, L. and Wechsler, H.: The Wigner Distribution and Its Usefulness for 2-D Image Processing, 6th International Joint Conference on Pattern Recognition, Munich, West Germany, 1982.

Jacobson, L., and Wechsler, H.: A paradigm for invariant object recognition of brightness, optical flow and binocular disparity images, Pattern Recognition Lett, vol. 1, pp. 61-68, 1982.

Jacobson, L., and Wechsler, H.: The Wigner Distribution as a Tool for Deriving an Invariant Representation of 2-D Images, Pattern Recognition and Image Processing Conference, Las Vegas, Nevada, 1982.

Jaggi, S., Quattrochi, D., and Lam, N. S.: Implementation of operation of three fractal measurement algorithms for analysis of remote sensing data. Computers and Geosciences, 19, 745–767, 1993.

Jain, A. K. and Farrokhnia, F.: Unsupervised Texture Segmentation Using Gabor Filters. In: Pattern Recognition, Vol. 24, No. 12, pp. 1167-1186, 1991.

Kaizer, H.: A quantification of textures on aerial photographs, Technical Note 121, AD 69484, Boston University Research Laboratory, 1955.

Kim, K. M., Park, J. J., Song, M. H., Kim, I. C., and Suen, C. Y.: Detection of ridges and ravines using fuzzy logic operations. Pattern Recognition Letters, 25, 743–751, 2004.

Krummel, J. R., Gardner, R. H., Sugihari, G., O'Neill, R. V., and Coleman, P.R.: Landscape Pattern in a Distributed Environment. Oikos, 48: 321-324, 1987.

Lam, N.S-N., Qiu, H. L., Quattrochi, D. A., and Emerson, C. W.: An Evaluation of Fractal Methods for Characterizing Image Complexity. Cartography and Geographic Information Science, 29(1): 25-35, 2002.

Lam N.S.-N., and De Cola, L. (eds): Fractals in Geography. Englewood Cliffs, NJ: Prentice Hall, 1993.

Lam, N.S.-N., Fan, M., and Liu, K. P.: Spatial-Temporal Spread of the AIDS Epidemic: A Correlogram Analysis of Four Regions of the United States. Geographical Analysis, 28(2): 93-107, 1996.

Lam, N.S.-N., Quattarochi, D. A., Qiu, H.-L., and Zhao, W.: Environmental Assessment and Monitoring with Image Characterization and Modeling System Using Multi-Scale Remote Sensing Data. Applied Geography Studies, 2(2): 77-93, 1998.

Laws, K.: Textured Image Segmentation, Ph.D. Dissertation, University of Southern California, 1980.

Laws. K.. Rapid texture identification. In SPIE Vol. 238 Image Processing for Missile Guidance, pages 376-380, 1980.

Lovejoy, S., and Schertzer, D.: Generalized Scale Invariance in Atmosphere and Fractal Models of Rain. Water Resources Research, 21: 1233, 1985.

Lu, S. Z., and Hellawell, A.: Using Fractal Analysis to Describe Irregular Microstructures. Journal of Materials, 47: 14-16, 1995.

Lucieer, A., Fisher, P. F. and Stein, A. (1): Texture-based segmentation of high-resolution remotely sensed imagery for identification of fuzzy objects, Proceedings of GeoCompuataion 2003, Southampton, UK, 2003.

Lucieer, A., Fisher, P. F. and Stein, A. (2): Fuzzy object identification using texture-based segmentation of high-resolution DEM and remote sensing imagery of a coastal area in England, Proceedings of the Seconds International Symposium on Spatial Data Quality, Hong Kong (2003).

Lucieer, A.: Uncertainties in Segmentation and their Visualization. Ph.D. Dissertation. Universiteit Utrecht, Utrecht, the Netherlands. 2004. Chapter 5 which was based on Lucieer et al. (2004); Lucieer et al. (1) (2003); and Lucieer, et al. (2) (2003).

Lucieer, A., Fisher, P. F. and Stein, A.: GeoDynamics, CRC Press LLC, chapter Texture-based Segmentation of Remotely Sensed Imagery to Identify Fuzzy Coastal Objects, 2004.

MacLennan, M. J., and Howarth, P. J.: The Use of Fractal Geometry to Identify Ranges of Scale Variance in Digital Remotely Sensed Data. Proc. 21st Int. Symp. Remote Sensing Environment, 2: 1089-1092, 1987.

Mallat S. G., A theory for multiresolution signal decomposition: The wavelet representation, IEEE T. Pattern Anal. Machine Intell. 11, 674--693, 1989.

Mandelbrot, B. B.: The Fractal Geometry of Natures. W. H. Freeman. 1982.

Mandelbort, B. B.: The Fractal Geometry of Nature. New York, N.Y.: W. H. Freeman, 1983.

Manjunath B. S. and Ma, W. Y.: Texture features for browsing and retrieval of image data, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 18, No. 8, pp. 837-842, 1996.

Marr, D.: Vision. Freeman, 1982, Chap 2, pp 54-78.

Matheron G. Eléments pour une théorie des milieux poreux. Paris: Masson, 1967.

Musleh, F. A.: Modeling Flow Resistance through Rigid Non-Submerged Vegetation. Ph.D. dissertation, Civil and Environmental Engineering, University of Alabama in Huntsville, Huntsville, Alabama, 2003.

Ohanian, P. P. and Dubes, R. C.: Performance Evaluation for Four Classes of Textural Features. Pattern Recognition, vol. 25, pp. 819–833, 1992.

Ojala T., Pietikäinen M., and Harwood D.: A comparative study of texture measures with classification based on feature distributions. Pattern Recognition 29:51-59, 1996.

Ojala, T., Valkealahti, K., Oja, E., and Pietikäinen, M.: Texture discrimination with multidimensional distribution of signed gray-level differences. Pattern Recognition, 34(3), 727-739, 2001.

Ojala, T. and M Pietikäinen: Texture Classification. Machine Vision and Media Processing Unit, University of Oulu, Finland. Available at http://homepages.inf.ed.ac.uk/rbf/CVonline/LOCAL_COPIES/OJALA1/texclas.htm. January, 2004.

Pentland, A. P.: Fractal-Based Description of Natural Scenes, IEEE Transactions on Pattern Analysis and Machine Intelligence 6, 6, 661-674, 1984.

Quattrochi D. A., Lam, N. S.-N., Qiu, H. L., and Zhao, W.: Image Characterization and Modeling System (ICAMS): A Geographic Information System for the Characterization and Modeling of Multiscale Remote Sensing Data. In: D. A. Quattroch and M. F. Goodchild (eds) Scale in remote sensing and GIS. Boca Raton, FL: CRC/Lewis Publishers. Pp. 295-307, 1997.

Quattrochi, D. A., C. W. Emerson, N. S.-N. Lam, and Qiu, H. L.: Fractal Characterization of Multitemporal Remote Sensing Data. In: N. J. Tate and P. M. Atkinson (eds), Modeling Scale in Geographic Information Science. Hoboken, N.J.: John Wiley & Sons, Ltd., pp. 13-33, 2001.

Reed, T. and Wechsler, H.: Texture Analysis and Clustering Using the Wigner Distribution, 9th Int. Conference on Pattern Recognition, Rome, Italy, 1988.

Reed, T. and Wechsler, H.: Tracking of Non-Stationarities for Texture Fields, Signal Processing, Vol. 14, No. 1, 95-102, 1988.

Reed, T. and Wechsler, H.: Texture Segmentation and Organization Using the Wigner Distribution, EUSIPCO, Grenoble, France, 1988.

Rosenfeld, A. and Thurston, M.: Edge and curve detection for visual scene analysis. *IEEE Transactions on Computers*, 20, 562-569, 1971.

Rosenfeld, A. and Kak, A.: Digital Picture Processing, Chapter 9, Geometry, 1976.

Serra J. Image Analysis and Mathematical Morphology. London: Academic Press, 1982.

Tomita, F., Tsuji, S.: Computer Analysis of Visual Textures. Kluwer Academic Publishers, Dordrecht, pp. 13-36, 1990.

Tuceryan, M., Jain, A. K.: Testure segmentation using Voronoi polygons. IEEE Transactions on Pattern Analysis and Machine intelligence 12, 211 216, 1990.

Tuceryan, M.: Moment Based Texture Segmentation. In Proceedings of 11th International Conference on Pattern Recognition, The Hague, Netherlands, August 1992.

Tuceryan M. and Jain, A. K.: Texture Analysis. In The Handbook of Pattern Recognition and Computer Vision (2nd Edition), by C. H. Chen, L. F. Pau, P. S. P. Wang (eds.), pp.207-248. World Scientific Publishing Co., 1998.

Turner, M.R.: Texture Discrimination by Gabor Functions. Biological Cybernetics, 55, pp.71-82, 1986.

Unser, M. and Eden, M.: Nonlinear Operators for Improving Texture Segmentation Based on Features Extracted by Spatial Filtering," IEEE Transactions on Systems, Man, and Cybernetics, 20, pp. 804-815, 1990.

Voorhees, H. and Poggio, T.: Detecting textons and texture boundaries in natural images. In: Proceedings of the First International Conference on Computer Vision. pp. 250-258, 1987.

Wang L., and Liu J.: Texture classification using multiresolution Markov random field models. Pattern Recognition Letters, 20(2), pp. 171-182, 1999.

Weszka, J. S., C. R. Dyer and A. Rosenfeld: A comparative study of texture measures for terrain classification. IEEE Transactions on Systems, Man and Cybernetics, vol. 6, no. 4, pp. 269-285, 1976.

Zhao, W.: Multiscale Analysis for Characterization of Remotely Sensed Images. Ph.D. Dissertation, Louisiana State University, Baton Rouge, LA, 2001.

Zucker, S. W.: Region growing: Childhood and adolescence, Computer Graphics and Image Processing 5, pp. 382--99, 1976.