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Land/Water Interface Delineation Using Neural Networks.

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LAND/WATER INTERFACE DELINEATION USING NEURAL NETWORKS

A Dissertation

Submitted to the Graduate Faculty of the
Louisiana State University and
Agricultural & Mechanical College
in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

in

The Department of Geography and Anthropology

by

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Abstract

The rapid decline in acreage of land areas in wetlands caused by frequent inundations and flooding has brought about an increased awareness and emphasis on the identification and inventory of land and water areas. This dissertation evaluates three classification methods – Normalized Difference Vegetation Index technique, Artificial Neural Networks, and Maximum-Likelihood classifier for the delineation of land/water interface conditions using Landsat-TM imagery. The effects of three scaling algorithms, including resampling by aggregation, Gaussian smoothing, and local variance analysis, on the classification accuracy are analyzed to determine how the delineation, quantification and analysis of land/water boundaries relate to problems of mixed pixels, scale and resolution.

Bands 3, 4, and 5 of a Landsat TM image from Huntsville, Alabama were used as a multispectral data set, and ancillary data included USGS 7.5 minute Digital Line Graphs for classification accuracy assessment. The 30 m resolution multispectral imagery was used as baseline data and the images were degraded to a series of resolution levels and Gaussian smoothed through various scaling constants to simulate images of coarser resolution. Local variance was applied at each aggregation and scaling level to analyze the textural pattern. Classifications were then performed to delineate land/water interface conditions. To study effects of scale and resolution on the land/water boundaries delineated, overall percent classification accuracies, fractal analysis (area-perimeter relationships), and lacunarity analysis were applied to identify the range of spatial resolutions within which land/water boundaries were scale dependent.

Results from maximum-likelihood classifier indicate that the method marginally produced higher overall accuracies than either NDVI or neural network methods. Effects from applying the three scaling algorithms indicate that overall classification accuracies decrease with coarser resolution, increase marginally with scaling constant, and vary non-linearly with local
variance mask sizes. It was discovered that the application of Gaussian smoothing to neural
network classifier produces very encouraging results in classifying the transition zone between
land and water (mixed pixels) areas.

Fractal analysis on the classified images indicates that coarser resolutions, higher scaling
constants and higher degrees of complexity, wiggliness or contortion of the perimeter of water
polygons span higher ranges of fractal dimension. As the water polygons become more complex,
the perimeter becomes increasingly plane filling. From the changes in fractal dimension,
lacunarity analysis and local variance analysis, it is observed that at 150 m, a peak value of
measured index is obtained, before dropping off. This suggests that at 150 m, the aggregated
water bodies shift to a different ‘characteristic’ scale and the water features formed are smooth,
compact, have more regular boundaries and form connected regions. This scale dependence
phenomenon can help to optimize efficient data resampling methodologies.
Chapter 1

Introduction

In the conterminous United States, there are 97.8 million acres (95%) of freshwater (inland) wetlands and 5.5 million acres (5%) of estuarine (coastal) wetlands (Dahl and Johnson, 1991). Marshes and islands that took centuries to evolve are changing so rapidly that numerous studies have been undertaken to analyze these changes. With the rapid decline in acreage of land areas in such ecosystems, there is more water than land in many of the nation's coastal areas and wetlands. This has caused an increased awareness and emphasis on the identification and inventory of the distribution of land and water acreages in these types of environments. Recent evidence of global change due to human activity such as deforestation, farming activities, and urbanization, or indirectly, through human induced climate change, has increased the importance of developing methods to map such ecosystems so that changes in these systems can be quickly detected and accurately measured across time scales.

To perform this land/water inventory, a reliable classification scheme must be devised that will provide the information necessary for inventory purposes. The system should be based primarily on enduring the ambiguity in wetland characteristics and process multi-source data so that accurate inventory can be maintained. Consequently, considerable research has been done to examine the utility of Landsat TM sensor data to identify and inventory wetlands. Although previous studies have reported success in their efforts to monitor changes in large rivers, wetlands and lakes (Jensen et al., 1995), the present study is different. It is designed to determine if neural network architectures can be easily and rapidly configured and trained to perform pattern recognition and feature extraction tasks accurately.

The rapid development of Geographic Information Systems (GIS) technology has facilitated the integration of diverse information from a variety of sources by GIS users.
Although the current generation of GIS performs general geometric and topologic analysis (such as buffer and overlay), the functionalities of most existing systems are confined to cartographic modeling procedures and are poor at integrating multi-scale, multi-resolution information. A consensus within the GIS field is that, so far, GIS technology is more successful as an information inventory and data maintainance tool than as a spatial analysis and modeling tool (Goodchild et al., 1995).

To remedy these shortcomings, researchers within both the GIS and remote sensing fields have devoted efforts to improve the data handling capabilities along two areas - the integration of traditional quantitative techniques with GIS and the development of rule based expert systems (Sui, 1994). Along the first thread, several different types of statistical and mathematical techniques have been incorporated into GIS, including spatial statistics (Anselin and Getis, 1992; Goodchild et al., 1992), exploratory data analysis (Fotheringham and Wong, 1991), and fuzzy set theory (Moody et al., 1994; Foody et al., 1994). All these efforts to link GIS with sophisticated statistical theory and techniques have not only widened the analytical capabilities of GIS but have also widened the scope of GIS applications from mere data inventory and information management to meaningful modeling and predictions (Fotheringham and Rogerson, 1994).

However, all these quantitative techniques are selective in the type of information they can handle. These techniques assume that the raw data conform to distributions such as Poisson, binomial, and Gaussian (Sui, 1994). In most cases, spatial data are in serious violation of such assumptions. The lack of robust techniques of integrated analysis of multi-source spatial data is a major hindrance for GIS and remote sensing applications (Davis et al., 1991).
1.1 Statement of problem

This study addresses the problem of land/water interface boundary delineation. This question becomes of crucial importance considering the rapid growth of powerful digital sampling tools and analytical techniques such as remote sensing and Geographic Information Systems (GIS). This study will explore the effectiveness of parametric and non-parametric classification methods in characterizing land/water patterns, and the advantages and disadvantages of using non-parametric techniques such as neural networks. Furthermore, this study attempts to answer such questions as how does the delineation, quantification and analysis of land/water boundaries relate to problems of scale and resolution.

1.2 Methods for detecting the scale and resolution effects

Neglecting the scale and pixel resolution when classifying remote sensing images can produce results having little correspondence with the objects of the scene. There is no unique spatial resolution appropriate for the detection and discrimination of all geographical entities (Marceau et al., 1994). The problem of selecting a proper scale comes from the spatial analysis field, in particular from a series of studies related to the scale and spatial aggregation problem inherent in the acquisition and manipulation of spatial data (Openshaw, 1984a,b; Dudley, 1991; Fotheringham and Wong, 1991). Researchers have long recognized the pervasive importance of the scale-dependent nature of the geometry of most geographic phenomena (Lam and Qiu, 1992; Woodcock and Jupp, 1988a, and 88b). Therefore, methods are needed to select an appropriate combination of spatial resolution and analysis methods (Woodcock et al., 1995).

Several statistical methods have been proposed to detect patterns in spatial data and to determine the effective range of scales (Turner et al., 1991). In particular, semivariograms (Cohen et al., 1990; Woodcock et al., 1988; Oliver and Webster, 1986), Fourier analysis (Townshend and Justice, 1988), scale variance analysis (Mollering and Tobler, 1972), local...
image variance (Woodcock and Strahler, 1987), fractal dimension (Lam and Quattrochi, 1992), and texture analysis (Jensen et al., 1987; Nellis and Briggs, 1989).

Semivariance analysis is an effective tool to study the effects of scale on spatial structure, because the variance of landscape properties is treated as a function of scale. The range of scales where spatial dependence is present can be identified from a plot of semivariance against the sampling interval. Semivariograms can be helpful in identifying the range of spatial scales within which the landscape property is spatially dependent, but they do not provide information on the degree of spatial dependence (Bian and Walsh, 1993).

In two-dimensional Fourier analysis the variability is depicted by the sums of sine and cosine curves and it is possible to determine the contribution of different frequencies present to the overall power of the image (from power spectrum). One disadvantage of this method is that sharp boundaries will show multiple frequencies being present, since this is the way that such a spatial variation is modeled by the sine and cosine curves (Townshend and Justice, 1990). In contrast, in scale variance analysis the approach is to determine the independent contribution of spatial variance at various scales and to partition the total sum of squares into the parts contributed at each scale.

A measure of local image variance (the mean of the standard deviation values computed from a n x n pixel window moving across the image) is often used to select an appropriate image scale for remotely sensed images. The graphs of local variance in images as a function of their spatial resolution can reveal appropriate scales of action. This approach assumes an idealized square-wave response on the part of the sensor, or that the measurement produced by the sensor is derived only from the area inside the pixel. This assumption is often unrealistic, but it suffices to study the basic relationships involved.

A technique which can be applied to quantify the degree of spatial dependence is fractal analysis (Goodchild and Mark, 1987; Lam and Quattrochi, 1992). Fractal analysis focuses on the
geometric pattern of phenomena, suggesting that the amount of resolvable detail is a function of scale. Theoretically, fractal phenomena should remain at a constant dimension through all scales. In the real world, natural phenomena behave differently. Instead, a fractal dimension may vary with scale or remain constant at a certain range of scales or over widely separated scales. The changes in the fractal dimension at specific scales are of interest, since certain driving processes or factors operate at a particular range of spatial scales within which a fractal dimension is constant. Fractal dimension can be calculated by many methods, but the underlying formula relates the slope of the logarithmic plot for the measured values against the measuring unit. Although no compromise has been reached on the best algorithm to use to detect the fractal dimension of a surface, the fractal method seems to be the most promising approach.

1.3 Research objectives

In studying the causes and effects of spatial processes, it is essential to consider the response of dynamic processes, such as land/water boundaries, to scale and resolution changes. The objective of this study is to examine the utility of neural networks in the classification of multispectral and multiscale Landsat TM imagery. The research presented in this work is most closely related to that of Marceau et al. (1992), who investigated the impact of measurement scale and aggregation level on image information content. Specific objectives of this study are:

1. Evaluate the effectiveness of classification methods including neural networks, maximum-likelihood and normalized difference vegetation index (NDVI) technique, in characterizing land/water patterns.
2. Evaluate the effects of spatial scale on classification methods and to identify and quantify the effective range of spatial scales at which satellite derived land/water boundaries are spatially dependent with different resolution levels.
Artificial Neural Networks (ANN's) have generally been used to characterize land cover classification. This dissertation will apply ANN to provide information that can be used in spatial aggregation at coarser resolutions and at varying scale constants. Specific objectives in this regard are:

3. To develop a neural network model to handle multispectral Landsat TM data.
4. To apply the trained neural network for producing an automatic delineation of shorelines (land and water categories) under varying scaling and resolution conditions.
5. Most classifiers code to give one class per pixel in an image. However, pixels that fall on a border between two fields, pixels that contain a sub-pixel feature such as a man-made structure and pixels that contain a homogeneous mixture of classes are not well represented by one class (Foody, 1996). Therefore, a method to analyze mixed class proportions using ANN outputs will be developed.

1.4 Hypothesis

1. It is hypothesized that the neural network yields more accurate classification, because ANN is able to use the spatial association of image objects at multiple scales to recognize features and patterns much as a human does in image recognition, unlike conventional statistical classifiers that rely primarily on spectral characteristics.

2. As specific environmental processes function at various ranges of spatial scales, these ranges vary and overlap among processes and factors. Based upon the assumption that the land/water boundaries are formed by environmental processes and factors whose effects vary with spatial scale, it is reasonable to hypothesize that the relationships between land/water boundaries and the processes and factors forming them are dependent on spatial scale. Hence, land/water interface boundaries may therefore be more clearly discernible at certain
spatial scales than at others. This hypothesis will be tested using methods of Gaussian smoothing, local variance, fractal dimension, and lacunarity analysis.

3. The surfaces, boundaries, and values that define land/water interface do not have permanent values with respect to spatial resolution. For heterogeneous landscapes, such as those used in this study, pixel reflectance will depend not only on the spatial distribution of land surface components, but also on pixel size. Therefore, as pixel size is varied from fine to coarse levels, the proportion of mixed pixels falling on the boundary of objects in the scene will increase. This should result in lower classification accuracies.

1.5 Expected results and significance

Artificial neural networks have been investigated in a diverse range of disciplines including geography, psychology, and computer science. Recent research on the integration of neural networks with remote sensing and GIS has revealed the tremendous potential of neural computing for spatial data handling and decision making (Sui, 1994). The neural network method does not require any assumption about the underlying statistics of the data (Lippmann, 1987) and the algorithm can easily be adapted to handle the significantly different problems of spatial pattern detection. Therefore, this dissertation will focus on implementing and evaluating a neural network classifier. Specific results to be obtained from this study are:

1. Sets of land/water classified images delineated by neural network, maximum-likelihood and NDVI technique.

2. Evaluate if the NDVI technique alone can be used for performing a simple land/water classification and if the technique can resolve the mixed pixel problem.

3. Evaluate effects of three different scaling algorithms: (1) resampling using aggregation technique, (2) Gaussian smoothing, and (3) local variance analysis on classification.
accuracies obtained using three classification techniques: (1) neural networks, (2) maximum-likelihood, and (3) NDVI.

4. Test if overall accuracy decreases / increases with coarsening resolution / scale constants. If so, is the effect more pronounced with neural networks, maximum-likelihood classifier or NDVI technique?

5. Compare if the neural network classification approach can perform more reliably on diversified image data than traditional statistical techniques such as maximum-likelihood classifier.

6. Test if the neural network classifier is able to extract automatically land/water features used in training and to apply them to the classification of data for the entire image.

7. Test effects of scale-resolution on land/water characterization through resampled and Gaussian smoothed image data and measured using fractal dimension and local variance analysis methods. The concept of detecting the “characteristic” scale at which data should be aggregated will be investigated.

8. Interpret the decay pattern of lacunarity function for resampled / Gaussian smoothed image data to indicate multiscale effects of resampled imagery.

9. Finally, investigate how the delineation of land and water bodies appears through Gaussian smoothing.

**Expected Significance**

1. This study will attempt to resolve issues on whether - neural network and NDVI techniques can provide land/water characterization accurately and reliably without extensive ground truth data.

2. This initial investigation of integrating two completely different methods of simulating data (resampling technique and Gaussian smoothing technique) with neural networks and
maximum-likelihood classifiers will provide insight on how to handle large geographical scale data for global change.

3. This study will try to prove that visual interpretation of neural network classified imagery is superior to that obtained from maximum-likelihood classifier. This is vital for tasks more focussed on the spatial association of features which is very critical to human processing of images.

4. Answer questions about scale effects such as whether land/water boundaries appear or apply across a broad range of scales, or whether it is limited to a narrow range of scales.

5. Identification of land/water patterns and the study of the effects of scale on classification accuracy is useful to environmental / ecological studies and will have a profound impact on global change studies as a whole.

6. According to Key et al (1989), as larger images are classified while the amount of training data remains the same, training time becomes a smaller proportion of overall classification time. Thus, with the advent of NASA's Earth Observation System (EOS), and the need for rapid large scale ground cover classification, a fast and reliable classification method such as neural network can be a more viable alternative.

1.6 Chapter organization

This dissertation is organized as follows - Chapter 2 introduces land/water interface delineation techniques with a review of the impacts of scale and resolution in mapping sciences. Several methods for detecting the scale and resolution effects in land cover classification are introduced. Chapter 3 summarizes the literature for application of classification methods to remotely sensed imagery. Specifically, the working principles of methods such as neural networks, maximum-likelihood and Normalized Difference Vegetation Index (NDVI) are described.
Chapter 4 discusses implementation of various scaling algorithms and neural network. The concept of scale-space smoothing using Gaussian smoothing filter and the method of resampling by aggregation are implemented. A thorough discussion of implementing the neural network is made at the end. Chapter 5 discusses data sources and research design adopted for this research. It outlines the basic thread of research for this dissertation with a description of the study area, acquisition and processing of data sets, and analysis tools required to synthesize the results. Methodological steps are provided that illustrate how the various concepts reviewed in Chapters 2 and 3 could be applied to the stated geographical problem with an emphasis on Artificial Neural Networks (ANN).

To demonstrate the capabilities of various classification methods employed for delineating land/water boundaries, a number of datasets and techniques were examined. The details of original, resampled, Gaussian smoothed and local variance analyses on images and the technique of NDVI adopted for land/water delineation are reported in Chapter 6. Chapter 7 provides results of the analysis from neural network classification. Chapter 8 describes results from applying maximum-likelihood. Chapter 9 provides a discussion about results obtained from the various classification methods. Overall classification accuracy and image standard deviations, fractal dimensions and percent overall accuracy are plotted against classification methods. Finally, Chapter 10 discusses conclusions obtained from this research.

In the remainder of this dissertation, the terms multi-scale and multi-resolution will be used interchangeably to refer to multiscale. An image can exist as a scale-resolution modified object at all times (i.e., same dimensions, but at varying pixel scales), but in this study it is restricted to the scale problem and is referred to as multiscale. This analogy can be described by the following logic. In order to determine the scales at which a feature is present, image filters with kernels of varying sizes are generally applied, and the scale/resolution range of that feature
is the range of kernel sizes for which that feature can be detected. Thus, the scale and resolution methods are equally affected by the image filter selected.

Throughout this dissertation, the term \textit{ANN} is used to refer to Artificial Neural Networks and the term \textit{NDVI} refers to Normalized Difference Vegetation Index. The various scaling algorithms and techniques proposed in this dissertation have been tested on available satellite imagery data sets with varying resolution levels and scale constants. These images were acquired from Landsat Thematic Mapper (TM) and include images of a wetland ecosystem in Huntsville, Alabama in seven different spectral bands.
Chapter 2

Land/water interface boundary delineation methods and scale effects

Spatial scale is inherently involved in recognizing spatial patterns in the landscape and in estimating the relationships between landscape features and environmental processes forming them. Therefore, a thorough explanation of the concepts in scale, resolution and methods in delineating these landscape patterns must be reviewed, so that factors whose effects vary with spatial scale can be better explained. This chapter reviews literature concerning land/water interface boundary delineation, with a focus on the impacts of scale and resolution on land cover classification accuracies. Various methods for detecting the effects of scale and resolution are also outlined.

2.1 Definitions of scale and resolution

To analyze spatial phenomena, the scale at which measurements are collected is of primary importance, since it controls the information content of the data related to the phenomenon of interest. For a mapping scientist, the term scale represents the measure by which proportions within and between objects can be described and illustrated. In a data acquisition context, it is closely related to the concept of spatial resolution and can be defined as the number and size of the spatial sampling units used to partition a geographic area (Lam and Quattrochi, 1992). In contrast, an ecologist typically uses the term spatial scale to imply two characteristics of data collection: grain, the finest spatial resolution within which data are collected, and extent, the size of the study area (Lillesand and kiefer, 1994). Lam and Quattrochi (1992) define at least three meanings of scale. First, the term scale may denote the spatial extent of a study (geographic scale or scale of observation). Second, the definition can mean cartographic scale, where a large-scale map covers a smaller area but generally with more detail, and a small-scale map covers
larger area with less detail. The third usage of scale refers to the spatial extent at which a particular phenomenon operates (operational scale).

Closely related to scale is the concept of resolution. Resolution refers to the size of the area on the ground from which the measurements that comprise the image are derived. Therefore, the fourth meaning of scale is the scale of measurement, which is analogous to spatial resolution (Cao and Lam, 1997). In this dissertation, the scale effects refer to the resolution effects.

2.2 Delineating land/water interface boundary

Mapping land/water boundaries in a wetland type of environment presents unique difficulties, owing to the dynamic nature of wetlands and the complicated interrelations between hydrology, soils and vegetation. Some specific factors contributing to the difficulty include: fluctuations in water levels, transitional areas between different vegetation communities, changes in water turbidity, accumulation and migration of free floating aquatic vegetation, and the inability to detect submerged aquatic vegetation (Lillesand and Kiefer, 1994). With the availability of high resolution Landsat Thematic Mapper (TM) data, interest has been drawn to its use in wetland mapping by means of a computer-assisted approach (Dottavio et al., 1984; Jensen et al., 1987). All these works indicate that the high spectral resolution of the TM data could improve the wetland mapping capability. In this chapter, I will examine the salient aspects of delineating land/water boundaries.

2.2.1 Using image processing techniques

Cherukuri (1994) evaluated various methods in image processing for the delineation of land/water boundary conditions using daytime and nighttime Advanced Very High Resolution Radiometer (AVHRR) imagery. Six methods were evaluated, including thresholding in near-infrared and thermal infrared regions, Normalized Difference Vegetation Index (NDVI),
principal component analysis, image classification and filtering. The results indicated that near-infrared and thermal-infrared analyses provided an approximate but clear distinction between land and water areas, and that NDVI variable is a better indicator of land-cover distribution than original bands. It was also found by visual comparisons that the principal component analysis procedure using NDVI variable outperforms other methods in discriminating the true land/water interface.

Visual interpretations of satellite imagery, density slicing, and classification of water bodies have been some common techniques for delineation of water bodies. Manavalan et al. (1993) discuss digital image analysis techniques adopted for extraction of water-spread contours (perimeter of water regions) and the error analysis of water-spread estimates with regard to land/water mixed pixels. By choosing a threshold from the histogram analysis of an individual near-infrared band, a distinct grouping of water pixels and a sharp transition from water pixels to land pixels was obtained. Selection of a boundary from the transition zone with the near-infrared band was made by verifying the resulting land/water boundary line on the false-color composite (FCC) of the near-IR and two visible bands. By density slicing of a subimage near large water areas while masking out land areas, water pixels were selected, and area estimation was performed by counting the total number of pixels and multiplying the total by the ground resolution of the pixel. For all mixed pixels considered and not considered for area estimation, the authors developed equations to calculate errors due to omission and commission.

Benson and MacKenzie (1994) illustrated the effects of changing spatial resolution with channel 4 (near-infrared) of Landsat TM. They generated land/water binary masks by simulating successively coarser pixel resolution through the application of a pixel aggregation algorithm. Three landscape parameters were extracted from each level - the percentage of the scene covered by water, the number of lakes, and the mean surface areas of lakes. They concluded that, as the ground resolution cell size increased from 30 m to 960 m, the percentages of the scene masked...
into the water class increased initially and then decreased. At the same time, the number of lakes
decreased non-linearly and the mean lake surface area increased linearly. Through this study, the
authors illustrated the interrelationships among the spatial resolution of the sensor, the spatial
structure of the environment, and the nature of information sought.

As fractal functions provide a good description of surface textures and their images, the
fractal model can be used for image segmentation, texture classification, shape-from-texture, and
the estimation of 3-d roughness from image data (Pentland, 1984). Therefore, the measurement
of the fractal dimension in an image can be useful in segmenting natural imagery. Using a
digitized image, Pentland (1984) computed the fractal dimension for each 8*8 block of pixels by
means of the Fourier technique (the parameter H was estimated by a least squares regression of
the fourier-domain fractal dimension onto the power spectrum of the block of pixels). The
histogram of fractal dimensions was then broken at the “valleys” between the modes of the
histogram, and the image segmented into pixel neighborhoods belonging to one mode or another.
Using a thresholding technique, a good segmentation into land and water was obtained, one that
cannot be obtained by thresholding on image intensity. To show that this segmentation is stable
over transformations of scale, the image was degraded spatially from 512*512 to 256*256 and to
128*128 pixels and the fractal dimension was recomputed for each degraded data set. By using
the same threshold as in the original full resolution image, the fractal dimension measured was
stable over wide variations in scale.

2.2.2 Using Neural Networks

Ryan et al. (1991) demonstrate the capability of using neural networks, in conjunction
with image processing techniques, as a tool for the delineation of shorelines using texture
measures (power spectral rings) derived from remotely sensed imagery. A multi-layer perceptron
using the back-propagation learning rule was adopted. The neural network was trained to
categorize small blocks of image data as land or water. After a category map was generated by the neural network, image processing techniques were used to delineate the shoreline down to the pixel level. The resulting categorization was a binary category map that is refined down to the pixel level to provide an estimate of shoreline location. A majority of the misclassified regions of the binary land/water category map were corrected by applying connected components labeling followed by the merging of small isolated regions into the surrounding area. For the land/water categorization, errors were corrected using three image processing algorithms - the morphological operations of erosion followed by dilation, application of a majority filter and connected components labeling.

McClellan et al. (1989) report on the use of a three-layer back-propagation neural network to do a classification of a multi-spectral image. A two category classification of a 4-band multi-spectral image containing areas of both land and water was carried out. Their results indicated an emergence of a distinctive, meaningful third class of pixels that was not represented in the training set. Those pixels tended to cluster near the output of (0.5, 0.5, 0.1), being the result of pixels that were a mixture of land and water. It can be interpreted that along the shoreline the two outputs for land and water were nearly equal in between the high and low training values and the network was clustering these areas into a separate mixed class.

In conclusion, the above studies agree that land/water boundary conditions can be distinguished based on differences in spectral signatures between land and water. By adopting image analysis techniques and neural networks, the authors successfully delineated shorelines. However, researchers (Paola and Schowengerdt, 1994; Benediktsson et al., 1990) have reported very long training times required by neural networks and the importance of selecting proper training regions. This study will explore classification accuracy and scale-resolution effects of land/water patterns delineated using neural networks. Specifically, the neural network is trained using data from bands 3, 4 and 5, and classified on multispectral - resampled, Gaussian smoothed
and local variance analysis images. Previous studies in general have not considered this approach. Also, emphasis will be given to selection of training regions and improvement of training time.

2.3 Scale - resolution impacts in mapping sciences

The basic question about scale consists of determining whether a given phenomenon appears or applies across a broad range of scales, or whether it is limited to a narrow range of scales. Therefore, the search for breaks in scale and the discovery of scales appropriate to different ecological phenomena are critical. One of the most important considerations in the use of remotely sensed data in environmental modeling is that of spatial scale. In wetland environments, frequent inundations and flooding is a major factor shaping land/water distribution. The effect of land/water boundaries may exist at all spatial scales, but the relative importance of processes affecting the delineation may change as scale changes (Gosz and Sharpe, 1989). Therefore, appropriate techniques are needed to model the scales of action where these land/water patterns can be delineated. A great number of quantitative models (Turner et al., 1991; Woodcock and Strahler, 1987; Woodcock et al., 1988a, b) have been developed to describe the relationship between landscape patterns and the driving processes and factors. The following section will outline several issues related to the scale and resolution problem with regard to remote sensing applications.

Several authors have investigated the spatial structure of images, usually at one or two discrete resolutions. Craig and Labovitz (1980) measured spatial autocorrelation in Landsat MSS images and tested the influence of factors related to the sensor, physical factors such as sun angle and cloud cover, and a geographic location factor. Labovitz et al. (1980) extended the study to include images at a resolution similar to the Landsat TM and found spatial autocorrelation to be higher in images with finer spatial resolution. Woodcock and Strahler (1985) used 1- and 2-d
variograms to investigate the spatial structure of both simulated and real images. Further research focused on the selection of an appropriate scale in the data and to determine the effective range of scales at which patterns were clearly manifested using several statistical methods (scale variance analysis, and discriminant analysis). Townshend and Justice (1988) applied scale variance and Fourier analysis on spatially degraded MSS data from 125 m to 4000 m to investigate the required spatial resolution for global monitoring of land transformations. They recommended an average resolution of 500 m as it provides the best compromise between detail of changes detected and the size of the resultant data volume.

Woodcock and Strahler (1987) developed a measure of local image variance (the mean of the standard deviation values computed from a 3*3 pixel window moving across the image) to help in selecting an appropriate image scale for forested, urban/suburban, and agricultural environments. The graphs of local variance in images as a function of their spatial resolution revealed that the variance is low when the spatial resolution is considerably finer than the objects in the scene because the neighboring pixels are highly correlated. A similar homogeneity is induced when the pixel size increases until many ground features are aggregated in a single resolution cell. However, when the dimension of the resolution cell is half of the size of the objects in the scene, the likelihood of neighboring pixels being similar decreases, and the local variance reaches a peak, corresponding to the appropriate image scale.

The effect of spatial scale on landscape characterization is a central issue in the landscape ecology literature. At the fine spatial scales, changes in the landscape pattern tend to be small because of the relative homogeneity within the objects. The successive aggregation of pixel values causes the local variance to decline at scales beyond the peak scales. The location of the peak was found dependent upon the size of the objects and their spatial structure (Nellis and Briggs, 1989; Woodcock and Strahler, 1987; Turner et al., 1989). All these studies simulate low spatial-resolution data from high spatial-resolution data using a range of techniques: pixel
averaging (Woodcock and Strahler, 1987), weighted filter (Cushnie, 1987) and Gaussian low-pass filter (Kong and Vidal-Madjar, 1988).

The effect of scaling on land-cover proportions has been explored in the research literature in recent years. Several studies have established that changing the spatial resolution of land-cover maps has important effects on the proportion of a landscape occupied by a particular land-cover type (Henderson-Sellers et al., 1985; Turner et al., 1989; Moody and Woodcock, 1994). In general, the proportions of smaller, more fragmented cover types decrease with aggregation, while those of the larger classes increase. Similar effects were noted by Townshend and Justice (1988), who observed large changes in the proportions of test site images falling within specific NDVI ranges as scenes were progressively degraded to coarser resolutions.

Moody et al. (1995) investigated the scale-dependence of the relationship between NDVI variability and variability in land cover. Their primary interest was to determine the “best” scales for characterizing the landscape regarding to the specific classification scheme employed. The authors used the ratio of between-class variance / within-class variance to determine the effectiveness of characterizing the landscape at the different scales. In general, if $N$ is the total sample size, $k$ is the number of classes, $\bar{x}$ is the mean for the whole sample, $\bar{x}_i$ is the mean for the $i$th class and the $i$th class contains $n_i$ observations, then the between-class variance is:

$$s_b^2 = \frac{1}{(k-1)} \sum_{i=1}^{k} n_i (\bar{x}_i - \bar{x})^2$$

the within-class variance is:

$$s_w^2 = \frac{1}{(N-k)} \sum_{i=1}^{k} \sum_{j=1}^{n_i} (x_{ij} - \bar{x})^2$$

A large $s_b^2 / s_w^2$ ratio indicates that a large proportion of the total image variance is taken up by the partitioning of the data into a given set of classes, and a low ratio indicates that the partitioning does little to explain the overall variance in the data. These observations conform
with more theoretical results obtained by Jupp et al. (1988, 1989) and Woodcock and Strahler (1987) on scaling, resolution and spatial pattern.

2.4 Effect of scale on land-cover classification accuracy

A comprehensive study of the effect of spatial resolution on classification accuracy was undertaken by Markham and Townshend (1981), and their conclusions represent the culmination of the results of many earlier studies. Markham and Townshend concluded that observed classification accuracy was the result of two factors. The first factor is the influence of boundary pixels on classification results. As spatial resolution becomes finer, the proportion of pixels falling on the boundary of objects in the scene will decrease. Reducing the number of mixed pixels will reduce confusion in the classification process, resulting in higher classification accuracy. The increased spectral variance of land-cover types associated with finer spatial resolution is the second factor identified as influencing classification accuracy. Within-class variance decreases the spectral separability of classes and results in lower classification accuracy. The net effect of finer spatial resolution is the result of the combination of these two opposing factors that vary as a function of environment (Cushnie, 1987).

The investigation of the influence of spatial resolution on the accuracy of land cover mapping has received a lot of interest in the remote sensing literature. These efforts have involved assessing the characteristics of several representations of a given area either sampled at different resolutions by different sensors or aggregated to a series of coarser scales from a single high resolution dataset. Moody and Woodcock (1994) degraded TM simulator data to a series of coarser resolutions and compared the results of a maximum-likelihood of the scene at different scales. The authors noted an improvement in classification accuracy as the data were coarsened within the range of 15m to about 75m resolution. Sadowski et al. (1977) found the same phenomena for forested landscapes using degraded MSS data. They noted that the improvements
of classification accuracy at coarser resolutions were related to the inherent scale associated with
the classification scheme employed, class-specific variance and covariance, the location of cover-
type units relative to the overall scene and mixed pixels at class boundaries. The works cited
above investigated the effect of resolution on classification performance for a series of
resolutions that were all coarser than the base resolution of the defined cover-type units.

2.5 Methods for detecting the scale-resolution effects

2.5.1 Semi-variograms for analysis of image structure

Remote sensing offers possibilities of characterizing the structure of ecosystems and can
yield assessments of functional features such as land/water boundaries up to coarser resolutions.
For many years, a lot of time and effort have been devoted to quantitative analysis of spectral
information using statistically based decision rules, but the extraction of information from the
spatial domain has been considerably less developed because of the lack of understanding of
spatial variations in the imagery (Fotheringham and Wong, 1991). Geostatistics have been
applied to remotely-sensed data in the form of the semivariogram as a basic tool (Curran, 1988;
Woodcock et al. 1988; Cohen et al. 1990) to exploit the spatial information inherent in image
data. A semivariogram is a graphical representation of the spatial variability in a given set of
data. The semivariogram, or \( \gamma(h) \) is calculated as (Curran et al., 1990):

\[
\gamma(h) = \frac{1}{2(n-h)} \sum_{i=1}^{n-h} (Z(x_i) - Z(x_i + h))^2
\]

where, \( h \) is the lag (or distance) over which \( \gamma(h) \) is measured
\( n \) is the number of observations used in the estimate of \( \gamma(h) \)
\( Z \) is the value of the variable of interest at spatial position \( x_i \)
\( Z(x_i + h) \) is the variable value at distance \( h \) from \( x_i \).

For spectral data, \( \gamma(h) \) estimates the variability of radiance \( Z \), as a function of spatial
separation. Typically, the shape of a semivariogram resembles one of three basic models. These
include the exponential, linear, and spherical models, the latter being the most commonly used (Curran et al., 1990). In the spherical model $\gamma(h)$ increases with $h$ until it reaches a maximum, or sill. The lag at which the sill is reached is called the range. The range and the sill are the two parameters of the semivariogram used to describe the data. The range can be used as a measure of spatial dependency, or homogeneity, whereas the sill reflects the amount of variability. Jupp et al. (1988a) demonstrated how the functional form of the relationship between the semivariogram of an image and the underlying scene covariance provides an analytical basis for scene inference. Jupp et al. (1988b) and Woodcock et al., (1988a, b) further explore this relationship using scene models and real images and note that a factor affecting the shape of the variogram is regularization.

Semivariogram analysis is an effective tool to study the effect of scale on landscape organization because the variance of landscape properties is treated as a function of scale. If semivariance increases with sampling interval, the landscape property is spatially dependent or spatially autocorrelated (Woodcock et al., 1988a). Spatial dependence may not exist at all scales. The range of scales where spatial dependence is present can be identified from a plot of semivariance against the sampling interval (Figure 2.1). The length of the range and the general form of spatial variation of the landscape property can be visualized from the plot. For many natural phenomena, the semivariance tends to increase with sampling intervals. After it reaches a maximum value, the semivariance levels off. At the peak spatial scale, the landscape presents the most obvious spatial dependence or greatest variance. The spatial pattern of the landscape can be easily recognized and studied at these peak scales (Meentemeyer, 1989).

2.5.2 Fractal Geometry

Semivariograms can be helpful in identifying the range of spatial scales within which the landscape property is spatially dependent, but they do not provide information on the degree
Figure 2.1  General form of a semivariogram (Source: Oliver and Webster, 1986)
of spatial dependence. A technique which can be applied to quantify the degree of spatial
dependence is fractal analysis (Goodchild and Mark, 1987; Lam and Quattrochi, 1992). Fractal
analysis focuses on the geometric pattern of phenomena, suggesting that the amount of
resolvable detail is a function of scale (Lam and De Cola, 1993). In theory, typical fractal
phenomena should remain at a constant dimension through all scales but, in the real world
natural phenomena behave differently. Instead, a fractal dimension may vary with scales or
remain near constant at a certain range of scales or over a few widely separated scales. In some
cases, a sharp break may appear. The changes in the fractal dimension at specific scales are
normally of significant geographic interest (Mark and Aronson, 1984), as it implies invariance of
probability distributions with respect to change of scale (self-similarity) that provides a
framework for the representation of the spatial properties of the landscape which are visible in
remote sensing imagery (De Cola, 1989; Burrough, 1983; Lacaze et al. 1994). I intend to
demonstrate the possibilities of identifying multiscale spatial patterns (land/water boundaries)
from the analysis of remotely sensed data and to suggest an interpretation of these patterns
through semivariograms and a measure of fractal property known as lacunarity.

2.5.3 Lacunarity Analysis

Coastal erosion and shoreline weathering is a dynamic and prevalent impact on the
landscape. Humans and environmental processes can change the distribution of land use types
very quickly and at a variety of spatial scales. An important goal in geography is the
quantification of such spatial patterns. However, these patterns exhibit scale-dependent changes
in structure, and are correspondingly difficult to identify and describe. The quantification of
these changes can allow appropriate scales for empirical studies to be quantitatively defined
(Plotnick et al., 1996). The sensitivity of lacunarity analysis will make these effects easily
detectable, because the effect of pattern on the landscape process is scale specific.
In this dissertation, the concept of lacunarity, which was originally developed to describe a property of fractals (Mandelbrot, 1983; Plotnick et al., 1993; Allain and Cloitre, 1991), is used to describe spatial patterns in Landsat TM remotely sensed imagery. The approach used here is an elaboration of the lacunarity algorithm developed by Allain and Cloitre (1991) to uncover scale-dependent changes of land/water boundaries, which should give insight into the underlying processes affecting these changes. The lacunarity index of an entire image (Allain and Cloitre, 1991) for a particular box size $r$ is calculated as:

$$
\Lambda(r) = \frac{z^2}{(z^1)^2}
$$

where,

- $z^1 = \Sigma S \times Q(S, r)$ — First moment
- $z^2 = \Sigma S^2 \times Q(S, r)$ — Second moment
- $S$ = Occupied sites (particular land cover type)
- $r$ = size of box
- $Q(S, r) = \text{number of boxes of size } r \text{ containing } S \text{ occupied sites} / \text{Total number of boxes of size } r$
- $= \frac{n(S, r)}{N(r)}$

As a texture measure, lacunarity quantifies the deviation of a geometric object (land/water patterns) from translational invariance (how similar are parts from different regions of an object to each other). A simple analogy can be extended to land/water patterns. Water bodies have a smooth or homogeneous texture (small gap distributions) at any given scale. Therefore at varying box sizes, water bodies will have a low lacunarity index as opposed to land features which are highly scale dependent. Land patterns that are heterogeneous at fine resolutions can be quite homogeneous when examined at coarser resolutions or vice versa.

Therefore, by varying the box size, the number of occupied sites (land areas) will also vary, resulting in higher lacunarity for land bodies at finer resolution. Therefore, the scale dependent distribution of land/water patterns can be quantified by using this simple multi-scale technique.

The statistical behavior of $\Lambda(r)$ can be best understood by knowing that:
\[ z^1 = \bar{S}(r), \]
\[ z^2 = S^2_s(r) + \bar{S}^2(r) \]

where, \( \bar{S}(r) \) is the mean and \( S^2_s(r) \) the variance of the number of sites per box.

Thus, \( \Lambda(r) = \frac{S^2_s(r)}{\bar{S}^2(r)} + 1 \)

The maximum value of \( \Lambda(r) \) occurs when the box size equals the spatial resolution of the image. The minimum value (= 1) occurs when the window equals the image dimensions as variance is zero. The decay pattern of the lacunarity function contains significant information about the spatial structure of the binary image (Figure 2.2). A spatially random image exhibits a swift decay to the minimum value (Figure 2.3). An image with self-similarity across some range of scales exhibits a linear decay, the slope of which is an estimate of the fractal dimension of the pattern within that image (Henebry and Kux, 1995). For an image with an arrangement of objects at a particular scale, the lacunarity decay is slow until the window size exceeds the scale of the objects and is rapid thereafter. By varying window shape as well as size, lacunarity functions can also identify departures from another aspect of spatial stationarity: rotational invariance or isotropy (Henebry and Kux, 1995).

Lacunarity as a texture measure for remotely sensed imagery offers several advantages. First, it is a multi-scale technique; dependence of texture on resolution can be identified. Second, from the graph of \( \log(\text{lacunarity index}) \) versus \( \log(\text{box size}) \), the decay of the lacunarity index as a function of window size follows characteristic patterns for random, self-similar, and structured spatial arrangements. This feature is especially useful in distinguishing the textural effects of noise from scene texture. Finally, lacunarity functions can provide a framework for linking differences in image sequences (images from different dates) to changes in scene structure (Henebry and Kux, 1995) for global change studies or studying the impacts of droughts/flooding.
Three 12x12 maps, with 1's representing occupied sites. The percentage of occupied sites $P = 0.5$ for all three maps. (a) random map, $\Lambda(r) = 1.04$, (b) map with a single large gap, $\Lambda(r) = 1.81$, and (c) perfectly regular map (checkerboard), $\Lambda(r) = 1.0$. Note: For a perfectly regular map, the position of the box at any location represents the overall pattern in the image and so variance is low resulting in minimal value of lacunarity. The contrasting behavior can be observed for the random map. (Source: Plotnick et al., 1993)
Figure 2.3 Decay patterns exhibited in remote sensing imagery in terms of changes in spatial structure. (a) a fundamental shift in the curves is produced as cover types changes from once sharp transitions to blurred effects, (b) suggests a spatially near-random landscape that becomes more homogenized through time, (c) exhibits initial self-similarity shifting to an almost constant level, and (d) the lacunarity index at smaller window sizes measures local heterogeneity and thus is more sensitive to changes in edges, whereas the slope, which measures changes in spatial structure remains unaffected. Note: Each curve stands for one land cover type, but for different time periods. (Source: Henebry and Kux, 1995).
The next chapter provides a detailed literature review of the application of neural networks, maximum-likelihood and normalized difference vegetation index (NDVI) for image classification. These are the methods to be used and compared.
Chapter 3
Classification methods – ANN, Maximum-Likelihood, and NDVI

This chapter provides a description of the techniques used in this study, which includes artificial neural networks, maximum-likelihood classifier and NDVI technique. The discussion includes a general literature review as well as details on the algorithms, topology, selected parameters, and methods to visualize classification results.

3.1 Interpretation of multispectral imagery

The inter-relationships in spectral reflectance among earth surface cover types can be interpreted with the aid of Figure 3.1 and Figure 3.2. In Figure 3.1, the large field of bare soil near the center of the image appears nearly white in tone in most of the images due to high reflectance in the three wavelength regions (0.4 – 2.6 µm). Vegetation reflects very little and therefore has a dark appearance in the visible band images. In the near-infrared (0.7 – 1.2 µm), the situation is reversed. Here the soil is relatively dark in tone and vegetation is relatively bright in tone (Swain and Davis, 1978). In the middle infra-red (1.3 - 1.8 µm) portion of the spectrum, the soil reflects much more highly than vegetation. Water, which has a high infrared absorption, becomes very dark on multispectral imagery throughout the near infrared portion (0.72 - 1.2 µm) of the spectrum as seen with the pattern displayed by the meandering river in the center of the image.

Figure 3.2 displays spectral data for vegetation, soil and both clear and turbid water. Examination of the curves indicates that the visible wavelength region is not as definitive as the near-infrared region for spectrally distinguishing among the basic cover types (vegetation, soil and water). In both the middle and near-infrared regions, both clear and turbid water has little reflectance and so can be easily separated from any soil or vegetation cover type. In the near-
Figure 3.1  Twelve wavelength bands of multispectral imagery in the visible, near-infrared, and middle-infrared wavelength regions (Source: Swain and Davis, 1978)
Figure 3.2 Spectral reflectance curves for vegetation, soils, clear and turbid water
(Source: Swain and Davis, 1978)
infrared portion of the spectrum (0.72 - 1.2 $\mu m$), vegetation is more reflective than soil and water, whereas in the middle-infrared wavelength soil is more reflective than vegetation. Therefore, by examining Figures 3.1 and 3.2 one can reveal the advantages of utilizing more than one wavelength band to distinguish various cover types.

3.2 Parametric versus non-parametric image classification (maximum-likelihood versus neural network classifiers)

A primary method for supervised classification of image data utilizes the maximum-likelihood decision rule, based on statistical theory (Swain and Davis, 1978). This type of classifier, called parametric, has been the most commonly applied classification technique because of its well developed theoretical base and its successful application with different data types and classification schemes (Bolstead and Lillesand, 1991). It also has the benefit of assigning every pixel to a class since the parametric decision space is continuous. With the parametric technique, the classifier must be trained with class signatures defined by a statistical summary (typically mean and covariance) acquired either by the analyst selecting samples in the image or by an unsupervised clustering algorithm. In either case, the statistics are accumulated from a sample of multispectral pixel vectors in the image space.

Another type of classifier, non-parametric, is not statistically based and thus makes no assumptions about the properties of the data. This classifier assigns pixels to classes based on the pixels position in discretely partitioned feature space. The feature space partitions could be thought of as objects, such as polygons, ellipses, or rectangles which have been derived from image samples or directly defined by the analyst (Kloer, 1994). With this method of classification, the decision rule simply determines whether a pixel lies inside or outside a feature space-object. Parallelepiped classification is an example of a non-parametric decision rule, using parallelepipeds which have been defined from an image sample, or specified by an analyst (Jensen, 1986). A neural-network could also be classified as a non-parametric classifier.
Aside from the independence from the sample data properties, the non-parametric classifier also has a performance advantage (faster and in some case more accurate) over the parametric classifier. The non-parametric classification method has limitation as well. The feature space object-based classifier has the problem of overlap. This problem is most serious for ellipses, but also exists for polygons. It is possible, and in many cases likely, for a pixel to lie inside more than one feature space object (Kloer, 1994). Since no probabilities are computed, the only means of resolution is to consider the order in which the classes are processed. The pixel in an overlapping region is assigned to the first or last class for which it is tested. Another disadvantage of non-parametric classifiers is that frequently many of the pixels in an image will not be assigned to any class producing an output classified image with a percentage of pixels unclassified.

3.3 What is a Neural Network?

When a neural network is defined, it is generally referred to as an artificial neural network (ANN). ANN is defined as a network of many simple processors (nodes), each node mimics the biological neuron. These units are connected by connections, which usually carry numeric data, encoded by various methods (Hinton, 1992). The nodes operate only on their local data and on the inputs they receive via the connections. The nodes perform two functions. First, it sums the values of its inputs. Second, this sum is then passed through an activation function to produce the node’s output value. The processing nodes are organized into layers, each fully interconnected to the following layer (Figure 3.3). There is an input layer that serves as a distribution structure for the data being presented to the network. No processing is done at this layer. More than one layer follows the input layer. The final processing layer is called the output layer. The layers between the input and output layers are called hidden layers (Rumelhart et al., 1986). The neural network has a training rule, whereby the weights of connections are adjusted
Figure 3.3  Generic three layer neural network (Source: Paola, 1994)

Figure 3.4  A neural network processing node (Source: Civco et al., 1993)
on the basis of data, i.e., neural networks learn from examples and exhibit capability for
generalization beyond the training data. When a value is passed through the interconnections, it
is multiplied by the weights. These weight values contain the learned information of the network
(Figure 3.4).

3.4 Neural Networks and Image Classification

In general, the progress made so far can be grouped into two major categories--the
applications of neural networks for satellite image processing; and the integration of neural
networks with GIS for spatial analysis and modeling (Sui, 1994). In applications related to
satellite image processing, back-propagation, which is also known as the generalized delta rule,
is one of the most popular and widely investigated methods for training neural networks.
Appendix-A provides a summary of related applications of neural networks to image
classification using the back-propagation rule. The foundation of the back-propagation learning
algorithm is the non-linear optimization technique of gradient descent on the sum of the squared
differences between the activation of nodes in the output layer and the desired output. The
objective is to minimize the sum of squares error (Rumelhart, 1986). The simplest structure for
data input (also used in most statistical classifiers) is that for reading one multispectral pixel into
the network. One input node or a set of input nodes is used to represent the data for each spectral
band (Dreyer, 1993; Bischof et al., 1992; Kiang, 1992; Kanellopoulos et al., 1991). More details
on the working principle of a back-propagation network will be described in Section 3.4.1.

The potential applications of neural networks for spatial data handling were first
recognized, among several others, by Ritter et al. (1988) as a new computing tool for automatic
pattern recognition in a GIS environment. In an attempt to test the ability of neural networks for
distinguishing the within-class variability, Key et al. (1989) developed a feed-forward back-
propagation neural network for classifying merged AVHRR and SMMR data. The results were
compared with those derived from manual interpretations and a supervised maximum-likelihood classifier. The neural network approach proved to be very useful for classifying pixels with spectral values significantly different from the pixels in the training data. Ritter and Hepner (1990) and Hepner et al. (1990) explored the feasibility of a neural network approach for land cover classification. A three layer back-propagation network was trained to do the land cover classification for a TM scene. They found the performance of a neural network approach to be better than a maximum-likelihood classifier, especially in situations involving small training sets.

In studies relating to application of texture for improving classification accuracies by incorporating structural information rather than spectral information, effects of various textural parameters were investigated. Dreyer (1983) calculated a number of textural features based on gray-level statistics. He found that the use of these features increased the accuracy of a "field" class, but had no effect for "urban" and "water" classes, and actually decreased the accuracy of a "forest class". Key et al. (1990) also used texture calculations such as second moment and entropy to produce a single texture measure for each pixel in the classification of land cover and cloud types in the Arctic, with classification results superior to those of spectral pixel values only. Civco (1991), in a land cover classification, presented the network with a single mean vector for each class of the training data in the form of a 3*3 input vector that introduced texture and forced a statistical measure into the training process.

In a comprehensive empirical evaluation of neural networks versus statistical methods, Benediktsson et al. (1990) revealed important differences. They concluded that the performance of a neural network may be better than traditional statistical methods, if high quality training data are available. In contrast, statistical methods tend to be less sensitive to the representativeness of the training data than the neural network approach. Statistical methods may outperform neural networks only when additional ancillary data, such as elevation, slope, and aspect are incorporated into the processing procedure.
Neural networks have also been proved useful in extracting linear features from remote sensing imageries. A back-propagation network was developed by Ryan et al. (1991) to delineate shorelines from TM data. They showed that the neural network can be trained to distinguish land from water using PSR (power spectral ring) data. With PSR data (derived from the power spectrum of the fourier transform), the misclassification rate was low and most misclassifications were removed from image processing. This work inferred the possibility of using neural networks to extract drainage network features from Digital Elevation Models (DEM's).

Heermann and Khazenie (1992) tested the feasibility of using a back-propagation network to classify very large multi-channel images. They modified the back-propagation algorithm to accommodate more bands and to include spatial and temporal information. This adaptive back-propagation algorithm also reduced training time and raised the accuracy of classification. In another study, Bischof et al. (1992) reported that an extension of the basic back-propagation network can incorporate textural information without explicit definition of a texture measure. The neural network demonstrated a better post-classification smoothing effect than some of the conventional filters. Using a large network architecture (two hidden layers with 12 to 18 nodes), Kanellopouloss et al. (1991, 1992) tested the possibility of discriminating a large number of land cover classes (20) using neural networks. They attained an average accuracy of 84% using the neural network approach, which outperformed traditional statistical methods.

The results from these studies have demonstrated the superiority of neural networks to statistical methods in terms of the requirements on the raw data and the classification accuracy for remote sensing applications.

3.4.1 Neural network topology

The activation function first computes the net input of the unit from the weighted output values of prior units. It then computes the new activation from this net input. The output function
takes this result to generate the output of the unit. A new activation is computed from the output of preceding units, multiplied by the weights connecting these predecessor units with the current unit, the old activation of the unit and its bias. The following equations were adopted from Stuttgart Neural Network Simulator (SNNS v4.1) users manual (1996).

\[ a_j(t+1) = f_{act}(net_j(t), a_j(t), \theta_j) \]  

(3.1)

where,  
- \( a_j(t) \) is the activation of unit \( j \) in step \( t \)
- \( net_j(t) \) is the net input in unit \( j \) in step \( t \)
- \( \theta_j \) is the threshold (bias) of unit \( j \)

The activation function computes the network input simply by summing over all weighted activations and then squashing the result with the logistic function

\[ f_{act}(x) = \frac{1}{1 + e^{-x}} \]. The new activation at time \((t+1)\) lies in the range \([0,1]\). One common activation function is the logistic activation function (Figure 3.5) given by -

\[ a_j(t+1) = \frac{1}{1 + e^{-\left(\sum w_{ij} o_i(t) - \theta_j\right)}} \]  

(3.2)

where,  
- \( a_j(t) \) is the activation of unit \( j \) in step \( t \)
- \( net_j(t) \) is the net input in unit \( j \) in step \( t \)
- \( o_i(t) \) is the output of unit \( i \) in step \( t \)
- \( j \) is the index for some unit in the net
- \( i \) is the index of a predecessor of the unit \( j \)
- \( w_{ij} \) is the weight of the link from unit \( i \) to unit \( j \)
- \( \theta_j \) is the threshold (bias) of unit \( j \).

The net input \( net_j(t) \) is computed with -

\[ net_j(t) = \sum_i w_{ij} o_i(t) \]  

where, \( \text{net} \) is the sum of weighted inputs to the processing node.

Some parameters of the sigmoid activation function are important to network performance. Output values of zero and one are possible only with inputs of \( \pm \infty \). To account for this, the values of 0.1 and 0.9 are generally used to represent the low and high values of network input data (Paola, 1994). The activation function has a nearly linear input/output relationship between these two extreme values.
Figure 3.5 The sigmoid activation function. NET is the weighted sum of the inputs to the processing node (Source: Paola, 1994)
The output function computes the output of every unit from the current activation of the unit. The output function is in most cases an identity function. The output function makes it possible to process the activation before an output occurs.

\[ O_j(t) = f_{out}(a_j(t)) \]  

where, \( a_j(t) \) is the activation of unit \( j \) in step \( t \)
\( O_j(t) \) is the output of unit \( j \) in step \( t \)
\( j \) is the index for all units of the net

The network training phase is analogous to the class mean and covariance matrix calculations of maximum-likelihood. Instead of calculating statistical measures, however the network is trained in an iterative fashion, typically by the back-propagation algorithm, until some targeted minimal error is achieved between the desired output (training classes) and actual output values of the network. For the classification phase, instead of calculating discriminant functions on the basis of the distributions as determined from the training data, as in maximum-likelihood, the network is used in a feed-forward mode. The entire image is feed into the network pixel-by-pixel, and a simple rule (maximum output) is used to process the network output to make a class selection for each pixel (Heermann and Khazenie, 1992).

Learning in Neural Nets: An important focus of neural network research is the question of how to adjust the weights of the links to get the desired system behavior. This modification is very often based on the back-propagation learning function (Rumelhart et al., 1986). In this research, back-propagation with momentum term and flat spot elimination is adopted (SNNS v4.1). The momentum term is used to avoid oscillation problems common with the regular back-propagation algorithm when the error surface has a very narrow minimum area. Then, a constant value is added to the derivative of the activation function to enable the network to pass flat spots of the error surface. Back-propagation like all gradient descent algorithms, is not guaranteed to find the global minimum error. During the training phase, the network takes the steepest descent from the current position to one of lower levels. If the network encounters a valley, or local minimum, it...
can become stuck and the error will not decrease to the global minimum value. Back-propagation
with momentum is employed to alleviate this problem in error space. The weight update formula
(SNNS v4.1 Users Manual) becomes:

\[ \Delta w_{ij}(t + 1) = \eta \delta_{ij} o_i + \mu \Delta w_{ij}(t) \]  \hspace{1cm} (3.4)

\[ \delta_j = (f_j'(net_j) + c)(t_j - o_j) \quad \text{if unit j is an output-unit} \]

\[ \delta_j = (f_j'(net_j) + c) \sum_k \delta_{kj} \quad \text{if unit j is a hidden-unit} \]

where, \( \eta \) is a learning parameter, specifying the step width of gradient descent.
\( \mu \) is a momentum term, specifying the amount of the old weight change
to be added to the current change.
\( c \) is a flat spot elimination value.

*Training a feed-forward neural network* with supervised learning consists of the following
procedure: An input pattern is presented to the network. The input is then propagated forward in
the net until activation reaches the output layer. This is called the forward propagation phase.
The output of the output layer is then compared with the teaching input. The error, i.e., the
difference \( \delta_j \) between the output \( o_j \) and the teaching input \( t_j \) of a target output unit \( j \) is then used
together with the output \( o_i \) of the source unit \( i \) to compute the necessary changes of the link \( w_{ij} \).

To compute the deltas of inner units for which no teaching input is available, (units of hidden
layers) the deltas of the following layer, which are already computed, are used in formula (3.4).
In this way, the errors (deltas) are propagated backward. The weight changes \( \Delta w_{ij} \) are applied to
the network after each training pattern (SNNSv4.1 Users Manual, 1996).

*Back-propagation Training Considerations:* Each set of weights before \( w_{jk} \) is updated by a
function that is described in terms of the error between the desired output and teaching input
from the previous set of weights. As each training pattern is presented, the \( \delta_j \) term at each node
is summed. The total error between desired and actual outputs is also summed. If this error is still
above some threshold when the training cycle is completed, the weights are adjusted using the
$\delta_j$ terms as shown in formula 3.4 and training continues. The back-propagation algorithm
provides weight change terms that should be summed for all training patterns to obtain a true
gradient descent of the overall training error. The neural network weights should be adjusted
after the entire sum is obtained. This is called batch or epoch training (SNNSv4.1 Users Manual,
1996).

It is assumed in this dissertation that the outputs represent one class each and are trained
to have “high” values for their given class. The simplest way to assign a class to the input data is
to choose the class of the output node with the highest value (Benediktsson et al., 1990; Key et
al., 1990). The pixel is unclassified if all the outputs are less than 0.5; otherwise it is given the
class of the highest valued output node. Higher values for an output would imply a higher
confidence that the pixel belongs to the corresponding class. Kiang (1992) discusses a method to
convert the output values to \textit{a posteriori} probability that can then be used to improve the
classification accuracy. Lippmann (1991) showed that many neural network classifiers provide
outputs which are estimates of Bayesian \textit{a posteriori} probabilities.

3.4.2 Advantages and problems of ANN

Recently, applications of neural networks to the classification of multispectral sensed
images have been increasing. This is due to the following characteristics:

1. their ability of learning provides an alternate to the maximum-likelihood classifier.

2. they make no assumptions about the underlying probabilistic distribution of data.

3. they are capable of forming highly nonlinear decision boundaries in the feature space and
   thus have the potential of outperforming a parametric Bayes classifier when a feature statistic
   deviates significantly from the assumed Gaussian statistics (Paola, 1994).
4. Maximum-likelihood classifiers are not designed to process multisource data (nominal thematic data, ordinal data or directional information) and they do not have a mechanism for dealing with information uncertainty.

5. ANN's may be used with minimal training sets and are tolerant to noise and missing data (Hepner et al. 1990), can adapt over time (Short, 1991), and weight the importance of data in the classification (Benediktsson et al., 1990).

6. Can be used to search large remote sensing databases such as NASA-(EOS) for patterns of interest in particular applications (Paola and Schowengerdt, 1992).

Problems

1. A major drawback of the back-propagation algorithm is the lengthy time necessary for training. When used as a feed-forward classifier, the network is usually fast. However, the iterative process required to produce that feed-forward classifier is time- and computation-intensive.

2. Another problem in the training stage arises from the initial assignment of random weights. Since this assignment is completely independent of the data, training time can be long and different training sessions can have different results (Paola, 1994).

3. A disadvantage of neural networks is the loss of interpretability due to departure from statistical theory (Kanellopoulos et al., 1991). Since classes are no longer assumed to have well defined normal distributions, the mechanisms behind a classification are difficult to interpret.

4. Back-propagation, like all gradient descent algorithms, is not guaranteed to find the global minimum error. During the training phase, the network takes the steepest descent from the current position to one of lower levels. If the network encounters a valley, or local minimum, it can become stuck and the error will not decrease to the global minimum value.
3.4.3 Visualizing neural network classification results using feature space images

Considerable insight can be gained into the behavior of neural network classifiers by making graphical visualizations of their behavior in feature space and by comparing their behavior to that of the more traditional parametric classifiers. Decision boundaries generated by a neural network rely on a completely different mathematical model (intersection of equiprobability surfaces). The nature of these surfaces however is very different from multivariate normal distributions (Fierens et al., 1994). The most basic surface shape available to a neural network is dictated by the transfer function of the individual nodes. In the case of a sigmoid transfer function, as used in all experiments, the value of the sigmoid defines the height of the surface (Rumelhart et al., 1986). The basic surface generated by one node in the network thus exhibits a sigmoid like shape. Analogous to what happens in statistical classifiers, the intersection of the equiprobability surface then generates the final decision boundaries (Fierens et al., 1994). In comparing the visualization of feature space behavior of statistical and neural classifiers of satellite imagery, Fierens et al., (1994), concluded that neural network classifiers produces higher accuracies than that of maximum-likelihood. But, noted that before drawing general conclusions, the scaling up behavior of the classifiers must be investigated.

3.5 Normalized Difference Vegetation Index (NDVI)

Normalized Difference Vegetation Index (NDVI) (Sellers, 1985) is calculated from bands 3 and 4 of Landsat TM using the following equation -

\[ \text{NDVI} = \frac{(\text{channel } 4 - \text{channel } 3)}{(\text{channel } 4 + \text{channel } 3)} \]

The NDVI has been shown to be highly correlated with vegetation parameters such as green-leaf biomass and green-leaf area (Justice et al., 1985). Vegetated areas will generally yield high values because of their relatively high near-infrared reflectance and low visible reflectance. In the region 0.73 - 1.1 μm (near-infrared), the absorption by green leaves is quite low, whereas
both the reflectance and the transmittance are high. Therefore, near-infrared reflectance is not only an indicator of vegetation cover but also of the vegetation biomass (Sellers, 1985). In the region 0.58 - 0.68 μm, however, the absorption by green leaves is relatively high (80 - 90%) and the reflectance and transmittance are correspondingly lower. Green leaves therefore have a high NDVI, whereas dry and yellow leaves have a lower value (Vande Griend and Orre, 1993). In contrast, clouds, water, and snow have larger visible reflectance than near-infrared reflectance. Thus these features yield negative NDVI values. Rocks and bare soil areas have similar reflectances in the two bands and result in vegetation indices near zero (Lillesand and kiefer, 1994). Table 3.1 provides NDVI values for various vegetated and soil cover types.

In this dissertation, bands 3 and 4 are degraded to four resolution levels and smoothed to four scaling constants. The NDVI values are then derived from the resampled and smoothed image sets. The outputs of the calculation will be scaled to 0-255 gray level range for display purposes.

3.6 Gaussian Maximum-Likelihood Classifier

The maximum-likelihood classifier assumes that the classes have some well-defined statistical distribution, such as a Gaussian (normal). This allows the classifier to make use of the higher order statistics of the data in making class decisions. Under this assumption, the distribution of a category response pattern can be completely described by the mean vector and the covariance matrix (Swain and Davis, 1978). The classifier quantitatively evaluates both the variance and covariance of the category spectral response patterns when classifying an unknown pixel. Figure 3.6 shows the probability values. The resulting bell-shaped surfaces are called probability density functions, and there is one such function for each spectral category (Lillesand and kiefer, 1994).
Table 3.1  NDVI values for different soils and vegetation types as found in the literature  
(Source: Van de Griend and Orre, 1993)

<table>
<thead>
<tr>
<th>Description</th>
<th>Source</th>
<th>Reflectances</th>
<th>Mean NDVI</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a) Soils</td>
<td>Source</td>
<td>NIR</td>
<td>Red</td>
</tr>
<tr>
<td>1. Dry bare grey -brown soil</td>
<td>Lillesand &amp; Kiefer 1979</td>
<td>35-5</td>
<td>25-5</td>
</tr>
<tr>
<td>2. Princeton silt</td>
<td>Johansen &amp; Baumgardiner 1968</td>
<td>58</td>
<td>44</td>
</tr>
<tr>
<td>3. Pembroke clay</td>
<td>Johansen &amp; Baumgardiner 1968</td>
<td>40</td>
<td>23</td>
</tr>
<tr>
<td>4. Chelsea sand</td>
<td>Johansen &amp; Baumgardiner 1968</td>
<td>36</td>
<td>20</td>
</tr>
<tr>
<td>5. Dry soil</td>
<td>Tucker &amp; Miller 1977</td>
<td>23</td>
<td>15</td>
</tr>
<tr>
<td>6. Wet soil</td>
<td>Tucker &amp; Miller 1977</td>
<td>17</td>
<td>10-5</td>
</tr>
<tr>
<td>Mean NDVI (σ, =0-049)</td>
<td></td>
<td></td>
<td>0-208</td>
</tr>
<tr>
<td>(b) Vegetation</td>
<td>Source</td>
<td>NIR</td>
<td>Red</td>
</tr>
<tr>
<td>1. Average, typical</td>
<td>Lillesand &amp; Kiefer 1972</td>
<td>48</td>
<td>11-5</td>
</tr>
<tr>
<td>2. Orange leaf (young)</td>
<td>Myers 1983 (p. 2139)</td>
<td>53</td>
<td>8</td>
</tr>
<tr>
<td>3. Orange leaf (mature)</td>
<td>Myers 1983 (p. 2139)</td>
<td>43</td>
<td>10</td>
</tr>
<tr>
<td>4. Cotton leaf</td>
<td>Myers 1983 (p. 2140)</td>
<td>47</td>
<td>9</td>
</tr>
<tr>
<td>5. Cotton leaves (stack of 4)</td>
<td>Myers 1983 (p. 2140)</td>
<td>67</td>
<td>10</td>
</tr>
<tr>
<td>6. Tulip tree leaf (green)</td>
<td>Myers 1983 (p. 2141)</td>
<td>50</td>
<td>8</td>
</tr>
<tr>
<td>7. Prairie grass (senescent, 45° look-angle)</td>
<td>Fraser et al. 1987</td>
<td>54</td>
<td>8</td>
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Mean NDVI (σ, =0-054) 0-700
Figure 3.6  Probability density function defined by a maximum-likelihood classifier
(Source: Lillesand and Kiefer, 1994)

Figure 3.7  Equiprobability contours defined by a maximum-likelihood classifier
(Source: Lillesand and Kiefer, 1994)
The maximum-likelihood classifier delineates ellipsoidal “equiprobability contours” in the scatter diagram. These decision regions are shown in the Figure 3.7. The shape of the equiprobability contours expresses the sensitivity of the likelihood classifier to covariance. However, the maximum-likelihood classifier has mathematical limitations and assumes certain properties of the sample data (Snedecor and Sneath, 1967). The sample covariance matrix must be invertible (not singular). A singular covariance matrix may result if the sample is too homogeneous in any one band if the sample size is too small, or if there is a high degree of linear dependence between bands. The classifier also assumes that the distribution of the sample data is normal in all bands, a condition which is sometimes violated for certain classes such as urban, residential, and some types of vegetation (Kloer, 1994).

3.7 Classification of mixed pixels

3.7.1 Overview

Remote sensing satellites have sensors that acquire images in many narrow spectral bands from visible to infrared. In ground cover maps each pixel of the acquired image is assigned to only one of the possible ground cover categories. Because of the limited spatial resolution, often more than one ground cover category is present in a single pixel (mixed pixel) (Foody et al., 1992). Small strips of land or patches of floating vegetation in marshes and wetlands are frequently not detected by standard computer-assisted classification of digital imagery because such landscape features are smaller than the pixel size of the image and are mixed with other classes (water). Most classification techniques are based only on spectral properties for a single data type source. Supplemental information, such as soils or elevation attributes and spatial attributes such as size, shape, texture and pattern, are not usually considered in conventional per-pixel procedures for pattern recognition (Civco, 1993).
The proportion of mixed pixels generally increases with a coarsening of the spatial resolution of the sensing system (Townshend and Justice, 1981; Moody et al., 1996). Consequently, the effects of the mixed pixel problem may be felt most strongly when mapping land-cover from coarse spatial resolution data sets. The relatively large proportions of mixed pixels in TM data encompassing coastal areas or wetlands can lead to significant errors in the estimation of land cover categories and its changes over time (Curran and Foody, 1994). Irrespective of their origin, mixed pixels can be a problem in land-cover mapping applications. The following section will introduce a model for tackling this problem.

3.7.2 Models

A range of spectral mixture models has been developed for detecting proportions of mixed pixel. Of these, linear mixture models are the most widely used (Holben and Shimabukuro, 1993). In spectral mixture analysis, the fractions of the ground cover categories present in a pixel are determined. This allows the construction of a mixture map, a series of images showing for each ground cover category and its concentration over the area in the image (Settle and Drake, 1993). In spectral mixture analysis usually a linear mixture model is used (Horowitz et al., 1971). The signal received for a pixel in band \( i \) is assumed to be -

\[
S_i = \sum_{j=1}^{c} f_j R_{ij} + e_i, \; i = 1, 2, 3, \ldots n
\]

where, \( n \) is the total number of bands
- \( R_{ij} \) is the reflectance of the \( j \)th ground cover category in the \( i \)th band
- \( f_j \) is the fraction of the pixel covered by end-member \( j \)
- \( e_i \) is the error in the \( i \)th band
- \( c \) is the total number of ground cover categories in the pixel

The purpose of the spectral mixture analysis is to find the best approximation of the fraction of the pixel covered by a class knowing the values of input radiance received at the
pixel and reflectance of the particular ground cover in that band and the statistical properties of e
(Horowitz et al., 1971).

3.7.3 Neural network handling of mixed pixels

Schouten and Gebbinck (1994) describe a neural network approach to spectral mixture
analysis. Using data from three spectrometers with 6, 30 and 220 bands and 3 ground cover
categories, they show that a back-propagation neural network with one hidden layer is able to
learn the relation between the intensities of a pixel and the fractions of its ground cover
categories. The distribution of the difference between true and calculated fractions show that a
neural network performs the same or better than a conventional least squares with covariance
method and better than a simple least squares method.

The continuous range of output values in a neural network can be interpreted as a
measure of class mixing. McClellan et al. (1989) discovered in a simple land and water
classification that along the shoreline the outputs for land and water were nearly equal and in
between the high and low training values. The ANN clusters these areas into a separate mixed
class. This is an inherent fuzzy logic property in the neural network outputs. An ANN with one
output node per class encoding can provide additional information beyond that of a “hard”
classifier (Foody, 1996). Heermann and Khazenie (1992) and Paola (1994) exhibit the class
mixing concept in a table showing the ANN classifier results. Along with the classification
percentages for each of their trained classes, they showed the percentages for some two class
mixtures.

By outputting solely the code of the class associated with the unit in the output layer with
the highest activation level, information on the magnitude of the activation level of the output
units is wasted in the same way that maximum-likelihood is wasteful of information by
discarding the probability of class membership (Wang, 1990; Foody et al., 1992). The activation
level of an output unit, however, indicates the strength of membership of a pixel to the class associated with the output unit. Typically, the activation level of a unit lies on a scale from 0 to 1 that reflects the variation from extremely low to extremely high strength of membership to the class associated with the output unit. One of the goals of this dissertation is to determine if the magnitude of the output unit activation levels may be related to the land-cover composition of mixed pixels.

Moody et al. (1995) showed that neural net output vectors need not be interpreted categorically, but under some conditions can be used as fuzzy predictors of class membership (Birdie, 1990). The authors demonstrate that, where pixels are mixed, neural net outputs can detect such mixtures, a result that leads the way for automatic categorization of classes of mixed covers. The output's of a multi-layer perceptron trained using back-propagation tend to approximate class-specific \textit{a posteriori} probability of the outputs, if one output node is assigned to each class. It should be possible therefore, to treat those values as directly related to the mixture of proportions within the pixel as long as the probabilities and subpixel proportions are related. In their analysis, Moody et al. (1996) assume that a priori probabilities are equal and that \textit{a posteriori} probabilities are related to subpixel proportions. Their findings suggest that the outputs of the ANN can relay information on the subpixel composition of scene components in remotely sensed data, and that neural networks are useful for classifying land cover at coarse scales where pixels typically contain mixtures of different cover types.

The following chapter describes implementation of resampling by aggregation, Gaussian smoothing, and neural network algorithms.
Chapter 4

Implementation of Gaussian smoothing, resampling and neural network algorithms

The problem of scale is a fundamental source of difficulty in image processing and pattern recognition. Features in images are present at various scales (resolution levels). Depending on a particular visual task it is important to determine the scale of interest. The interpretation of an image depends on the scale at which it is measured. In practical situations, features in an image only exist over a restricted range of scale. If no a priori knowledge of the image being measured is available, the scale which we should choose is unknown. In this case no preferred scale is present and it makes sense to interpret the image at different scales simultaneously. One way to achieve this is to construct a one-parameter family of images which are derived from the highest resolution image. The parameter which is allowed to vary measures the degree of resolution or scale of the derived image. The parameter chosen must satisfy the following two conditions (Lindberg, 1994): (1) Causality- the process of increasing scale (decreasing resolution) should be a causal one. Any feature at a coarser resolution should have a cause at a lower level of scale. This means that no spurious detail should be generated when increasing scale / decreasing resolution; (2) Homogeneity and isotropy- the analysis must be independent of spatial coordinates, that is, there is no preferred direction in space. The Gaussian kernel is the unique kernel which satisfies these conditions. It allows to build upon unbiased multiscale image representation. Therefore, by using image analysis algorithms such as Gaussian filtering and resampling algorithm, we can describe how objects behave through scale space filtering and aggregation. In this dissertation, when the term scale is referenced with Gaussian smoothing it implies to the area of objects being measured (measurement scale). Interested readers can refer to Lam and Quattrochi (1992) for explanation of the term measurement scale. A thorough description of implementing the neural network is described at the end of this chapter.
4.1 Gaussian smoothing

One of the results from image processing theory is that, the computation of derivatives in a discrete domain should incorporate low-pass filtering. If we have an image \( f \), we can filter this with a point-spread function \( h \) to obtain an output image \( g \), which can be seen as an approximation to the original image \( f \):

\[
g = f \otimes h
\]

where, \( \otimes \) denotes convolution. If we differentiate \( g \) with respect to either \( x \) or \( y \) we obtain -

\[
g' = f \otimes h \quad \text{or} \quad g' = f \otimes h'
\]

where, \( g' \) is the derivative of the input image \( f \). The same result can be obtained by filtering the original image \( f \) with a derivative of the point-spread function of the low-pass filter \( h \) (Bernsen, 1991). This result can be extended in analyzing the structure of natural images.

Features in natural images occur at specific scales, and the convolution with a 2-d Gaussian kernel transforms the scale of the image. The Gaussian filtering concept is reviewed in the following section.

Algorithm description: The Gaussian smoothing operator is a 2-d convolution operator that is used to "blur" images and remove detail and noise. In this sense, it is similar to the mean filter, but it uses a different kernel that represents the shape of a Gaussian (bell-shaped) hump. The idea of Gaussian smoothing is to use this 2-d distribution as a "point-spread" function (probability density function distribution) and this is achieved by convolution. The Gaussian kernel has some special properties. In 2-d, an isotropic (circularly symmetric) Gaussian has the form (Gonzalez and Woods, 1992) -

\[
G(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right)
\]
This distribution is shown in Figure 4.1. The effect of Gaussian smoothing is to blur an image in a similar fashion to the mean filter. The degree of smoothing is determined by the standard deviation of the Gaussian. Sigma ($\sigma$) sets the scale at which information is preserved in the convolved image. Objects whose area is small compared with $\sigma$ will be removed, while objects of a larger area are retained. Also, the scale of the Gaussian determines the amount of noise reduction, the larger the Gaussian the larger the smoothing effect (blurring effect). The kernel is normalized (weights in the kernel sum to 1) which avoids increasing or decreasing the average grey-level when the mask is used for smoothing. Hence, the intensity of a constant image remains unchanged. As a smoothing mask, it removes small-scale texture and noise as effectively as possible for a given spatial extent in the image.

The Gaussian outputs a “weighted average” of each pixel's neighborhood, with the average weighted more towards the value of the central pixels. This is in contrast to the mean filters uniformly weighted average. Because of this a Gaussian provides gentler smoothing and preserves edges better than a similarly sized mean filter (Haralick and Shapiro, 1992). One of the principal justifications for using the Gaussian as a smoothing filter is due to its frequency response. Most convolution based smoothing filters act as low-pass frequency filters. This means that their effect is to remove low-spatial frequency components from an image. The frequency response of a convolution filter, i.e., its effect on different spatial frequencies, can be seen by taking the fourier transform of the filter. Figure 4.2 shows the frequency response of a 1-d mean filter with width 7 and also of a Gaussian filter with sigma = 3.0. Both filter attenuate high frequencies more than low frequencies, but the mean filter exhibits oscillations in its frequency response. The Gaussian on the other hand shows no oscillations. In fact, the shape of the frequency response curve is itself (half a) Gaussian. So by choosing an appropriately sized Gaussian filter, we can be fairly confident about what range of spatial frequencies are still present in the image after filtering, which is not the case of the mean filter.
Figure 4.1  2-d Gaussian distribution with mean (0,0) and sigma (1.0).
(Source: Hypermedia image processing reference, J. Wiley & Sons Ltd, 1994)
Figure 4.2 Frequency response of box (mean) and Gaussian filter (sigma=3.0)
(Source: Hypermedia image processing reference, J. Wiley & Sons Ltd, 1994)
The Gaussian smoothing filter therefore has the above mentioned optimal properties. It removes small-scale texture and noise as effectively as possible for a given spatial extent in the image. High spatial frequencies correspond to small-scale structure, low frequencies to large-scale structure. It is possible therefore to separate an image into its constituent spatial frequencies. Since small-scale texture contains a lot of grey-level variation at high spatial frequencies, the aim of the Gaussian smoothing is to remove high spatial frequencies without distorting lower spatial frequencies. As the Gaussian filter is itself smooth, it is good at separating high and low spatial frequencies without using information from a larger area of the image than necessary.

I will now illustrate the aforementioned properties of Gaussian smoothing to the land/water delineation problem. As land patterns have a high spatial frequency (i.e., fine texture) than water patterns (low spatial frequency i.e., coarse), the effect of Gaussian smoothing with increasing sigma will effectively filter out the fine patterns leaving only the broad and smooth patterns (water bodies). If the same procedure is used with a uniform mean filter, it is impossible to do it as effectively. Because the uniform mean filter has abrupt cut-off at its boundaries, sharp changes in output values are obtained when the filter passes over areas adjoining contrasting patterns (land/water). It is this sharp cut-off that the Gaussian filter avoids. Therefore, by increasing the value of sigma used in Gaussian smoothing, there is an increasing reduction in detail (fine textures) and the removal of all but the main shape in the final image (large water bodies). It is reasonable to think of sigma as setting the scale at which we preserve information in the convolved image. Structures on a scale small compared with sigma will be removed, whilst structures on a larger scale are retained. The location of most land and water bodies will be accurately represented in the small-scale output which will include a lot of detailed texture. Whilst the large-scale output will retain the main features (such as water bodies) but will have
only approximate positions for the edges. By increasing the value of sigma, small scale objects such as land bodies will be filtered out.

The Gaussian smoothing algorithm was implemented for convolving with discrete raster images in 2-d using the program written by this author. The program listing is included as Appendix-B. The template values for various $\sigma$ values and filter sizes were derived and the values tabulated in Table 4.1.

4.2 Resampling by aggregation

The spatial resolution of the Landsat TM data is changed by aggregating groups of $n$ adjacent pixels into a single data unit. The band value of all pixels in a moving window are averaged and the average value assigned to the new pixel. Resolution was varied through four aggregations, such that an equal number of aggregations fit into the center portion of the image and no artifacts result from omitting a few rows or columns. By spatially averaging data from the original band 3 and band 4 images of spatial resolution $R$, I derive spatially degraded NDVI images of resolution $R = x \times y$ by aggregating $x$ pixels in columns and $y$ pixels in rows. Also, bands 3, 4, and 5 were spatially degraded to create the various multispectral data sets. The values of $x$ and $y$ were chosen to be 3, 5, 7 and 9 (the values were chosen based on the software implementation). The resulting images have a spatial resolution degraded by a factor of $x$ and $y$. Therefore, the finest aggregation was $3 \times 3$ ($n = 9$ original pixels forming each aggregate, resulting in 90 m resolution); followed by $5 \times 5$ ($n = 25$, resolution = 150 m); $7 \times 7$ ($n = 49$, resolution = 210 m) and the coarsest resolution was $9 \times 9$ ($n = 81$, resolution = 270 m). See Appendix-C for the aggregation program listing.
Table 4.1  Gaussian smoothing filter normalized template values

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4.3 Implementation of neural network

The neural network algorithm employed for this dissertation was carried out using the Stuttgart Neural Network Simulator (SNNS). SNNS can be obtained via anonymous ftp from host ftp.informatik.uni-stuttgart.de in the subdirectory /pub/SNNS as the file SNNS4.1.tar.gz. Figure 4.3 shows fundamental components of the SNNS software shell.

Training a neural network involves setting several initial parameters. The first step is to determine the training data (Figure 4.4) and corresponding desired outputs for the training data. The selection of the training data is more important for accurate classification than the size of the training data. The training regions should be small (roughly 40*40 pixels) and as homogeneous as possible. Table 4.2 shows the mean and standard deviation for each class as defined by the training samples.

SNNS data files have a header component and a data component (Figure 4.5). The header defines how many patterns the file contains as well as the dimensionality of the input and target vectors. The files are saved as ASCII for input to the neural network. After the patterns are extracted, they must be transformed to match the input structure of the neural network. After reviewing the literature, it was decided that the input data should be scaled to values from 0.1 to 0.9 (see Appendix-D for pattern09 program listing). The number of outputs and the value of the desired outputs for each class are determined to be a simple one output per class with desired outputs of 0.1 for nodes not representing the class and 0.9 for the node that do represent the class. The training patterns are passed on to the training stage.

The overall network topology must then be defined. The topology of the network is determined experimentally and is fully user configurable. Five hidden nodes (their purpose is to reduce the error between the actual output and the desired output by repeated backpropagation from the output layer to the input layer) were finally chosen and the sigmoid activation function.
Figure 4.3  Fundamental components of the SNNS software shell
(Source: SNNSv4.1 users manual, 1996)
Figure 4.4  Training regions selected for training the neural network
Table 4.2 Descriptive statistics for training regions

<table>
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<td>2.34</td>
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</table>
SNNS pattern definition file V3.2
generated at Fri Nov 31 12:00:00 1996

| No. of patterns : 2 |
| No. of input units : 3 |
| No. of output units : 3 |
| No. of variable input dimensions : 2 |
| Maximum input dimensions: [ 512 512 ] |
| No. of variable output dimensions : 2 |
| Maximum output dimensions : [ 512 512 ] |

# Input pattern 1 : water1 (TRAINING)

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</tr>
<tr>
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# Output pattern 1 : water1

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# Output pattern 2 : land1

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</tr>
<tr>
<td>0.900000 0.900000 0.900000 0.900000 0.900000 0.900000 0.900000 0.900000</td>
</tr>
</tbody>
</table>

Figure 4.5  SNNS pattern definition format for training regions
was chosen for the single hidden layer and output layer nodes (Figure 4.6). Each multispectral pixel vector of the training sites is used as a training pattern. The input scheme is a 3*3 window of inputs in each band and this method introduces a measure of texture into the classification. The weight updating method - sequential, is chosen as the training algorithm. When the training process begins, all of the weights of the network are set to random values (random weights), because it is not possible to obtain a set of unequal weights containing the distributed knowledge of the network (Paola, 1994). If a set of equal weights is used for the initial configuration (Rumelhart et al., 1986) then the learning rate parameter must be set, generally by trial and error.

Adaptive learning rates are one way to avoid this trial and error process (Heermann and Khazenie, 1992). The adaptive strategy used here is to adjust the learning rate downward after some training interval if the overall training error has increased and upward if the overall error has decreased.

In this research, a three-layer back-propagation neural network with a sigmoid transfer function is used. The back-propagation procedure minimizes global error of the entire network if all neurons are potentially responsible for the classification errors generated. Error is propagated backward through the interconnections to the previous layer and connection weights are adjusted accordingly (Rumelhart et al., 1986). Back-propagation, like all gradient descent algorithms, is not guaranteed to find the global minimum error. During training, the network takes the steepest descent from the current position to one of lower error. If the network encounters a valley, or local minima, it can become stuck and the error will not decrease to the global minimum value (SNNSv4.1 Users Manual, 1996). One way to alleviate this problem is to add some fraction of the weight change calculated in the previous iteration to the weight update formula. The added push from this term can keep the network from becoming stuck in a local minimum during training. The momentum parameter $\alpha$, like the learning rate, is set at the beginning of the
Figure 4.6  Network topology defined for the neural network classifier. The weights shown at the bottom of each node are final and are determined through training and validating the network.
training and is determined experimentally. The final parameters chosen were - *learning rate* (0.3); *momentum term* (0.5); *flat spot elimination* (0.1) and *ignored error* (0.1).

The final parameter is the training convergence criterion. Only in simple cases, it is possible to train the network to zero training error. Most of the error convergence occurs early during training, and the rate of improvement falls off dramatically as learning progresses. Thus, the convergence criterion is an important factor in determining training time. Also, some criterion for terminating the training process must be established, such as the mean-square error falling below a specific threshold. When the criterion is met, the network training is complete and the network may be used as a feed-forward classifier. This threshold is another parameter that must be determined experimentally. It controls the degree of generalization versus specialization. If the network is trained too well on the training data, it might not function accurately on the rest of the image (Paola, 1994).

Since controlling the network performance is a tedious procedure requiring a lot of fine tuning of initial parameters, the entire task of setting and changing parameter values is implemented using a batch script (see Appendix-E for batch script listing). The "Batchman" component of SNNS is employed to write, compile and execute the batch script.

Once a set of weights has been obtained that yields a satisfactory mean square error, the network is ready to run the classification routines. These routines feed the entire image into the network, using the same feature extraction and scaling as for the training patterns. Probability density maps are produced in which the continuous value of a single output node is scaled to the range 0-255. See Appendix-F for pattern255 program listing.

In recent years a number of approaches to neural network representation and implementations have been developed, which are more or less related to standard back-propagation theory. Notably, the theories of Adaptive Resonance Theory (ART), Self-Organizing
Maps (SOM), and Kohonen networks. Despite their qualitative differences, the increasing popularity of each of these approaches indicates that the crucial notion of computing and classification by artificial neurons is increasingly being appreciated by geographers and computer scientists.
Chapter 5

Data sources and methodology

5.1 Study site

A USGS 7.5 minute quadrangle of Decatur, Alabama is chosen as the study area (Figure 5.1). This quadrangle was chosen because of its diversity in land cover categories and the availability of a corresponding Landsat TM scene. Three bands of Landsat TM data (bands 3, 4, and 5) are used as the multispectral data set (Figure 5.2). The Thematic Mapper image was acquired on September 4, 1994. A False Color Composite (FCC of bands 4, 5, and 3) of the study area is shown in Figure 5.3. Ancillary spatial data include USGS 7.5 minute Digital Line Graphs (DLG) of Decatur and Trinity (Figure 5.4) acquired via anonymous ftp from host edcftp.cr.usgs.gov in the subdirectory /pub/data/DLG/LARGE_SCALE. The DLG data were compiled in 1992.

The study area lies to the southwest of Huntsville city (Alabama). The area is drained by the Tennessee River and its tributaries. The city of Decatur is located in the upper northwest region of the image. The study area is a complex mosaic of lakes, streams, hills, mountains, marshes, swamps, and urban areas. Numerous hills and mountains flank the main tributary of the Tennessee River in the lower right portion of the image. Marshes, Swamps, and land which is subjected to controlled inundation (woodlands) are extensively spread out in the lower right portion of the image. The large rectangular area at the upper left portion of the image is Wheeler Reservoir (Figure 5.2).

The area around Decatur county consists of soils of two soil associations, the Holston-Monongahela-Tyler-Tupelo association and Decatur-Waynesboro-Cumberland-Etowah association (Federal Insurance Study: Decatur County, 1988). The former occupies nearly level to undulating areas of old stream terraces and benches. Drainage ranges from very slow to
Figure 5.1 Study area location
Figure 5.2 Landsat TM bands 3, 4, 5, and NDVI images of study area (resolution = 30m)
Figure 5.3 False Color Composite (FCC) of bands 4, 5, and 3
Figure 5.4  USGS 7.5 minute Digital Line Graph (hydrography layer) of study area.
(a) Vector representation, (b) Raster representation
moderate. The Decatur county is located on the physiographic division known as the redlands and alluvial plains. Loblolly, shortleaf and Black Locust are the principal trees in Decatur county. Post, White, Red and Black Jack Oaks, Hickory, Poplar, Walnut, Cherry, Cedar and Pine trees can also be found in the area around Decatur city and its adjoining areas.

5.2 Methodology

Figure 5.5 schematically illustrates the research design adopted for this research. The 30 m resolution imagery of the study area (512*512 pixels) is used as baseline data and the images (bands 3, 4, and 5) are degraded to a series of resolution images produced through an aggregation procedure (Section 4.2). Resolutions considered are 30 m, 90 m, 150 m, 210 m and 270 m. Images are scale degraded using Gaussian smoothing in scale-space domain. Scaling constants used in Gaussian smoothing are 0.50, 1.0, 2.0 and 4.0 (Section 4.1). The resulting datasets will allow examination of changes in land/water proportions as a function of scale and resolution. The goal of degrading the images is to provide data sets of registered images over a range of spatial resolutions and scales. These data sets would be identical in terms of spectral sensitivity, radiometric sensitivity and noise, viewing geometry and all other properties with the exception of spatial resolution and sampling. The following section describes in detail the methodology employed.

1. In this dissertation, bands 3, 4, and 5 of Landsat TM are used as a multi-spectral combination for input into a maximum-likelihood classifier (Figure 5.6) and neural network classifier (Figure 5.7). Bands 3 and 4 are used to derive the normalized difference vegetation index (NDVI) data.

2. Data for training and testing the ANN and maximum-likelihood classifier are acquired through interactive pixel sampling of the Landsat TM data. In total, approximately 1800 pixels (900 pixels in training samples for water class and 900 pixels in training samples for
Data
Landsat Thematic Mapper imagery (bands 3, 4, and 5)

Methods for synthesizing scale-resolution effects
- Gaussian smoothing (Four scaling constants)
- Resampling by aggregation (Four resolution levels)
- Local variance analysis (Four mask sizes)

land/water classification methods
- NDVI
- Neural network
- Maximum Likelihood

Derive land/water boundaries
(from resampled, Gaussian smoothed, Local variance multispectral images)

Test scale-resolution effects on thematic images using reference data
(Three methods, four scaling constants, four resolution levels)

Visualization and analysis of land/water regions
- Percent overall accuracy
- Fractal analysis
- Lacunarity analysis

Figure 5.5 Schematic illustration of research design
Data
Landsat TM imagery
(bands 3, 4, and 5)

Subset 512 x 512 samples

Synthesize scale-resolution effects

Extract homogeneous training regions
using region growing method
Selecting 900 pixels for each class

Evaluate signature sets
(Class statistics calculation of variance and covariance)

Implement Maximum-likelihood classifier
(Select class with highest discriminant)

Calculate classification accuracy
(using DLG’s and Error matrix)

Figure 5.6 Flow chart for maximum-likelihood method for delineating land/water regions

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Data
Landsat TM imagery (bands 3, 4 and 5)

Subset 512 * 512 samples

Synthesize scale-resolution effects

Extract homogeneous training regions for neural network
Four regions (30*30 pixels) for training network
Two regions (30*30 pixels) for validating network

Train neural network (back-propagation)

Test neural network (back-propagation)

Implement neural network classifier for classifying various datasets

Select class with highest output

Produce probability density maps

Calculate classification accuracy using (DLG's and Error matrix)

Figure 5.7 Flow chart for neural network classifier for delineating land/water regions
land class) are selected to represent the two training land cover categories. The two classifiers are independently trained to recognize the two land cover classes in the data sets. After the network is trained with the SNNS software shell, each multispectral dataset of varying resolution and scale constants are presented to the network. The knowledge acquired in the training stage is recalled to calculate the weights for the output categories for each pixel.

3. When data sets are processed, each of the neurons in the output layer will receive a calculated weight. It is assumed in this dissertation that the outputs represent one class each and are trained to have "high" values for their given class. Based on a simple decision rule, the category corresponding to the processing element which receives the greatest weight during the network classification process is assigned as the pixel's land cover category. If the neural network output is in the range 0.5 - 0.55 it is considered to be representative of a mixed pixel and is classified as a transition area between land/water. The range 0.5-0.55 is chosen as it lies in between the possible minimum (0.1) and maximum (0.9) values in the neural network output.

4. In order to compare the three classifiers, sets of training and verification pixels are extracted from the Landsat TM imagery using ground information obtained from 1:24000 USGS Digital Line Graphs. The classified images and the corresponding ground truth are compared pixel-by-pixel. Omission-commission matrix and classification accuracies are derived.

As with any classification accuracy assessment study, a conservative biased estimate of accuracy is assumed in this research. It is assumed that the ancillary data (DLGs) is of higher accuracy than the actual classification images generated. This argument is supported by the following facts: (1) the DLGs have a very high locational accuracy (90% of the points surveyed have a horizontal positional accuracy less than 0.02 inches from their actual location), (2) the DLGs are the least expensive and accurate ground truth information.
compared to other Federal Geographic data set sources, and (3) acquisition of a Digital Orthophoto Quadrangle (DOQ) for the study area at the same season and time frame as the Landsat TM image is very difficult and cumbersome. Therefore, even though there is a time gap of two years in acquisition of the Landsat TM data and ancillary data, the high accuracy of DLGs subdues any temporal differences (conservative bias).

5. Regression analysis is applied at each aggregation and scale level for the classified images to quantify the relationship between water area and water perimeter. The rationale behind this approach is to choose variables that could be both spatially and ecologically related to determine the fractal dimension (De Cola, 1989). The fractal dimension was calculated for water perimeter regions as an indicator of spatial dependence. The basic procedure is to plot log(area) versus log(perimeter). The slope value from the regression is used to indicate the quantitative relationship. The fractal dimension is then calculated as \( D = 2 \times \text{slope of regression} \). Figure 5.8 shows the fractal analysis for water regions delineated from the classification methods.

6. The relationship between landscape texture and coastline features may be obscured when landscapes are frequently disturbed. When disturbances affect landscape texture (i.e., creation of large gaps by storms, flooding and distribution of mass), then pattern of land/water interface will be altered in a manner that reflects texture changes. These natural disturbances increase lacunarity by the removal of segments. The process of measuring this change in land/water interface should be related to the change in landscape texture.

7. Lacunarity analysis is applied to the data sets (from a base scale of 30 m*30 m to systematic increments to simulate coarser data) to identify the effective range of spatial scales within which the variables are spatially dependent and the degree of spatial dependence within these ranges. Calculating the lacunarity index across a series of window sizes and plotting the
Figure 5.8  Flow chart for fractal analysis of water regions from classification methods
logarithm of the index against the logarithm of the window size, the resulting lacunarity function should illustrate how changes in cover type proportions (land/water) are related to aggregation of spatial data.

8. Image texture is described by local variance in brightness values in a 3*3 pixel neighborhood. Local variance is calculated for the images at each resolution and scale range. Mean local variance of the study area is plotted against resolution window size and scaling constant.

9. Finally, qualitative analysis, descriptive statistics, classification accuracies, fractal dimension and lacunarity analysis are evaluated at each aggregation level and compared across scales using different classification methods.

5.3 Data sets

Two land cover categories are defined for neural network, maximum-likelihood and NDVI classification methods. These are "water" (include rivers, lakes, reservoirs, and ponds), and "land" (include agricultural land, natural vegetation, forest land and urban and built-up land) (Anderson et al., 1972). Once training regions are determined, the remotely sensed image data and training region information are input to the Normalized Difference Vegetation Index, maximum-likelihood classifier, and the neural network. The classifications are performed on the multispectral (bands 3, 4, and 5) image data for each combination given by four scaling constants and four spatial aggregation levels.

Reference data (Metadata for USGS 1:24,000 scale Digital Line Graphs)

Digital line graphs (DLG's) are digital representations of cartographic information. DLG's depict information about geographic features on or near the surface of the earth, including terrain, political, and administrative units. DLG map features were converted to digital form from
USGS maps of 1:20,000, 1:24,000, and 1:25,000-scale 7.5 minute topographic maps. Each element in the digital file is represented as a node, an area, or a line. All DLG data distributed by the USGS are DLG-level 3 (DLG-3), which means the data contain a full range of attribute codes, have full topological structuring, and have passed certain quality control checks. Each map can have as many as eleven layers, as shown in Figure 5.9. Four layers related to this research are briefly discussed below:

- **Hydrography category** consists of all flowing water, standing water, and wetlands.
- **Boundaries** consist of political boundaries that identify states, counties, cities and other municipalities, and administrative boundaries that identify areas such as national and state forests.
- **Vegetative surface cover** consists of information about vegetation such as woods, scrub, orchards, and vineyards.
- **Non-vegetative surface cover** consists of information about the natural surface of the earth as symbolized on the map such as lava, sand, and gravel features.

Spatial reference information for the study area’s DLG’s includes:

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<tr>
<td>False Northing</td>
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</tbody>
</table>

5.4 **Analysis tools**

Intergraph Microstation Base Imager (MBI) software is used for preparing multispectral spatial data and selecting the training and testing sites for the neural network development.

Stuttgart Neural Network Simulator (SNNS) software, a simulator for neural networks developed
Figure 5.9 Digital Line Graph layers (Source: USGS, 1996)
at the Institute for Parallel and Distributed High Performance Systems at the University of Stuttgart since 1989, is used for building the neural network (Section 4.3).

Erdas Imagine classification software is used to perform maximum-likelihood and classification accuracy assessment. Accuracy assessment is carried out for all thematic images using the three classification methods. Classification accuracy assessment is performed using error matrices. Two measures for calculating accuracy are derived - percent overall classification accuracy and kappa coefficient.

The following chapter provides results and discussion for land/water delineation using the Normalized Difference Vegetation Index technique.
Chapter 6

Results - I: NDVI analysis

To demonstrate the capabilities of various classification methods for delineating land/water boundaries, a number of datasets and techniques were examined. This chapter discusses the results from the NDVI analysis.

As discussed in the previous chapter, the original Landsat TM imagery (bands 3, 4, and 5) was analyzed by applying resampling, Gaussian smoothing and local variance scaling algorithms. Bands 3, 4, and 5 were individually aggregated to coarser scales using the resampling technique to form multispectral data sets at each aggregation level. Similarly, Gaussian smoothing was applied to bands 3, 4, and 5 individually to form multispectral data sets at each value of sigma. Local variance analysis was then applied to bands 3, 4, and 5 individually at each mask size to form multispectral data sets at the specified mask size. The relationship between the three sets of descriptive statistics were evaluated at each aggregation level to examine the effects of scale and resolution.

Then, the technique of NDVI (see Section 3.5) was applied to the original as well as aggregated data sets. Land/water region delineation was then performed on the datasets and the results were evaluated using qualitative analysis, descriptive statistics, classification accuracies, fractal dimension and lacunarity analysis.

6.1 Analysis of original, aggregated and Gaussian smoothed imagery

Figure 6.1 shows images of bands 3, 4, and 5 applied in this dissertation. Figure 6.2 shows their respective histogram distributions. Figure 6.3 shows the result of resampling individual channel data to form multispectral images of the study area using aggregation. Figure 6.4 shows the histogram distributions for the multispectral resampled images. Figure 6.5 shows
Figure 6.1 Landsat TM bands 3, 4, and 5 of study area
Figure 6.2  Histogram distributions for bands 3, 4, and 5
False color composite of bands 4, 5, and 3 (resolution = 30m)

Figure 6.3 Result of resampling by aggregation for bands 3, 4, and 5
(Images are not shown at the same scale)
Grey level values

(Resolution = 90m, Band 3)

Grey level values

(Resolution = 90m, Band 4)

Grey level values

(Resolution = 90m, Band 5)

Grey level values

(Resolution = 150m, Band 3)

Grey level values

(Resolution = 150m, Band 4)

Grey level values

(Resolution = 150m, Band 5)

Grey level values

(Resolution = 210m, Band 3)

Grey level values

(Resolution = 210m, Band 4)

Grey level values

(Resolution = 210m, Band 5)

Grey level values

(Resolution = 270m, Band 3)

Grey level values

(Resolution = 270m, Band 4)

Grey level values

(Resolution = 270m, Band 5)

Figure 6.4  Histogram distributions for multispectral resampled images

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FCC of Bands 4, 5, and 3 (Sigma = 0.5)  
(Sigma = 1.0)  
(Sigma = 2.0)  
(Sigma = 4.0)

Figure 6.5  Result of Gaussian smoothing on bands 3, 4, and 5
the result of Gaussian smoothing on bands 3, 4, and 5 to form multispectral images at each scaling constant. Figure 6.6 shows their histogram distributions.

6.1.1 Visual analysis

Qualitative comparison of the images presented in Figure 6.1 shows major parts of the river in dark tone across band 4 (near-infrared) and band 5 (middle-infrared). But in band 3 (visible red), branches of the river visible in the center portion of the image appear in bright tone as turbid water has a high reflectance in this portion of the spectrum. Cultivated land in the lower right portion of the image appear in bright tone in bands 4 and 5. The same areas have a dark appearance in the visible band images. Bare soil and developed areas visible in the left portion of the image appear nearly white in tone due to high reflectance in the three bands.

Qualitative comparison of the images presented in Figure 6.3 shows the similarity in appearance at the 30 m, 90 m, 150 m, 210 m and 270 m resolutions. At 90 m, the majority of the river and other water bodies is still apparent, but at coarser resolutions they lose their definitions and are represented by darker values because surrounding vegetated areas possess higher values than water bodies. At 210 m, the individual pixels become apparent and the boundaries of water bodies take on a stepped appearance.

Figure 6.5 shows the result of Gaussian smoothing on individual bands to create multispectral smoothed imagery at each scaling constant. We can see a gradual blurring of detail associated with higher scaling constants. This is a natural consequence of a very important property of differential filters - regularization of the convolution process. The location and position of most land and water areas are accurately represented in the output from a scaling constant 0.5. A lot of detailed texture is included at this scaling constant. Small objects such as urban areas (visible in the upper left portion of the image) are clearly preserved at sigma = 0.5. At higher scaling constants (sigma = 1.0 and sigma = 2.0) small-scale texture objects that contain
Figure 6.6  Histogram distributions for multispectral Gaussian smoothed images

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a lot of gray level variation at high spatial frequencies are blurred out without distorting lower spatial frequencies (meandering river). This effect is clearly visible at sigma = 4.0. There is an increasing reduction in detail (fine textures) and the removal of all but the main shape (river) is present at scaling constant 4.0. At this large scaling constant, the effect of Gaussian smoothing is such that fine patterns are left out and only broad and smooth patterns such as water areas are preserved. Therefore, depending on the particular patterns we are interested in an image, it is important to determine the optimal scaling constant used to preserve these patterns and blur out extraneous features.

Figure 6.7 shows the output of local variance analysis of mask sizes 3*3, 5*5, 7*7 and 9*9 on individual band 3, 4, and 5 data to create multispectral images at the specified mask sizes (though primarily the output of local variance analysis is a statistical measure, the resulting images were also analyzed). A visual comparison details the inherent internal spatial structure associated between water bodies and surrounding objects. The contrast between land/water bodies stands out due to variations in spatial structure.

6.1.2 Descriptive statistics

Table 6.1 shows summary statistics for various data sets. The standard deviation for the entire multispectral images at each of the four spatial resolutions is shown in Figure 6.8. A monotonic decrease can be seen in the standard deviation values with coarsening resolution which is associated with an increase in the number of pure water pixels. The averaging effect of lower spatial resolution decreases the variance of the data. This decrease in variance gives an indication of a reduction in information content with decreasing resolution.

The images were degraded through aggregation and Gaussian smoothing. At each resolution level, local variance is measured as the mean value of the standard deviation of a moving n*n window. See Appendix-G for local variance analysis program listing. In an image.
Figure 6.7  Result of local variance on bands 3, 4, and 5 (resolution = 30 m)
Table 6.1 Summary of descriptive statistics for various image sets

<table>
<thead>
<tr>
<th>IMAGE</th>
<th>SPATIAL RESOLUTION</th>
<th>30m</th>
<th>90m</th>
<th>150m</th>
<th>210m</th>
<th>270m</th>
</tr>
</thead>
<tbody>
<tr>
<td>Band 3 (Mean)</td>
<td>39.81</td>
<td>39.84</td>
<td>39.84</td>
<td>39.83</td>
<td>39.92</td>
<td></td>
</tr>
<tr>
<td>Band 3 (Std. Dev)</td>
<td>10.81</td>
<td>10.04</td>
<td>9.42</td>
<td>8.91</td>
<td>8.57</td>
<td></td>
</tr>
<tr>
<td>Band 4 (Mean)</td>
<td>39.60</td>
<td>39.56</td>
<td>39.56</td>
<td>39.58</td>
<td>38.43</td>
<td></td>
</tr>
<tr>
<td>Band 4 (Std. Dev)</td>
<td>17.74</td>
<td>17.10</td>
<td>16.55</td>
<td>16.13</td>
<td>15.82</td>
<td></td>
</tr>
<tr>
<td>Band 5 (Mean)</td>
<td>59.27</td>
<td>59.16</td>
<td>59.17</td>
<td>59.22</td>
<td>58.85</td>
<td></td>
</tr>
<tr>
<td>Band 5 (Std. Dev)</td>
<td>37.08</td>
<td>35.93</td>
<td>34.85</td>
<td>34.00</td>
<td>33.41</td>
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<table>
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<th>0.00</th>
<th>0.50</th>
<th>1.00</th>
<th>2.00</th>
<th>4.00</th>
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<tr>
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<td>22.17</td>
<td>16.60</td>
<td>1.50</td>
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<tr>
<td>Band 3 (Std. Dev)</td>
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<td>8.38</td>
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<td>Band 4 (Mean)</td>
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<tr>
<td>Band 4 (Std. Dev)</td>
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<td>17.61</td>
<td>13.43</td>
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<td>7.88</td>
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<td>Band 5 (Mean)</td>
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<td>56.49</td>
<td>42.52</td>
<td>32.43</td>
<td>12.26</td>
</tr>
<tr>
<td>Band 5 (Std. Dev)</td>
<td>37.08</td>
<td>37.01</td>
<td>31.09</td>
<td>23.63</td>
<td>14.26</td>
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<table>
<thead>
<tr>
<th>LOCAL VARIANCE</th>
<th>3*3</th>
<th>5*5</th>
<th>7*7</th>
<th>9*9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Band 3 (Mean)</td>
<td>5.26</td>
<td>6.72</td>
<td>7.70</td>
<td>8.45</td>
</tr>
<tr>
<td>Band 3 (Std. Dev)</td>
<td>4.15</td>
<td>4.99</td>
<td>5.94</td>
<td>6.71</td>
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<tr>
<td>Band 4 (Mean)</td>
<td>7.74</td>
<td>10.27</td>
<td>12.19</td>
<td>13.70</td>
</tr>
<tr>
<td>Band 4 (Std. Dev)</td>
<td>6.70</td>
<td>8.58</td>
<td>10.33</td>
<td>11.61</td>
</tr>
<tr>
<td>Band 5 (Mean)</td>
<td>5.16</td>
<td>6.41</td>
<td>7.20</td>
<td>7.78</td>
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<tr>
<td>Band 5 (Std. Dev)</td>
<td>3.64</td>
<td>4.24</td>
<td>4.97</td>
<td>5.56</td>
</tr>
</tbody>
</table>

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Figure 6.8  Plot of standard deviation versus spatial resolution for bands 3, 4, and 5
each pixel can be considered as the center of a \( n \times n \) window. The standard deviation of the \( n \times n \) values is computed, and the mean of these values over the entire image is taken as an indication of the local variability in the image.

Graphs of local variance in images as a function of spatial resolution is used to measure spatial structure in band 4 images (multispectral combination was not chosen, as the local variance algorithm adopted here is mono-dimensional). Figure 6.9a shows results of local variance analysis (5*5 mask) on resampled imagery. At 90 m, spatial resolution is finer than objects in the scene and most of the measurements in the image are correlated with their neighbors and the measure of local variance is low. At 150 m, the objects in the scene approximate the size of the resolution pixels and the likelihood of neighbors being similar decreases and local variance rises. At 210 m and 270 m, the resolution pixel size increases and many objects are found in a single pixel and local variance decreases. Therefore, we can infer that at 150 m spatial resolution the characteristic scale of the image is revealed and this is the optimal scale to sample the images.

Plots of the graph between local variance and Gaussian smoothing (Figure 6.9b) shows the same trend as in Figure 6.9a. Local variance rises at scaling constant 1.0 and drops off considerably at higher scaling constants. The effects of Gaussian smoothing are clearly visible with increasing scaling constant, most fine texture features are blurred out leaving only large scale patterns with low spatial frequencies. This causes variance to decrease at larger scaling constants.

6.2 Analysis of regions segmented using normalized difference vegetation index (NDVI) technique

6.2.1 Qualitative analysis

Figure 6.10 shows NDVI created from bands 3 and 4 by resampling. The two bands were resampled to four different resolutions from 30 m to 270 m. NDVI was then calculated for each
Figure 6.9 Plots of mask size versus local variance for resampled and Gaussian smoothed images

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Figure 6.10 Result of creating NDVI images from resampled band 3 and band 4 images (Images are not shown at the same scale)
resolution and the images in Figure 6.10 created. Figure 6.11 shows histogram distributions for the images in Figure 6.10. A simple method of thresholding was used to segment out land and water regions by interactively selecting a suitable threshold (-0.098) for each image. The NDVI value of -0.098 (scaled value of 90) was chosen as it lies in between the bi-modal histogram distributions for both the resampled and Gaussian smoothed NDVI images. Figure 6.12 shows classified land/water regions from thresholding method. A qualitative evaluation of the images reveals that at 30 m, most of the water bodies and land features are accurately delineated (comparing with Figure 5.4). At 90 m most of the river is accurately delineated, but at higher resolutions there is a marked decrease in area of water bodies and at 270 m, only parts of the river are visible.

Figure 6.13 shows NDVI created from bands 3 and 4 by Gaussian smoothing. The two bands were Gaussian smoothed at four different scaling constants from 0.5 to 4.0. NDVI was then calculated for each scaling constant and the images in Figure 6.13 created. Figure 6.14 shows histogram distributions for the images in Figure 6.13. The method of interactive thresholding was used to classify land and water regions by selecting a suitable threshold (-0.098) for each image. Figure 6.15 shows classified land/water regions. At scaling constants 0.5, 1.0, and 2.0 most water bodies are delineated, but at $\sigma = 4.0$, there is a major blurring effect, which averages out land features over the entire image. Structures on a scale small compared with $\sigma$ are removed, while structures on a large scale are retained. As water tends to have low mean values, it is the only feature which is preserved at this scale. Thus, there is more water delineated than land at this scaling constant than at others.

6.2.2 Descriptive statistics

Figure 6.16 shows plots of spatial resolution and scaling constants versus image mean from NDVI imagery created from aggregation and Gaussian smoothing. A slight increase can be
Figure 6.11    Histogram distributions for multispectral resampled NDVI images
Figure 6.12 Result of land/water region delineation from resampled NDVI images (Images are not shown at the same scale)
Figure 6.13  Result of creating NDVI from Gaussian smoothed band 3 and band 4 images
Figure 6.14  Histogram distributions for multispectral Gaussian smoothed NDVI images
Figure 6.15  Result of land/water region delineation from Gaussian smoothed NDVI images
Figure 6.16 Plots of spatial resolution and scaling constant versus image mean from NDVI images.
seen in mean values with coarsening resolution and smoothing, which is associated with a decrease in number of pure water pixels with low NDVI values.

Figure 6.17 shows the NDVI images masked at different mask sizes 3*3, 5*5, 7*7 and 9*9 on NDVI (resolution = 30 m). Figure 6.18 shows histogram distributions associated with the images in Figure 6.16. A visual evaluation of Figure 6.17 details the distinct land/water interface boundaries associated with marked variations in variance between the objects. The boundary between water bodies and surrounding areas is distinct at 5*5 mask size and at higher mask sizes, the boundaries appear larger and distinct.

Figure 6.19 shows a plot of local variance (5*5 mask) versus resolution and scaling constants. At 90 m, the spatial resolution is finer than the objects in the scene and measurements in the image are correlated with their neighbors and the measure of local variance is low. But, with coarser resolutions, local variance rises. This can be interpreted as - at lower resolutions most of the objects approximate the size of resolution pixels and the likelihood of neighbors being similar decreases and local variance rises. The lower spatial resolutions delineate a mixture of ground features extending outside the land and water patterns. Interclass variance increases at all lower resolution levels with a large proportion of the total image variance taken up by partitioning the data into different land cover categories, and local variance rises. Therefore, we can infer that the local variance analysis of NDVI images created using the mentioned procedures is primarily related to the relationship between number of land cover categories and size of objects composing the NDVI scene.

6.2.3 Classification accuracy assessment

Classification accuracy assessment is based upon statistical analysis of the classified images and ground truth data using the error matrix technique (Congalton, 1991) and computation of the Kappa coefficient (Lillesand and Kiefer, 1994). The error matrix is the
Figure 6.17  Result of local variance on 30m resolution NDVI image
Figure 6.18  Histogram distributions from local variance on 30 m resolution NDVI images

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Figure 6.19  Plots of local variance for NDVI images versus spatial resolution and Gaussian smoothing methods

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generally accepted method for tabulating results of classification. The error matrix not only reports the errors for each land use category, but visually portrays the pattern of misclassification around each category (Luman, 1992).

The assessment of classification accuracy was performed using test pixels from the reference image (rasterized digital line graphs). The classified images were registered to the same coordinate system (UTM) as the DLGs. Using Erdas Imagine software, error matrices were constructed for each of the classified images (from different classification methods) and the reference data (DLG's). Two methods of assessing the overall accuracy of the final classification were used – Overall percentage correct (calculated from only the diagonal entries in the error matrix) and the Kappa coefficient (calculated from all entries in the error matrix). The Kappa coefficient usually ranges between 0 and 1, with values closer to 1 indicating an ideal classification and values closer to 0 indicating poor classification performance (Luman, 1992). Error matrices were produced by a comparison of the test pixels (from DLGs) with the classified pixels at the corresponding position in the image (for each pixel) for each classification performed (Table 6.2 and Table 6.3). The reference data were aggregated and Gaussian smoothed to the same resolution and smoothing levels as the original band 3 and band 4 data, so that classification accuracies could be evaluated for resampled and Gaussian smoothed classified images. The accuracy measures were then calculated from each of the error matrices generated.

The results of the accuracy assessment (Figures 6.20 and 6.21) for the NDVI technique indicate that the classification methodology produced an average overall percentage correct of 71% and a average Kappa coefficient of 0.35. From Figures 6.20 and 6.21, we can infer that classification accuracy and kappa coefficient decrease with a decrease in spatial resolution, but increase at 210 m, followed by a drop in accuracy at higher resolutions. The average classification accuracy (78%) and average Kappa coefficient (0.65) remain constant for Gaussian smoothed NDVI datasets for increasing scale constants before dropping off at $sigma = 4.0$. Thus,
Table 6.2  Results of classification accuracy assessment on classified NDVI images created through resampling

<table>
<thead>
<tr>
<th>NDVI (RESOLUTION = 30m)</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>W</td>
<td>L</td>
</tr>
<tr>
<td>W</td>
<td>37831</td>
<td>18811</td>
</tr>
<tr>
<td>L</td>
<td>17278</td>
<td>99930</td>
</tr>
<tr>
<td></td>
<td>55109</td>
<td>118741</td>
</tr>
<tr>
<td>Producers Accuracy for Water</td>
<td>68.64759</td>
<td></td>
</tr>
<tr>
<td>Producers Accuracy for Land</td>
<td>84.15796</td>
<td></td>
</tr>
<tr>
<td>Users Accuracy for Water</td>
<td>66.78966</td>
<td></td>
</tr>
<tr>
<td>Users Accuracy for Land</td>
<td>85.25869</td>
<td></td>
</tr>
<tr>
<td>Overall Accuracy</td>
<td>79.2413</td>
<td></td>
</tr>
<tr>
<td>Kappa Coefficient</td>
<td>0.524149</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>NDVI (RESOLUTION = 90m)</th>
<th>NDVI (RESOLUTION = 210m)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>W</td>
</tr>
<tr>
<td>W</td>
<td>1835</td>
</tr>
<tr>
<td>L</td>
<td>3295</td>
</tr>
<tr>
<td></td>
<td>5130</td>
</tr>
<tr>
<td>Producers Accuracy for Water</td>
<td>35.76998</td>
</tr>
<tr>
<td>Producers Accuracy for Land</td>
<td>73.4093</td>
</tr>
<tr>
<td>Users Accuracy for Water</td>
<td>38.61532</td>
</tr>
<tr>
<td>Users Accuracy for Land</td>
<td>70.96405</td>
</tr>
<tr>
<td>Overall Accuracy</td>
<td>61.41615</td>
</tr>
<tr>
<td>Kappa Coefficient</td>
<td>0.093629</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>NDVI (RESOLUTION = 150m)</th>
<th>NDVI (RESOLUTION = 270m)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>W</td>
</tr>
<tr>
<td>W</td>
<td>367</td>
</tr>
<tr>
<td>L</td>
<td>1059</td>
</tr>
<tr>
<td></td>
<td>1426</td>
</tr>
<tr>
<td>Producers Accuracy for Water</td>
<td>25.73633</td>
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<tr>
<td>Producers Accuracy for Land</td>
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<tr>
<td>Users Accuracy for Water</td>
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<td>Users Accuracy for Land</td>
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<td>Overall Accuracy</td>
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<td>Kappa Coefficient</td>
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W represents water areas
L represents land areas
Table 6.3 Results of classification accuracy assessment on classified NDVI images created through Gaussian smoothing

<table>
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<tr>
<th>NDVI (SIGMA = 0.5)</th>
<th>NDVI (SIGMA = 2.0)</th>
</tr>
</thead>
<tbody>
<tr>
<td>W</td>
<td>L</td>
</tr>
<tr>
<td>W</td>
<td>39568</td>
</tr>
<tr>
<td>L</td>
<td>8250</td>
</tr>
<tr>
<td>47818</td>
<td>125666</td>
</tr>
</tbody>
</table>

Producers Accuracy for Water = 82.74708  Producers Accuracy for Water = 83.93835
Producers Accuracy for Land = 86.51744  Producers Accuracy for Land = 86.28064
Users Accuracy for Water = 70.01823  Users Accuracy for Water = 69.19184
Users Accuracy for Land = 92.94709  Users Accuracy for Land = 93.60365
Overall Accuracy = 85.4782  Overall Accuracy = 85.6177
Kappa Coefficient = 0.655722  Kappa Coefficient = 0.657823

<table>
<thead>
<tr>
<th>NDVI (SIGMA = 1.0)</th>
<th>NDVI (SIGMA = 4.0)</th>
</tr>
</thead>
<tbody>
<tr>
<td>W</td>
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<td>W</td>
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</tr>
<tr>
<td>L</td>
<td>8250</td>
</tr>
<tr>
<td>47818</td>
<td>125666</td>
</tr>
</tbody>
</table>

Producers Accuracy for Water = 82.74708  Producers Accuracy for Water = 42.55125
Producers Accuracy for Land = 86.51744  Producers Accuracy for Land = 92.29035
Users Accuracy for Water = 70.01823  Users Accuracy for Water = 93.22256
Users Accuracy for Land = 92.94709  Users Accuracy for Land = 39.19537
Overall Accuracy = 85.4782  Overall Accuracy = 56.79429
Kappa Coefficient = 0.655722  Kappa Coefficient = 0.247888

W represents water areas
L represents land areas

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Figure 6.20  Plots of percentage overall accuracy assessment for classified NDVI images

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Figure 6.21 Plots of Kappa coefficient calculation for classified NDVI images
we can infer that NDVI derived from Gaussian smoothed bands 3 and 4 has lower misclassification results than NDVI derived from resampled bands 3 and 4 imagery.

The overall trend illustrated by the tests reveals the following interpretation. At 30 m, the pixel size is small compared to the ground features of interest and many spatial details are revealed by the image. Consequently, for the “water” class, adjacent pixels tend to exhibit similar spectral values that differ in various regions across the image, i.e., pixels have a tendency to cluster resulting from spatial aggregation. With the decrease of spatial resolution, spectral detail is gradually aggregated and the pixel values vary more randomly above and below the median resulting in clusters that are not grouped into any one category (misclassifications). The effect is more pronounced at higher resolutions, where the overall accuracy diminishes considerably.

6.2.4 Fractal analysis of classified imagery (water regions)

Fractal concepts were applied to water regions (to measure spatial dependence of homogeneous bodies) by measuring area (number of pixels in a region * area of each pixel) and perimeter (pixels that bound a region). Fractal phenomena for curves and shapes have the characteristic of revealing more detail at a larger scale; and at a given scale, larger features manifest significantly larger perimeters than do smaller ones (De Cola, 1989). Using this concept of comparing area and perimeter between inter-features, fractal dimension \( D \) is calculated for water bodies from all classified images as indicator of spatial dependence. The total areas of land regions and water regions were calculated for the study area using the area and perimeter program (listings in Appendix-H). Table 6.4 tabulates the results. Table 6.5 tabulates mean area and mean perimeter for NDVI images derived with resampled and Gaussian smoothed images. Figure 6.22 shows a plot of spatial resolution and scaling constant versus mean area. Mean area increases in an approximately linear fashion with increase in resolution and scaling constants.
Table 6.4  Results for total area-perimeter calculations on classified NDVI images

<table>
<thead>
<tr>
<th>METHOD</th>
<th>IMAGE</th>
<th>PIXEL SIZE (meters)</th>
<th># OF LAND PIXELS</th>
<th>TOTAL LAND AREA (sq.meters)</th>
<th># OF WATER PIXELS</th>
<th>TOTAL WATER AREA (sq.meters)</th>
<th>PERIMETER FOR WATER</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDVI</td>
<td>Original</td>
<td>30</td>
<td>186773</td>
<td>168095700</td>
<td>60727</td>
<td>54654300</td>
<td>14223</td>
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<td>NDVI derived by Resampling</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>90 m</td>
<td>90</td>
<td>14562</td>
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<td>117952200</td>
<td>6159</td>
<td>49887900</td>
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<td>150 m</td>
<td>150</td>
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<td></td>
<td>40162500</td>
<td>912</td>
<td>20520000</td>
<td>566</td>
</tr>
<tr>
<td>210 m</td>
<td>210</td>
<td>166</td>
<td></td>
<td>7320600</td>
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<td>441000</td>
<td>167</td>
</tr>
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<td>270 m</td>
<td>270</td>
<td>166</td>
<td></td>
<td>12101400</td>
<td>12</td>
<td>874800</td>
<td>166</td>
</tr>
<tr>
<td>NDVI derived by Gaussian smoothing</td>
<td></td>
<td></td>
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<td>167817600</td>
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<td>57950100</td>
<td>183081</td>
<td>164772900</td>
<td>27964</td>
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Figure 6.22  Plots of spatial resolution and sigma versus mean water area from classified NDVI images

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Table 6.5  Results for mean water area-perimeter calculations on classified NDVI images

<table>
<thead>
<tr>
<th>IMAGE</th>
<th>RESAMPLING BY AGGREGATION</th>
<th>GAUSSIAN SMOOTHING OF ORIGINAL 30 m IMAGE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>30 m</td>
<td>90 m</td>
</tr>
<tr>
<td>NDVI Mean Area (Sq.m)</td>
<td>119606.81</td>
<td>342375.97</td>
</tr>
<tr>
<td>NDVI Mean Perimeter (m)</td>
<td>1264.90</td>
<td>2560.66</td>
</tr>
<tr>
<td></td>
<td>0.00</td>
<td>0.50</td>
</tr>
<tr>
<td>NDVI Mean Area (Sq.m)</td>
<td>119606.81</td>
<td>140984.82</td>
</tr>
<tr>
<td>NDVI Mean Perimeter (m)</td>
<td>1264.90</td>
<td>1419.67</td>
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</tbody>
</table>

Linear regression was performed using log(area) as the independent variable and log(perimeter) as the dependent variable for the NDVI images derived from resampled and Gaussian smoothed images. Figure 6.23 shows the results of the regression for the resampled images and Figure 6.24 for the Gaussian smoothing. The average $R^2$=0.97 in both cases. Table 6.6 summarizes the fractal dimension for each image. Fractal dimension was calculated as $D = 2 \times$ slope of regression. The values of $D$ range widely. While $D$ is constrained to be in the range 1.00-2.00, actual values of $D$ span the interval 1.24-1.33.

Table 6.6  Calculated fractal dimension from area-perimeter relationships of classified NDVI images

<table>
<thead>
<tr>
<th>IMAGE</th>
<th>SPATIAL RESOLUTION</th>
<th>GAUSSIAN SMOOTHING</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fractal Dimension</td>
<td>30 m</td>
<td>90 m</td>
</tr>
<tr>
<td></td>
<td>1.246</td>
<td>1.329</td>
</tr>
<tr>
<td>Fractal Dimension</td>
<td>0.00</td>
<td>0.50</td>
</tr>
<tr>
<td></td>
<td>1.246</td>
<td>1.246</td>
</tr>
</tbody>
</table>

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Figure 6.23 Results of regression (area-perimeter) for classified NDVI images created through resampling.

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Figure 6.24  Results of regression (area-perimeter) for classified NDVI images created through Gaussian smoothing.
Figures 6.25 and 6.26 show plots of resolution and sigma against fractal dimension respectively. In the resolution plot, fractal dimension increases with coarsening resolution as image complexity increases. But, at 150 m, there is a sudden drop in $D$. In the scaling constant plot, fractal dimension gradually decreases. This is expected as Gaussian smoothing results in noise reduction and decrease in overall complexity associated with features. Thus, there is more water delineated at this resolution than at other resolutions. Figure 6.27 shows the fractal dimension (water polygons) for each classified resampled image and Figure 6.28 shows fractal dimension for each classified Gaussian smoothed image. In general, the results suggest that most complicated (high $D$) water regions are formed at resolution 210 m, and sigma 0.5. From this analysis, fractal dimension ($D$) calculated from area-perimeter relationships provides a method for extrapolating land-cover patterns such as delineation of water regions, from fine to coarse scale-resolutions.

### 6.2.5 Lacunarity analysis

Lacunarity (see Section 2.5.3) describes a property of fractals, which is used to describe the spatial distributions of patterns (water regions) across resolution and scale levels. Table 6.7 tabulates the lacunarity function for the relationship between box size, aggregation and sigma.

<table>
<thead>
<tr>
<th>IMAGE</th>
<th>LOG (BOX SIZE)</th>
<th>0.47712</th>
<th>0.69897</th>
<th>0.84510</th>
<th>0.95434</th>
<th>1.04139</th>
<th>1.11934</th>
<th>1.17609</th>
<th>1.23945</th>
<th>1.27875</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original</td>
<td></td>
<td>1.06453</td>
<td>1.06446</td>
<td>1.06438</td>
<td>1.06431</td>
<td>1.06420</td>
<td>1.06412</td>
<td>1.06405</td>
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</tr>
<tr>
<td>90 m resolution</td>
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<td>0.96685</td>
<td>0.96478</td>
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<td>0.96237</td>
<td>0.96142</td>
<td>0.96038</td>
<td>0.95966</td>
<td>0.95914</td>
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</tr>
<tr>
<td>150 m resolution</td>
<td></td>
<td>0.87309</td>
<td>0.86356</td>
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<td>0.84553</td>
<td>0.84117</td>
<td>0.83659</td>
<td>0.83149</td>
<td>0.82341</td>
<td>0.81671</td>
</tr>
<tr>
<td>210 m resolution</td>
<td></td>
<td>0.75435</td>
<td>0.74099</td>
<td>0.68025</td>
<td>0.66633</td>
<td>0.66323</td>
<td>0.66143</td>
<td>0.65868</td>
<td>0.64138</td>
<td>0.60304</td>
</tr>
<tr>
<td>270 m resolution</td>
<td></td>
<td>0.75389</td>
<td>0.75097</td>
<td>0.72049</td>
<td>0.65858</td>
<td>0.26316</td>
<td>0.06082</td>
<td>0.01452</td>
<td>0.00000</td>
<td>0.00000</td>
</tr>
<tr>
<td>Sigma = 0.5</td>
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<td>1.06472</td>
<td>1.06465</td>
<td>1.06457</td>
<td>1.06450</td>
<td>1.06442</td>
<td>1.06435</td>
<td>1.06423</td>
<td>1.06397</td>
<td>1.06303</td>
</tr>
<tr>
<td>Sigma = 1.0</td>
<td></td>
<td>1.06472</td>
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<td>1.06435</td>
<td>1.06423</td>
<td>1.06397</td>
<td>1.06303</td>
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<tr>
<td>Sigma = 2.0</td>
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<td>1.06371</td>
<td>1.06360</td>
<td>1.06352</td>
<td>1.06345</td>
<td>1.06337</td>
<td>1.06330</td>
<td>1.06243</td>
<td>1.06209</td>
</tr>
<tr>
<td>Sigma = 4.0</td>
<td></td>
<td>1.10356</td>
<td>1.10336</td>
<td>1.10312</td>
<td>1.10291</td>
<td>1.10271</td>
<td>1.10250</td>
<td>1.10230</td>
<td>1.10199</td>
<td>1.10103</td>
</tr>
</tbody>
</table>

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Figure 6.25  Plot of fractal dimension versus resolution level for classified NDVI images

Figure 6.26  Plot of fractal dimension versus scaling constant for classified NDVI images
Figure 6.27 Result of fractal analysis on classified NDVI images - original & aggregated images. Note: The water polygons were vectorized from classified raster images.
Figure 6.28 Result of fractal analysis on classified NDVI images - Original and Gaussian smoothed images
Figure 6.29 shows a plot of log(box size) vs log(lacunarity index) for the resampled and Gaussian smoothed classified images. See Appendix-I for lacunarity program listing. The shifts observed in the plot of spatial resolution can be understood in terms of changes of spatial structure in the scene. At 30 m, 90 m, 150 m, and 210 m the spatial arrangement of objects is such that there are sharp transitions between land/water boundaries. But at 270 m, the details become blurred due to increase in size of scene objects. This causes differences in spatial structure to decrease resulting in low lacunarity values and a swift decrease to the minimum value. Thus, we can infer that the 270 m image represents a spatially random image, whereas the 90 m, 150 m and 210 m images exhibit self-similarity across some range of scales and thus have a linear decay. For the arrangement of objects at finer spatial resolutions, the lacunarity decay is slow until the box size (9*9) exceeds the scale of the objects (at 270 m) and is rapid thereafter. From the Gaussian smoothing plot, we can infer that smoothing produces an averaging or blurring of patterns, resulting in a gradual decay pattern of the lacunarity function.

The results from applying the NDVI technique to delineate land/water regions indicate that the method has the ability to estimate the delineation from histogram analysis of individual NDVI datasets. A distinct grouping of water pixels and a sharp transition from water pixels to land pixels is obtainable by employing a thresholding approach. Furthermore, classification accuracy assessment provides an overall classification of 64% for resampled NDVI imagery and 78% for Gaussian smoothed imagery. The high overall accuracy assessment indicates that the adoption of the NDVI technique is a fast and accurate recognition of land and water areas. But, it should be pointed out that the adoption of a thresholding technique alone on NDVI data can result in ambiguity when classifying transitional areas between land and water pixels. Other classification methods such as neural networks and maximum-likelihood classifiers should be employed to improve accuracies in these areas.
Figure 6.29  Plots of lacunarity index against box size on classified NDVI images

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Chapter 7

Results - II: Neural network analysis

The neural network classifier training was run for 50,000 iterations. The mean square error versus number of cycles for training is shown in Figure 7.1. It can be seen that the mean square error decreases steadily with increasing number of cycles, but never reaches zero. After the network was trained, the network was validated with a different training set. Once the mean square error had reached a minimum value (lower than or equal to the training time mean square error), the network validation was stopped and the neural network was ready for testing the various multispectral images.

7.1 Qualitative analysis

7.1.1 Original and resampled multispectral imagery

Figure 7.2 is the output of the neural network for original and resampled multispectral imagery. Figure 7.3 is the histogram distribution. Figure 7.4 is the result obtained by applying a threshold value derived from the histogram distributions (see Appendix-J). This threshold roughly corresponds to the trained output values for land (0.6-0.75) and water (0.8) categories in the training set. The predominant spike visible in the histogram distributions (Figure 7.3) indicates that the network is able to learn to categorize dark relatively homogeneous textures such as water and produces higher values for the water regions. Thus, water appears with a brighter contrast to its surroundings in Figure 7.2 at 30 m resolution. At coarser resolutions, the network is still able to categorize homogeneous textures such as water, but produces lower values resulting in a dark tone for all water bodies. The transition between land/water categories in Figure 7.2 provides a coarse estimate of the shoreline.

A visual comparison of Figure 7.4 and DLGs (Figure 5.4) illustrates that areas of water correspond in both images. The white areas (land) in the DLGs correspond to areas of land in
Figure 7.1  Plot of number of cycles versus mean square error for training the neural network

<table>
<thead>
<tr>
<th>EPOCH</th>
<th>MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.02471</td>
</tr>
<tr>
<td>5000</td>
<td>0.0173</td>
</tr>
<tr>
<td>10000</td>
<td>0.01455</td>
</tr>
<tr>
<td>15000</td>
<td>0.0125</td>
</tr>
<tr>
<td>20000</td>
<td>0.01158</td>
</tr>
<tr>
<td>25000</td>
<td>0.011</td>
</tr>
<tr>
<td>30000</td>
<td>0.01052</td>
</tr>
<tr>
<td>35000</td>
<td>0.00989</td>
</tr>
<tr>
<td>40000</td>
<td>0.00982</td>
</tr>
<tr>
<td>45000</td>
<td>0.00975</td>
</tr>
<tr>
<td>50000</td>
<td>0.00982</td>
</tr>
</tbody>
</table>
Figure 7.2  Regions delineated by neural network from original and resampled multispectral imagery (Images are not shown at the same scale)
Figure 7.3  Histogram distributions for original and resampled multispectral images from ANN
Figure 7.4  Land/water region delineation by neural network from original and resampled multispectral imagery (images are not shown at the same scale)
Figure 7.4. The ANN is able to distinguish small areas of land in between the river at the center and upper left portion of the scene at 30 m resolution. But, at coarser resolutions, there is a progressive disappearance of these land features as a result of aggregation. Most water bodies are delineated across resolution levels. But at 150 m resolution (Figure 7.4) the river takes on a “blocky” appearance covering extensive areas of the image. The image seems to have a large number of misclassified pixels and a sizable area in the lower right portion of the scene is misclassified as water. At 150 m resolution, the signal produced by the network contains only predominantly large values (“water” class). This is in marked contrast with other resolution levels. Thus, the network was able to learn the patterns it was presented with, and was able to characterize the two land-cover types.

7.1.2 Gaussian smoothed multispectral imagery

Figure 7.5 is the output of the neural network for multispectral Gaussian smoothed imagery. Figure 7.6 shows the histogram distributions. Figure 7.7 is the result of applying a threshold derived from the histogram distributions (see Appendix-J). The purpose of thresholding the neural network output is solely for displaying the results from the two classes in a comparative manner. There are several interesting phenomena visible in Figure 7.5. It can be seen that at sigma 1.0 and 2.0, there are major errors in the overall classification. The “water” class is larger than it should be. There is a dominant “leakage” of “water” class to surrounding areas. This is due to the fact that the “water” class has a much higher output from the output node of the network that it dominates between the classes. The confusion between water features and wetlands present in the lower left portion of the scene can be observed.

The image with a sigma of 0.5 (Figure 7.5) illustrates the ability of a neural network classifier, unlike many statistical classifiers (such as maximum-likelihood) to resolve ambiguity present between mixed pixels. The transition zone between water features and their surroundings.
Figure 7.5  Regions delineated by neural network from Gaussian smoothed multispectral image
Figure 7.6  Histogram distributions for multispectral Gaussian smoothed images from ANN
Figure 7.7  Land/water region delineation for Gaussian smoothed multispectral images from neural network
produces a shadowing effect (darker gray tones). This is indicative of a land/water transition region. The ANN is able to characterize the area between the two cover types as mixed class (either land/water) resulting from the ambiguity of the signals. These pixels have an output value between 0.5 and 0.55. These pixels indicate the ability of the network to produce a fuzzy membership value to the boundary pixels (ambiguous boundary zones of land-cover areas). At a value of sigma 4.0, a sizable area in the image is classified as water. This is due to the large sigma applied. The filter blurs sufficient details smaller than the size of the kernel, at the expense of smoothing out large areas. Thus, from Figure 7.7 (derived from histogram analysis of actual neural network output, Figure 7.5), it is shown that a neural network can indeed be trained to distinguish land from water and resolve ambiguity between classes.

The network was able to accurately learn the different patterns and produce high output values for homogeneous regions (water bodies). Thus, water areas appear brighter (Figure 7.5). This indicates that the neural network has generalized from the training samples and described patterns from different data sets very well. The neural network's non-statistical approach seems to have aided in discriminating these different test sites.

7.1.3 Local variance analysis of multispectral imagery

Figure 7.8 shows the result of neural network classification on local variance images. Figure 7.9 shows the histogram distributions. Figure 7.10 is the result of applying a threshold derived from the histogram distributions (see Appendix-J). All of the images were produced using the same training regions employed to train the network. The network did not produce any meaningful output for 3*3 and 7*7 mask sizes. But, results were obtained for 5*5 and 9*9 local variance mask sizes. The “land” class does not have enough training samples and thus breaks down and becomes noise in the images. The rest of the classification is still fairly accurate (comparing with Figure 5.4). Overall, the images have a noisy appearance relative to the original
Figure 7.8  Regions delineated by neural network from local variance analysis on multispectral imagery.
Figure 7.9 Histogram distribution for local variance analysis on multispectral images from ANN

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Figure 7.10  Land/water region delineation by neural network from local variance analysis on multispectral imagery
multispectral image. Visual interpretation of Figure 7.8 reveals that the resulting images have "salt-pepper" (sporadic and random) noise. The application of a 3*3 median filter to the classifications removes isolated misclassified pixels but does not improve the result. Figure 7.8 also reveals the inherent spatial structure as reflected by differences in texture between the two cover types. The boundary between the river and surrounding areas appears as a shadow (possibly indicating mixed pixels).

7.2 Classification accuracy assessment

The assessment of classification accuracy was performed using test pixels from the reference image (DLG's) and neural network classified images, at different aggregation levels and sigma values. Error matrices were created for each dataset and the overall accuracy and kappa coefficients were calculated (Tables 7.1, 7.2, 7.3). Table 7.4 summarizes the accuracy assessment results. The results of the overall accuracy assessment (Figure 7.11 and Figure 7.12) indicate that classification methodology produced an average overall percentage correct of 59% and an average Kappa coefficient of 0.2 for multispectral original and resampled imagery. Two major trends are visible from the plots. First, in general, the accuracy results decrease with a decrease in spatial resolution. Second, after the 150 m resolution level, there is a slight increase in accuracy with decreasing spatial resolution (at 210 m and 270 m). This result validates the hypothesis that classification accuracies decrease with coarsening resolution.

Figure 7.11b and Figure 7.12b indicate that classification accuracy progressively increases with increase in sigma before dropping off at the highest sigma. The average overall percentage accuracy for Gaussian smoothed multispectral imagery was 79%. The average kappa coefficient was calculated as 0.5. Figures 7.11c and 7.12c display classification results for local variance images. The average overall accuracy was calculated to be 59% and the average kappa coefficient to be 0.25.
Table 7.1 Results of classification accuracy assessment on ANN classified multispectral resampled images

<table>
<thead>
<tr>
<th>RESAMPLING BY AGGREGATION</th>
</tr>
</thead>
<tbody>
<tr>
<td>(RESOLUTION = 30m)</td>
</tr>
<tr>
<td>W</td>
</tr>
<tr>
<td>W</td>
</tr>
<tr>
<td>L</td>
</tr>
<tr>
<td>56523</td>
</tr>
<tr>
<td>Producers Accuracy for Water = 45.6416</td>
</tr>
<tr>
<td>Producers Accuracy for Land = 89.90746</td>
</tr>
<tr>
<td>Users Accuracy for Water = 68.39524</td>
</tr>
<tr>
<td>Users Accuracy for Land = 77.56005</td>
</tr>
<tr>
<td>Overall Accuracy = 75.58062</td>
</tr>
<tr>
<td>Kappa Coefficient = 0.389255</td>
</tr>
</tbody>
</table>

| (RESOLUTION = 90m)       | (RESOLUTION = 210m) |
| W | L           | W | L           |
| W | 2690       | 5600 | 8290 | 243 | 551 | 794 |
| L | 2144       | 6464 | 8608 | 355 | 966 | 1321 |
| 4834 | 12064  | 9154 | 598 | 1517 | 1209 |
| Producers Accuracy for Water = 55.64751 |
| Producers Accuracy for Land = 53.5809 |
| Users Accuracy for Water = 32.44873 |
| Users Accuracy for Land = 75.09294 |
| Overall Accuracy = 54.172099 |
| Kappa Coefficient = 0.076002 |

| (RESOLUTION = 150m)       | (RESOLUTION = 270m) |
| W | L           | W | L           |
| W | 987        | 2488 | 3475 | 41 | 148 | 189 |
| L | 438        | 1193 | 1631 | 248 | 543 | 791 |
| 1425 | 3681  | 2180 | 289 | 691 | 584 |
| Producers Accuracy for Water = 69.26316 |
| Producers Accuracy for Land = 32.40967 |
| Users Accuracy for Water = 28.40288 |
| Users Accuracy for Land = 73.14531 |
| Overall Accuracy = 42.69487 |
| Kappa Coefficient = 0.01161 |

W represents water areas
L represents land areas

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Table 7.2  Results of classification accuracy assessment on ANN classified multispectral Gaussian smoothed images

<table>
<thead>
<tr>
<th>GAUSSIAN SMOOTHING</th>
<th></th>
</tr>
</thead>
<tbody>
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<td><strong>Sigma = 0.0</strong></td>
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<td><strong>L</strong></td>
</tr>
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<td>W</td>
<td>25798</td>
</tr>
<tr>
<td>L</td>
<td>30725</td>
</tr>
<tr>
<td></td>
<td>56523</td>
</tr>
<tr>
<td>Producers Accuracy for Water =</td>
<td>45.6416</td>
</tr>
<tr>
<td>Producers Accuracy for Land =</td>
<td>89.90746</td>
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<tr>
<td>Users Accuracy for Water =</td>
<td>68.39524</td>
</tr>
<tr>
<td>Users Accuracy for Land =</td>
<td>77.56005</td>
</tr>
<tr>
<td>Overall Accuracy =</td>
<td>75.58062</td>
</tr>
<tr>
<td>Kappa Coefficient =</td>
<td>0.389255</td>
</tr>
<tr>
<td><strong>Sigma = 0.5</strong></td>
<td><strong>Sigma = 2.0</strong></td>
</tr>
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<td><strong>L</strong></td>
</tr>
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</tr>
<tr>
<td>L</td>
<td>29419</td>
</tr>
<tr>
<td></td>
<td>56523</td>
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<tr>
<td>Producers Accuracy for Water =</td>
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<td>88.32117</td>
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<tr>
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<tr>
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<td><strong>Sigma = 4.0</strong></td>
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<td><strong>L</strong></td>
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<td></td>
<td>56523</td>
</tr>
<tr>
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<tr>
<td>Producers Accuracy for Land =</td>
<td>91.24004</td>
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<tr>
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</tr>
<tr>
<td>Kappa Coefficient =</td>
<td>0.587415</td>
</tr>
</tbody>
</table>

W represents water areas  
L represents land areas

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Table 7.3 Results of classification accuracy assessment on ANN classified multispectral local variance analysis images

<table>
<thead>
<tr>
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</tr>
<tr>
<td>W</td>
</tr>
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<td>L</td>
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<td></td>
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<tr>
<td>Producers Accuracy for Water =</td>
</tr>
<tr>
<td>Producers Accuracy for Land =</td>
</tr>
<tr>
<td>Users Accuracy for Water =</td>
</tr>
<tr>
<td>Users Accuracy for Land =</td>
</tr>
<tr>
<td>Overall Accuracy =</td>
</tr>
<tr>
<td>Kappa Coefficient =</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
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<th>7*7 MASK</th>
</tr>
</thead>
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<td>W</td>
<td>L</td>
</tr>
<tr>
<td>W</td>
<td>56468</td>
</tr>
<tr>
<td>L</td>
<td>55</td>
</tr>
<tr>
<td></td>
<td>56523</td>
</tr>
<tr>
<td>Producers Accuracy for Water =</td>
<td>99.90269</td>
</tr>
<tr>
<td>Producers Accuracy for Land =</td>
<td>0.140539</td>
</tr>
<tr>
<td>Users Accuracy for Water =</td>
<td>32.37491</td>
</tr>
<tr>
<td>Users Accuracy for Land =</td>
<td>75.11312</td>
</tr>
<tr>
<td>Overall Accuracy =</td>
<td>32.2429</td>
</tr>
<tr>
<td>Kappa Coefficient =</td>
<td>0.00028</td>
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<table>
<thead>
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<th>9*9 MASK</th>
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</tr>
<tr>
<td></td>
<td>56332</td>
</tr>
<tr>
<td>Producers Accuracy for Water =</td>
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</tr>
<tr>
<td>Producers Accuracy for Land =</td>
<td>0.140539</td>
</tr>
<tr>
<td>Users Accuracy for Water =</td>
<td>32.37491</td>
</tr>
<tr>
<td>Users Accuracy for Land =</td>
<td>75.11312</td>
</tr>
<tr>
<td>Overall Accuracy =</td>
<td>32.2429</td>
</tr>
<tr>
<td>Kappa Coefficient =</td>
<td>0.00028</td>
</tr>
</tbody>
</table>

W represents water areas
L represents land areas

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Figure 7.11  Plots of percentage overall accuracy assessment for ANN classified images

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Figure 7.12 Plots of Kappa coefficient calculation for ANN classified images
Table 7.4 Summary of results of classification accuracy assessment on ANN Classified images

<table>
<thead>
<tr>
<th>SPATIAL RESOLUTION</th>
<th>30 m</th>
<th>90 m</th>
<th>150 m</th>
<th>210 m</th>
<th>270 m</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall Accuracy</td>
<td>75.58</td>
<td>54.172</td>
<td>42.694</td>
<td>57.163</td>
<td>59.591</td>
</tr>
<tr>
<td>Kappa Coefficient</td>
<td>0.389</td>
<td>0.076</td>
<td>0.011</td>
<td>0.039</td>
<td>-0.080</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>GAUSSIAN SMOOTHING</th>
<th>0.00</th>
<th>0.50</th>
<th>1.00</th>
<th>2.00</th>
<th>4.00</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall Accuracy</td>
<td>75.58</td>
<td>81.102</td>
<td>82.726</td>
<td>84.283</td>
<td>73.391</td>
</tr>
<tr>
<td>Kappa Coefficient</td>
<td>0.389</td>
<td>0.509</td>
<td>0.587</td>
<td>0.613</td>
<td>0.475</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>LOCAL VARIANCE</th>
<th>0</th>
<th>3*3</th>
<th>5*5</th>
<th>7*7</th>
<th>9*9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall Accuracy</td>
<td>75.58</td>
<td>32.420</td>
<td>73.630</td>
<td>32.975</td>
<td>77.526</td>
</tr>
<tr>
<td>Kappa Coefficient</td>
<td>0.389</td>
<td>0.000</td>
<td>0.418</td>
<td>0.005</td>
<td>0.461</td>
</tr>
</tbody>
</table>

7.3 Fractal analysis

Fractal analysis were applied to water regions derived from neural network classification. The areas and perimeters of all water bodies were measured & tabulated in Table 7.5. Table 7.6 tabulates mean water area and mean perimeter for all image sets used. Figure 7.13 shows a plot of mean area versus spatial resolution, Gaussian smoothing, and local variance methods employed. The mean area increases with increasing spatial resolution, and sigma.

Fractal dimension was calculated from the regression between water area and perimeter. The basic procedure was to use log(area) as the independent variable and log(perimeter) as the dependent variable for all image sets. Figure 7.14 shows the results of the regression for the original and resampled imagery; Figure 7.15 for Gaussian smoothing and Figure 7.16 for local variance. The average $R^2$ equals 0.96. Fractal dimension ($D$) was then calculated as $2 \times$ slope of regression. Table 7.7 summarizes the fractal dimension calculations for each image and Figure 7.17a shows the relationship between fractal dimension and spatial resolution.
Table 7.5  Results for total area-perimeter calculations on classified ANN images

<table>
<thead>
<tr>
<th>METHOD</th>
<th>IMAGE</th>
<th>PIXEL SIZE (meters)</th>
<th># OF LAND PIXELS</th>
<th>TOTAL LAND AREA (sq.meters)</th>
<th># OF WATER PIXELS</th>
<th>TOTAL WATER AREA (sq.meters)</th>
<th>PERIMETER OF WATER</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original</td>
<td>Multispectral (3,4,5)</td>
<td>30</td>
<td>196344</td>
<td>176709600</td>
<td>49135</td>
<td>44221500</td>
<td>15674</td>
</tr>
<tr>
<td>Spatial resolution</td>
<td>90 m</td>
<td>90</td>
<td>8863</td>
<td>71790300</td>
<td>11878</td>
<td>96211800</td>
<td>2890</td>
</tr>
<tr>
<td></td>
<td>150 m</td>
<td>150</td>
<td>859</td>
<td>19327500</td>
<td>1654</td>
<td>37215000</td>
<td>442</td>
</tr>
<tr>
<td></td>
<td>210 m</td>
<td>210</td>
<td>171</td>
<td>7541100</td>
<td>10</td>
<td>441000</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>270 m</td>
<td>270</td>
<td>163</td>
<td>11882700</td>
<td>10</td>
<td>729000</td>
<td>1</td>
</tr>
<tr>
<td>Gaussian smoothing</td>
<td>Sigma = 0.5</td>
<td>30</td>
<td>207443</td>
<td>186698700</td>
<td>38051</td>
<td>34245900</td>
<td>14892</td>
</tr>
<tr>
<td></td>
<td>Sigma = 1.0</td>
<td>30</td>
<td>182381</td>
<td>164142900</td>
<td>63047</td>
<td>56742300</td>
<td>13270</td>
</tr>
<tr>
<td></td>
<td>Sigma = 2.0</td>
<td>30</td>
<td>193658</td>
<td>174292200</td>
<td>51832</td>
<td>46648800</td>
<td>18890</td>
</tr>
<tr>
<td></td>
<td>Sigma = 4.0</td>
<td>30</td>
<td>116628</td>
<td>104965200</td>
<td>128832</td>
<td>115948800</td>
<td>17360</td>
</tr>
<tr>
<td>Local variance</td>
<td>3 * 3 Local variance</td>
<td>30</td>
<td>127</td>
<td>114300</td>
<td>245204</td>
<td>220683600</td>
<td>117565</td>
</tr>
<tr>
<td></td>
<td>5 * 5 Local variance</td>
<td>30</td>
<td>152905</td>
<td>137614500</td>
<td>91180</td>
<td>82062000</td>
<td>80132</td>
</tr>
<tr>
<td></td>
<td>7 * 7 Local variance</td>
<td>30</td>
<td>11142</td>
<td>1027800</td>
<td>244218</td>
<td>219796200</td>
<td>60061</td>
</tr>
<tr>
<td></td>
<td>9 * 9 Local variance</td>
<td>30</td>
<td>184807</td>
<td>166326300</td>
<td>59189</td>
<td>53270100</td>
<td>47530</td>
</tr>
</tbody>
</table>
Figure 7.13  Plots of mean area versus spatial resolution, Gaussian smoothing, and local variance methods obtained from ANN.
Figure 7.14 Results of regression (area-perimeter) for ANN classified multispectral resampled images.
Figure 7.15  Results of regression (area-perimeter) for ANN classified multispectral Gaussian smoothed images
Figure 7.16 Results of regression (area-perimeter) for ANN classified Local variance analysis images
Figure 7.17 Plots of fractal dimension versus spatial resolution, Gaussian smoothing, and local variance methods obtained from ANN

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Table 7.6 Results for mean water area-perimeter calculations on ANN classified images

<table>
<thead>
<tr>
<th>IMAGE</th>
<th>SPATIAL RESOLUTION</th>
<th>30 m</th>
<th>90 m</th>
<th>150 m</th>
<th>210 m</th>
<th>270 m</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Area (Sq.m)</td>
<td>40707.00</td>
<td>233242.00</td>
<td>499934.00</td>
<td>622132.00</td>
<td>1745365.00</td>
<td></td>
</tr>
<tr>
<td>Mean Perimeter (m)</td>
<td>731.00</td>
<td>1698.00</td>
<td>3142.00</td>
<td>4828.00</td>
<td>6251.00</td>
<td></td>
</tr>
</tbody>
</table>

| GAUSSIAN SMOOTHING     |                   |      |      |       |       |       |
| Mean Area (Sq.m)       | 40707.00           | 52526.00 | 95500.00 | 124666.00 | 123796.00 |
| Mean Perimeter (m)     | 731.00             | 1085.00 | 1739.00 | 1230.00 | 1166.00 |

| LOCAL VARIANCE         |                   |      |      |       |       |       |
| Mean Area (Sq.m)       | 40707.00           | 18000.00 | 78800.00 | 64200.00 | 35447.00 |
| Mean Perimeter (m)     | 731.00             | 623.00 | 1262.00 | 1453.00 | 646.00 |

Table 7.7 Calculated fractal dimension from area-perimeter relationships for ANN classified images

<table>
<thead>
<tr>
<th>IMAGE</th>
<th>SPATIAL RESOLUTION</th>
<th>30 m</th>
<th>90 m</th>
<th>150 m</th>
<th>210 m</th>
<th>270 m</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fractal Dimension</td>
<td>1.269</td>
<td>1.256</td>
<td>1.317</td>
<td>1.301</td>
<td>1.312</td>
<td></td>
</tr>
</tbody>
</table>

| GAUSSIAN SMOOTHING     |                   |      |      |       |       |       |
| Fractal Dimension      | 1.269              | 1.213 | 1.241 | 1.206 | 1.219 |

| LOCAL VARIANCE         |                   |      |      |       |       |       |
| Fractal Dimension      | 1.269              | 1.261 | 1.263 | 1.235 | 1.218 |

In general, fractal dimension increases with decreasing resolution, with the maximum value of $D$ at 150 m resolution. This is expected, as overall scene complexity increases with coarser resolutions resulting in a decrease in inter-class variance. Thus, we can infer that at this resolution (150 m), the image exhibits maximum spatial complexity, indicating that the most
complicated water regions are formed at this resolution. Figure 7.17b shows the relationship between $D$ and Gaussian smoothing. In general, $D$ decreases with increasing sigma, as the image exhibits a blurring effect with increasing sigma. The same trend appears in Figure 7.17c. Figure 7.18 shows values of $D$ for each classified original and resampled image; Figure 7.19 for Gaussian smoothed images and Figure 7.20 for local variance analysis images.

### 7.4 Lacunarity analysis

Table 7.8 shows the lacunarity index against spatial resolution, Gaussian smoothing, and local variance methods adopted in this study.

<table>
<thead>
<tr>
<th>IMAGE LOG (BOX SIZE)</th>
<th>0.47712</th>
<th>0.69877</th>
<th>0.84510</th>
<th>0.95424</th>
<th>1.04139</th>
<th>1.11394</th>
<th>1.17609</th>
<th>1.23045</th>
<th>1.27875</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original</td>
<td>1.05607</td>
<td>1.05599</td>
<td>1.05591</td>
<td>1.05584</td>
<td>1.05576</td>
<td>1.05572</td>
<td>1.05561</td>
<td>1.05542</td>
<td>1.05530</td>
</tr>
<tr>
<td>90 m resolution</td>
<td>0.99839</td>
<td>0.99704</td>
<td>0.99616</td>
<td>0.99537</td>
<td>0.99449</td>
<td>0.99357</td>
<td>0.99273</td>
<td>0.99242</td>
<td>0.99216</td>
</tr>
<tr>
<td>150 m resolution</td>
<td>0.90714</td>
<td>0.89988</td>
<td>0.89226</td>
<td>0.88801</td>
<td>0.88338</td>
<td>0.87858</td>
<td>0.87338</td>
<td>0.87309</td>
<td>0.87268</td>
</tr>
<tr>
<td>210 m resolution</td>
<td>0.75618</td>
<td>0.74099</td>
<td>0.68024</td>
<td>0.16542</td>
<td>0.01249</td>
<td>0.00365</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
</tr>
<tr>
<td>270 m resolution</td>
<td>0.82315</td>
<td>0.82066</td>
<td>0.72501</td>
<td>0.67173</td>
<td>0.30243</td>
<td>0.13265</td>
<td>0.04876</td>
<td>0.00000</td>
<td>0.00000</td>
</tr>
<tr>
<td>Sigma = 0.5</td>
<td>1.04622</td>
<td>1.04614</td>
<td>1.04610</td>
<td>1.04607</td>
<td>1.04603</td>
<td>1.04599</td>
<td>1.04595</td>
<td>1.04591</td>
<td>1.04583</td>
</tr>
<tr>
<td>Sigma = 1.0</td>
<td>1.06547</td>
<td>1.06539</td>
<td>1.06532</td>
<td>1.06524</td>
<td>1.06517</td>
<td>1.06509</td>
<td>1.06498</td>
<td>1.06487</td>
<td>1.06423</td>
</tr>
<tr>
<td>Sigma = 2.0</td>
<td>1.05812</td>
<td>1.05808</td>
<td>1.05805</td>
<td>1.05801</td>
<td>1.05797</td>
<td>1.05793</td>
<td>1.05786</td>
<td>1.05774</td>
<td>1.05751</td>
</tr>
<tr>
<td>Sigma = 4.0</td>
<td>1.09135</td>
<td>1.09121</td>
<td>1.09103</td>
<td>1.09086</td>
<td>1.09072</td>
<td>1.09054</td>
<td>1.09036</td>
<td>1.09029</td>
<td>1.09019</td>
</tr>
<tr>
<td>3*3 Local variance</td>
<td>0.726401</td>
<td>0.72501</td>
<td>0.7221</td>
<td>0.72049</td>
<td>0.71975</td>
<td>0.7197</td>
<td>0.71892</td>
<td>0.7186</td>
<td>0.7189</td>
</tr>
<tr>
<td>5*5 Local variance</td>
<td>1.079615</td>
<td>1.07944</td>
<td>1.0793</td>
<td>1.07907</td>
<td>1.07889</td>
<td>1.0787</td>
<td>1.07857</td>
<td>1.0783</td>
<td>1.07813</td>
</tr>
<tr>
<td>7*7 Local variance</td>
<td>0.879612</td>
<td>0.87944</td>
<td>0.8793</td>
<td>0.8791</td>
<td>0.87892</td>
<td>0.8787</td>
<td>0.87858</td>
<td>0.8781</td>
<td>0.87789</td>
</tr>
<tr>
<td>9*9 Local variance</td>
<td>1.064008</td>
<td>1.06401</td>
<td>1.0639</td>
<td>1.06367</td>
<td>1.06355</td>
<td>1.0634</td>
<td>1.0633</td>
<td>1.063</td>
<td>1.06247</td>
</tr>
</tbody>
</table>

Figure 7.21 shows a plot of log(lacunarity index) against log(box size). In Figure 7.21a there is a gradual decay of the lacunarity function at 90 m and 150 m. But, at coarser resolutions, there is a sudden drop to the minimum value. The decay pattern of the lacunarity function
Figure 7.18  Result of fractal analysis on ANN classified images - original and aggregated images
Figure 7.19  Result of fractal analysis on ANN classified images - original and Gaussian smoothed images
Figure 7.20 Result of fractal analysis on ANN classified images - original and local variance analysis images.

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Figure 7.21 Plots of lacunarity index against box size on classified ANN images

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contains information about the spatial structure of the binary image. Thus, at 90 m and 150 m the images exhibit self-similarity (linear decay). But, at 210 m and 270 m, the images exhibit spatial randomness. For the arrangement of objects at fine resolutions, the lacunarity decay is slow until the box sizes (0.85 for the 210 m image and 1.04 for the 270 m) exceeds the size of objects, and is rapid thereafter.

Figure 7.21b shows the plot of lacunarity function against box size for Gaussian smoothing. The plot exhibits a gradual decrease in lacunarity index with increase in box size. Fractal patterns such as water bodies have the same appearance at all scales, thus producing straight lacunarity plots (from the curves of sigma = 1.0, 2.0 and 4.0). The above explanation can also be extended to the plot observed in Figure 7.21c (local variance method).

Therefore, we can infer from these plots that the arrangement of objects at finer resolutions results in linear decay pattern of the curve. But, when box size exceeds the size of objects in the image (Figure 7.21a), the drop is sudden. Thus, by varying box size, lacunarity functions can identify departures from spatial stationarity (isotropy or rotational invariance).

The results obtained from employing neural network for classifying Landsat TM image data have been described both qualitatively and quantitatively. Visual inspection of the classification results seems to suggest that the classification produced by the neural network is comparative to that of the NDVI technique. In general, there are more homogeneous areas with sharper boundaries between land/water areas. It was discovered that the neural network provides an accurate classification of the transition areas between land and water (mixed pixels) from Gaussian smoothed data. Visually the results also show that spectral-based region delineation is not optimal, and that land/water region delineation based on image spatial structure (local variance) can result in a more homogeneous regions.

As neural networks are not based upon the assumption of normal distribution which is the basis for other classification methods, they are more amenable to accepting and handling data
from diverse sources with different distributions. They are in fact non-parametric classifiers, learning the distribution properties of the data during the training process. This fact is supported by the results here. The neural network has enough generalization capability to extend the training patterns to the rest of the images. Therefore, we can conclude that the neural network based classifiers for the classification of satellite imagery is feasible and potentially useful in providing a fast and efficient tool for land/water delineations.

Fractal analysis of area-perimeter relationships from neural network classified images has shown that coarser resolutions and certain local variance mask sizes result in higher $D$. No particular trend is observed from fractal analysis of Gaussian smoothed images. Lacunarity analysis of original and resampled images was found to be primarily related to changes in scene texture, box size and arrangement of mass (water bodies) at 210 m and 270 m. We can conclude that land/water boundaries from neural network classification method exhibit scale dependent behavior and are clearly discernible at certain spatial resolutions up to (150 m).
Chapter 8

Results - III: Maximum-likelihood analysis

The maximum-likelihood classifier was implemented using the same number of training pixels as employed for the ANN classification. The training samples were interactively defined using the region growing method. Table 8.1 shows the mean and standard deviation for each class. For selection of training samples, 900 pixels are identified for both ‘land’ and ‘water’ classes where the standard deviation is within ten percent of the mean spectral value in each band. Once the training signatures were evaluated, the classifications were performed using multispectral - resampled, Gaussian smoothed, and local variance images.

8.1 Qualitative analysis

Figure 8.1 shows the maximum-likelihood results for imagery at different resolutions. It is apparent that many regions of the river are clearly discernible across all resolution levels. Linear features that intersect the river in the upper left and center portion of the scene are visible only at 30 m, 90 m, and 150 m resolutions. With coarser resolutions, water bodies and linear segments of land that are smaller than the resolution cell size are completely eliminated. A visual comparison of Figure 8.1 and Figure 5.4 illustrates that areas of water and land correspond accurately in both images. Overall, this classification is visually accurate and probably could be refined by using a better training region selection.

Figure 8.2 shows the classification results for multispectral Gaussian smoothed images. At sigma = 0.5, areas of land and water are accurately delineated with features appearing alike between the classified image and the reference image (Figure 5.4). At sigma=1.0, errors of omission are produced. Linear features such as bridges and thin strips of land in the top left portion of the image are classified as water. Many areas adjoining the river are misclassified as
Table 8.1  Descriptive statistics for training regions defined for maximum-likelihood classification

<table>
<thead>
<tr>
<th>REGION</th>
<th>PIXELS</th>
<th>BAND</th>
<th>MINIMUM</th>
<th>MAXIMUM</th>
<th>MEAN</th>
<th>STD. DEVIATION</th>
</tr>
</thead>
<tbody>
<tr>
<td>LAND1</td>
<td>50</td>
<td>3</td>
<td>47</td>
<td>53</td>
<td>49.940</td>
<td>1.570</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td>4</td>
<td>44</td>
<td>51</td>
<td>47.900</td>
<td>1.753</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td>5</td>
<td>101</td>
<td>116</td>
<td>110.180</td>
<td>3.361</td>
</tr>
<tr>
<td>LAND2</td>
<td>50</td>
<td>3</td>
<td>29</td>
<td>34</td>
<td>32.280</td>
<td>1.310</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td>4</td>
<td>36</td>
<td>44</td>
<td>40.520</td>
<td>1.887</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td>5</td>
<td>67</td>
<td>85</td>
<td>76.840</td>
<td>4.735</td>
</tr>
<tr>
<td>LAND3</td>
<td>50</td>
<td>3</td>
<td>31</td>
<td>47</td>
<td>38.000</td>
<td>2.740</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td>4</td>
<td>41</td>
<td>55</td>
<td>47.460</td>
<td>2.597</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td>5</td>
<td>76</td>
<td>100</td>
<td>84.620</td>
<td>4.873</td>
</tr>
<tr>
<td>LAND4</td>
<td>50</td>
<td>3</td>
<td>31</td>
<td>39</td>
<td>35.260</td>
<td>2.319</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td>4</td>
<td>59</td>
<td>75</td>
<td>66.420</td>
<td>4.708</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td>5</td>
<td>73</td>
<td>87</td>
<td>79.020</td>
<td>2.853</td>
</tr>
<tr>
<td>LAND5</td>
<td>50</td>
<td>3</td>
<td>34</td>
<td>48</td>
<td>40.300</td>
<td>3.209</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td>4</td>
<td>43</td>
<td>59</td>
<td>50.840</td>
<td>3.961</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td>5</td>
<td>70</td>
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<td>78.840</td>
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( table con’d. )
Figure 8.1  Land/water region delineation by maximum-likelihood classifier from resampled imagery (Images are not shown at the same scale)
Figure 8.2  Land/water region delineation by maximum-likelihood classifier from Gaussian smoothed imagery

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land. The reverse phenomena occurs at \(\sigma = 2.0\). Errors of commision are produced with more land areas misclassified as water. At \(\sigma = 4.0\), details are blurred out resulting in fewer high frequency components such as land features. Only low frequency components such as the river and its branches are retained, while the river takes on a 'blocky' appearance and dominates the scene. Therefore, by carefully selecting the value of \(\sigma\) used in Gaussian smoothing we can produce an approximate delineation between land and water areas.

Figure 8.3 shows the maximum-likelihood output for multispectral local variance analysis. At 3*3 mask size, the outline of the river is faintly visible. The classification completely breaks down at 5*5 and higher mask sizes. This is due to: (1) the signature for land has a much higher mean and covariance (Table 8.1) in each band than the signature for water class, and (2) the histograms for the original multispectral local variance images do not have a Gaussian or bell shaped distribution in all three bands. Therefore, from the results obtained with local variance analysis classification, we can conclude that the heart of a maximum-likelihood classifier is its parametric distribution assumption in all bands.

### 8.2 Classification accuracy assessment

The assessment of classification accuracy was performed using test pixels from the reference image (DLG) and maximum-likelihood classified images at different resolutions, \(\sigma\) values, and mask sizes. Error matrices were created for each dataset and the overall accuracy and kappa coefficients were calculated (Tables 8.2, 8.3, and 8.4). Table 8.5 summarizes results obtained from percent overall accuracy and kappa coefficient calculations.

The results from overall accuracy assessment (Figure 8.4a and Figure 8.5a) indicate that the classification methodology for imagery at different resolutions produced an average overall percentage correct of 71% and an average kappa coefficient of 0.2. The accuracy results initially decrease with decreasing spatial resolution. However, at 210 m, the overall accuracy increases.
Figure 8.3  
Land/water region delineation by maximum-likelihood classifier from multispectral local variance analysis imagery
<table>
<thead>
<tr>
<th>RESAMPLING BY AGGREGATION</th>
<th>(RESOLUTION = 30m)</th>
<th>(RESOLUTION = 90m)</th>
<th>(RESOLUTION = 210m)</th>
<th>(RESOLUTION = 150m)</th>
<th>(RESOLUTION = 270m)</th>
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<td>Users Accuracy for Water =</td>
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<td>47.68756</td>
<td>72.32763</td>
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<tr>
<td>Users Accuracy for Land =</td>
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<td>77.37088</td>
<td>72.56356</td>
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<tr>
<td>Overall Accuracy =</td>
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<td>70.62908</td>
<td>64.28299</td>
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<tr>
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W represents Water areas
L represents Land areas

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Table 8.3  Percentage overall accuracy for maximum-likelihood classified multispectral Gaussian smoothed images

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<th>SIGMA = 2.0</th>
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<td>118609</td>
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Producers Accuracy for Water = 61.59835
Producers Accuracy for Land = 91.81856
Users Accuracy for Water = 78.27819
Users Accuracy for Land = 83.32058
Overall Accuracy = 82.03615
Kappa Coefficient = 0.565585

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<td>110440</td>
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Producers Accuracy for Water = 68.37294
Producers Accuracy for Land = 93.11266
Users Accuracy for Water = 82.6136
Users Accuracy for Land = 86.01581
Overall Accuracy = 85.10434
Kappa Coefficient = 0.628841

W represents Water areas
L represents Land areas

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Table 8.4  Percentage overall accuracy for maximum-likelihood classified multispectral local variance analysis images

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<tr>
<td>Producers Accuracy for Land = 91.81851</td>
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<td>Users Accuracy for Water = 78.27819</td>
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<td>Users Accuracy for Land = 83.32058</td>
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<tr>
<td>Overall Accuracy = 82.03615</td>
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<td>Kappa Coefficient = 0.56585</td>
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<td>Producers Accuracy for Land = 99.99831</td>
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W represents Water areas
L represents Land areas

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Figure 8.4 Plots of percentage overall accuracy for multispectral classified images
Figure 8.5  Plots of Kappa coefficient calculation for maximum-likelihood classified images
Table 8.5  Summary of results of classification accuracy on maximum-likelihood multispectral classification images

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<td>0.046</td>
</tr>
<tr>
<td>GAUSSIAN SMOOTHING</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overall Accuracy</td>
<td>82.036</td>
<td>84.451</td>
<td>85.104</td>
<td>86.545</td>
<td>80.067</td>
</tr>
<tr>
<td>Kappa Coefficient</td>
<td>0.565</td>
<td>0.628</td>
<td>0.644</td>
<td>0.682</td>
<td>0.542</td>
</tr>
<tr>
<td>LOCAL VARIANCE</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overall Accuracy</td>
<td>82.036</td>
<td>67.978</td>
<td>67.661</td>
<td>67.631</td>
<td>67.630</td>
</tr>
<tr>
<td>Kappa Coefficient</td>
<td>0.565</td>
<td>0.015</td>
<td>0.005</td>
<td>0.003</td>
<td>0.001</td>
</tr>
</tbody>
</table>

before dropping off again. The interpretation is that at 30 m the pixel size is small compared to ground features of interest and many spatial details are revealed in the image. Consequently, for the 'water' class, adjacent pixels exhibit similar spectral values that differ in various regions across the image resulting in homogeneous clusters. But, with a decrease in resolution (blurring effect) spectral detail is lost and pixel values vary more randomly from the median, resulting in clusters that are not grouped into any one category (misclassifications). Thus, overall accuracy decreases considerably at coarser resolution. At 210 m, pixel size approximates the size of most water bodies (river) and adjacent pixels show similarity in spectral values resulting in a rise of classification accuracy.

The results from overall accuracy assessment (Figure 8.4b and Figure 8.5b) indicate that Gaussian smoothing produces an average overall percentage correct of 83% and an average kappa coefficient of 0.61. Overall, accuracy increases with increasing sigma.
Figure 8.4c and Figure 8.5c show an average overall percentage classification of 71% and an average kappa coefficient of 0.11 for multispectral local variance analysis imagery. Though, the classification accuracy numbers generated from local variance analysis classification are high, the maximum-likelihood classification method completely breaks down. Errors of commission are produced with large areas of the scene being misclassified as land.

8.3 Fractal analysis of classified images (water regions)

Fractal concepts were applied to water regions classified from the maximum-likelihood classifier by measuring area and perimeter of all water bodies delineated in the classified images. Total area of land and water regions were calculated for the raster images. Table 8.6 shows the calculations. Table 8.7 lists mean area and mean perimeter for all image sets. Figure 8.6 shows plots of mean area versus spatial resolution, Gaussian smoothing, and local variance analysis methods employed. The mean area increases with a decrease in spatial resolution, increases with an increase in scaling constant, and decreases with an increase in local variance mask size.

Linear regression was performed using $\log(\text{area})$ as the independent variable and $\log(\text{perimeter})$ as the dependent variable for all images. Figure 8.7 shows the results of the regression imagery at different spatial resolutions; Figure 8.8 for multispectral Gaussian smoothed imagery; and Figure 8.9 for multispectral local variance imagery. Average $R^2$ was calculated to be 0.975 for all the three methods. Fractal dimensions were then calculated using $D = 2 * \text{slope of regression}$. Table 8.8 summarizes fractal dimension calculations for each image and Figure 8.10a shows the relationship between fractal dimension and spatial resolution. In general, fractal dimension increases with decrease in resolution with a maximum value of $D$ occurring at 150 m before levelling off at coarser resolutions. Figure 8.10b shows the plot of fractal dimension against scaling constant. The maximum value of $D$ occurs at $\sigma = 0.5$. The plot then drops off at higher scaling constants. Therefore, the most complicated water regions are
Table 8.6 Results for total area-perimeter calculations on classified maximum-likelihood images

<table>
<thead>
<tr>
<th>METHOD</th>
<th>IMAGE</th>
<th>PIXEL SIZE (meters)</th>
<th># OF LAND PIXELS</th>
<th>TOTAL LAND AREA (sq.meters)</th>
<th># OF WATER PIXELS</th>
<th>TOTAL WATER AREA (sq.meters)</th>
<th>PERIMETER OF WATER</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original</td>
<td>Multispectral (3,4,5)</td>
<td>30</td>
<td>189714</td>
<td>170742600</td>
<td>57626</td>
<td>51863400</td>
<td>13232</td>
</tr>
<tr>
<td>Spatial resolution</td>
<td>90 m</td>
<td>90</td>
<td>15477</td>
<td>125363700</td>
<td>5755</td>
<td>46615500</td>
<td>2775</td>
</tr>
<tr>
<td></td>
<td>150 m</td>
<td>150</td>
<td>1932</td>
<td>434700000</td>
<td>805</td>
<td>18112500</td>
<td>398</td>
</tr>
<tr>
<td></td>
<td>210 m</td>
<td>210</td>
<td>356</td>
<td>156996000</td>
<td>31</td>
<td>1367100</td>
<td>143</td>
</tr>
<tr>
<td></td>
<td>270 m</td>
<td>270</td>
<td>653</td>
<td>476037000</td>
<td>11</td>
<td>801900</td>
<td>48</td>
</tr>
<tr>
<td>Gaussian smoothing</td>
<td>Sigma = 0.5</td>
<td>30</td>
<td>186779</td>
<td>168101100</td>
<td>60556</td>
<td>5450400</td>
<td>13697</td>
</tr>
<tr>
<td></td>
<td>Sigma = 1.0</td>
<td>30</td>
<td>186649</td>
<td>167984100</td>
<td>60706</td>
<td>54635400</td>
<td>11583</td>
</tr>
<tr>
<td></td>
<td>Sigma = 2.0</td>
<td>30</td>
<td>185450</td>
<td>166905000</td>
<td>61915</td>
<td>55723500</td>
<td>11620</td>
</tr>
<tr>
<td></td>
<td>Sigma = 4.0</td>
<td>30</td>
<td>173534</td>
<td>156180600</td>
<td>73803</td>
<td>66422700</td>
<td>17494</td>
</tr>
<tr>
<td>Local variance</td>
<td>3 * 3 Local variance</td>
<td>30</td>
<td>245439</td>
<td>220895100</td>
<td>1923</td>
<td>1730700</td>
<td>3068</td>
</tr>
<tr>
<td></td>
<td>5 * 5 Local variance</td>
<td>30</td>
<td>246709</td>
<td>222038100</td>
<td>653</td>
<td>587700</td>
<td>852</td>
</tr>
<tr>
<td></td>
<td>7 * 7 Local variance</td>
<td>30</td>
<td>247222</td>
<td>222499800</td>
<td>140</td>
<td>126000</td>
<td>223</td>
</tr>
<tr>
<td></td>
<td>9 * 9 Local variance</td>
<td>30</td>
<td>247179</td>
<td>222461100</td>
<td>183</td>
<td>164700</td>
<td>227</td>
</tr>
</tbody>
</table>
Figure 8.6 Plots of mean area versus spatial resolution, Gaussian smoothing, and local variance analysis methods from maximum-likelihood classified images
Figure 8.7  Results of regression (area-perimeter) at different resolutions

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Figure 8.8 Results of regression (area-perimeter) for multispectral Gaussian smoothed images
Figure 8.9  Results of regression (area-perimeter) for multispectral local variance analysis images

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Figure 8.10 Plots of fractal dimension versus spatial resolution, Gaussian smoothing, and local variance methods from multispectral classified images.
Table 8.7 Results for mean water area-perimeter calculations on classified maximum-likelihood images

<table>
<thead>
<tr>
<th>IMAGE</th>
<th>SPATIAL RESOLUTION</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>30 m</td>
</tr>
<tr>
<td>Mean Area (Sq.m)</td>
<td>151579.92</td>
</tr>
<tr>
<td>Mean Perimeter (m)</td>
<td>1517.72</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>GAUSSIAN SMOOTHING</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Area (Sq.m)</td>
</tr>
<tr>
<td>Mean Perimeter (m)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>LOCAL VARIANCE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Area (Sq.m)</td>
</tr>
<tr>
<td>Mean Perimeter (m)</td>
</tr>
</tbody>
</table>

Table 8.6 Calculated fractal dimensions from area-perimeter relationships from classified maximum-likelihood images

<table>
<thead>
<tr>
<th>IMAGE</th>
<th>SPATIAL RESOLUTION</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>30 m</td>
</tr>
<tr>
<td>Fractal Dimension</td>
<td>1.268</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>GAUSSIAN SMOOTHING</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fractal Dimension</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>LOCAL VARIANCE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fractal Dimension</td>
</tr>
</tbody>
</table>

formed at 150 m resolution and a sigma of 0.5. Figure 8.11 shows the calculated fractal dimension for images with different spatial resolution; Figure 8.12 for Gaussian smoothed images and Figure 8.13 for local variance analysis images.
Figure 8.11 Result of application of fractal analysis on maximum-likelihood classified images - original and resampled images
Figure 8.12 Result of fractal analysis on maximum-likelihood classified images - original and Gaussian smoothed images

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Figure 8.13 Result of fractal analysis on maximum-likelihood classified images - local variance analysis
8.4 Lacunarity analysis

Table 8.9 tabulates box size against spatial resolution, Gaussian smoothing, and local variance analysis methods.

Table 8.9 Results of lacunarity analysis on maximum-likelihood classified images

<table>
<thead>
<tr>
<th>IMAGE</th>
<th>0.4712</th>
<th>0.69897</th>
<th>0.84510</th>
<th>0.95424</th>
<th>1.04139</th>
<th>1.13939</th>
<th>1.17669</th>
<th>1.23045</th>
<th>1.27875</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original</td>
<td>1.06200</td>
<td>1.06200</td>
<td>1.06200</td>
<td>1.06200</td>
<td>1.06200</td>
<td>1.06200</td>
<td>1.06200</td>
<td>1.06200</td>
<td>1.06100</td>
</tr>
<tr>
<td>90 m resolution</td>
<td>0.96500</td>
<td>0.96500</td>
<td>0.96400</td>
<td>0.96400</td>
<td>0.96300</td>
<td>0.96200</td>
<td>0.96200</td>
<td>0.96200</td>
<td>0.96200</td>
</tr>
<tr>
<td>150 m resolution</td>
<td>0.86000</td>
<td>0.85500</td>
<td>0.85000</td>
<td>0.84400</td>
<td>0.83800</td>
<td>0.83200</td>
<td>0.82600</td>
<td>0.82600</td>
<td>0.82500</td>
</tr>
<tr>
<td>210 m resolution</td>
<td>0.79800</td>
<td>0.79000</td>
<td>0.65200</td>
<td>0.62300</td>
<td>0.23700</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
</tr>
<tr>
<td>270 m resolution</td>
<td>0.81700</td>
<td>0.70600</td>
<td>0.66600</td>
<td>0.63200</td>
<td>0.42900</td>
<td>0.33600</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
</tr>
<tr>
<td>Sigma = 0.5</td>
<td>1.06400</td>
<td>1.06400</td>
<td>1.06400</td>
<td>1.06400</td>
<td>1.06400</td>
<td>1.06400</td>
<td>1.06300</td>
<td>1.06300</td>
<td>1.06300</td>
</tr>
<tr>
<td>Sigma = 1.0</td>
<td>1.06400</td>
<td>1.06400</td>
<td>1.06400</td>
<td>1.06400</td>
<td>1.06400</td>
<td>1.06400</td>
<td>1.06400</td>
<td>1.06400</td>
<td>1.06400</td>
</tr>
<tr>
<td>Sigma = 2.0</td>
<td>1.06500</td>
<td>1.06500</td>
<td>1.06500</td>
<td>1.06500</td>
<td>1.06500</td>
<td>1.06500</td>
<td>1.06500</td>
<td>1.06500</td>
<td>1.06500</td>
</tr>
<tr>
<td>Sigma = 4.0</td>
<td>1.07100</td>
<td>1.07100</td>
<td>1.07100</td>
<td>1.07100</td>
<td>1.07100</td>
<td>1.07100</td>
<td>1.07100</td>
<td>1.07100</td>
<td>1.07100</td>
</tr>
<tr>
<td>3*3 Local variance</td>
<td>0.91</td>
<td>0.91</td>
<td>0.91</td>
<td>0.91</td>
<td>0.909</td>
<td>0.909</td>
<td>0.909</td>
<td>0.909</td>
<td>0.907</td>
</tr>
<tr>
<td>5*5 Local variance</td>
<td>0.847</td>
<td>0.847</td>
<td>0.847</td>
<td>0.847</td>
<td>0.847</td>
<td>0.846</td>
<td>0.846</td>
<td>0.846</td>
<td>0.845</td>
</tr>
<tr>
<td>7*7 Local variance</td>
<td>0.734</td>
<td>0.733</td>
<td>0.733</td>
<td>0.733</td>
<td>0.732</td>
<td>0.732</td>
<td>0.731</td>
<td>0.731</td>
<td>0.731</td>
</tr>
<tr>
<td>9*9 Local variance</td>
<td>0.757</td>
<td>0.757</td>
<td>0.756</td>
<td>0.756</td>
<td>0.755</td>
<td>0.755</td>
<td>0.755</td>
<td>0.754</td>
<td>0.754</td>
</tr>
</tbody>
</table>

Figure 8.14a shows a plot of log(lacunarity index) against log(box size) for multispectral original and resampled imagery. A gradual linear decay pattern can be observed at 30 m, 90 m, and 150 m. But, at 210 m and 270 m there is a sudden drop in the curve. A likely explanation is that, at finer spatial resolutions (30 m, 90 m, and 150 m), self-similarity exists across some constants of scale and there is a linear decay. On the other hand, at 210 m and 270 m, when box
Figure 8.14 Plots of lacunarity index against box size on classified maximum-likelihood images
size (.95) becomes larger than the size of objects in the scene, the image exhibits complete randomness and the curve drops.

From Figure 8.14b and Figure 8.14c, we can observe that the graphs of lacunarity function versus Gaussian smoothing and lacunarity function versus local variance exhibit self-similarity across some range of scales (linear decay). Due to smoothing (blurring) at higher scaling constants and decrease in inter-class variance at higher local variance mask sizes, the decay pattern of the lacunarity function is gradual.

The results obtained from implementing maximum-likelihood classifier for classifying Landsat-TM image data have been described both qualitatively and quantitatively. At the heart of a maximum-likelihood classifier is its parametric distribution assumption. Most results obtained with local variance analysis imagery validate this. Aggregation of imagery from the base resolution to coarser resolutions maintains a Gaussian probability density distribution and percent overall classification accuracy remains moderately high at lower resolutions. The same explanation can be extended to results obtained from Gaussian smoothed data. But, in the case of local variance analysis data, the classification breaks down completely as the images no longer have a normal distribution. In general, the high overall classification accuracies obtained with maximum-likelihood classifier suggest that it is an accurate tool for land/water delineation.
CHAPTER 9
Discussion

The results from the three classification methods (NDVI technique, neural network, and maximum-likelihood classifier) and three scaling algorithms (aggregation, Gaussian smoothing, and local variance analysis) are discussed below by individual category.

9.1 Qualitative analysis

When comparing maximum-likelihood images and neural network classification images, it is apparent that the neural network output has more relatively homogeneous regions and sharper boundaries. The network was able to classify all datasets using the same training regions used to train the network. From results obtained with ANN training and classification, we can conclude that neural network performs well when given only the most homogeneous (and minimal) training regions.

Classification results obtained from maximum-likelihood using Gaussian smoothed data present more contrasting results than those obtained from neural network. At sigma values 2.0 and higher, the maximum-likelihood classifier completely breaks down with a large number of land areas being misclassified as water. This pattern is not observed with results from neural network. One property of Gaussian smoothing is that spurious detail would not be introduced into the smoothing process at higher sigma values. All patterns observed at higher constants should have a 'cause' at lower sigmas. By contrast, the images obtained from ANN classification using Gaussian smoothed data reveal clearly the transition zone between land and water areas. At sigma = 0.5 and 1.0 (Figure 7.5), mixed pixels are clearly distinguishable between the surrounding land and water features.

The test results from local variance analysis indicate that local variance decreases as resolution of the image becomes coarser. The local variance tests for Gaussian smoothed images
also indicate that as sigma becomes larger, local variance of the image decreases. Local variance analysis of neural network images results in a consistent presence of salt-pepper noise due to differences in spatial structure (texture) between land and water features. The application of a 3x3 median filter did not improve classification results. Local variance analysis of maximum-likelihood classified images suggests that the signature for 'land' class has a much higher mean and covariance in each band than the signature for 'water' class and thus large number of commission errors are produced. Application of texture input to neural network classifier (Figure 7.8) visually produced the most appealing classified image. Therefore, classification based also on image spatial structure can result in more meaningful homogeneous regions.

Overall, the ANN classifier performs more reliably than maximum-likelihood classifier on diversified image data. The neural network classifier, as with any classifier, occasionally makes categorization errors. For the land/water delineation, these errors can be corrected with simple image processing algorithms such as low-pass filtering, median-filtering, and contrast stretching to the binary land/water category images.

9.2 Classification accuracy assessment

The assessment of overall percent classification accuracy from the three land/water region classification methods are summarized below.

Figure 9.1a shows overall accuracies for the three classification methods plotted against resolution. It is observed that the maximum-likelihood classifier produces higher classification accuracy results across all resolution levels than either NDVI technique or neural network method. Changing the resolution levels of the land/water classes greatly affects the overall accuracy. Overall classification accuracy decreases with decreasing resolution and increases marginally at coarser resolutions. This is explained by the fact that at 30 m, the pixel size is small compared to the ground features of interest. Many spectral details are revealed by the image and...
Figure 9.1  Plots of percent overall accuracy versus classification methods and scaling algorithms tested
pixels have a tendency to cluster. With decrease of spatial resolution, spectral detail is progressively combined with higher proportions of land/water classes resulting in a drop in classification accuracy. It is discovered that at 210 m and 270 m, classification accuracies increased for both maximum-likelihood and neural network methods.

Figure 9.1b shows that at small sigmas both maximum-likelihood classifier and NDVI technique provide higher classification accuracies than neural network classifier. At higher sigmas (2.0 and larger) even though the maximum-likelihood method outperforms neural network classifier, land/water boundaries from ANN method are visually more appealing.

Figure 9.1c shows that when texture (local variance) is introduced into the classification process, neural network method outperforms maximum-likelihood across mask sizes 5*5 and 9*9. At other mask sizes (3*3 and 7*7) the classified images from neural network have a consistent presence of noise, and the results from maximum-likelihood do not show any valid classification.

9.3 Fractal analysis of classified images (water regions)

Figure 9.2a shows a plot of fractal dimension versus resolution for the three classification methods. In general, fractal dimension \((D)\) increases with decreasing resolution of images. As expected, complexity of landscape increases with coarser spatial resolution, resulting in higher values of \(D\). The highest value of \(D\) occurs at 150 m for both the maximum-likelihood \(1.317\) and neural network classifiers \(1.32\), before dropping off to lower resolutions. The NDVI technique displays the reverse trend. From the plot, it is also observed that the rate of increase in \(D\) with resolution is steepest for neural network versus other methods. \(D\) increases from 1.25 at 90 m to 1.32 at 150 m for the neural network technique. As resolution decreases, the output of the neural network yields more homogeneous and compact regions with sharper boundaries between classes. Large water features manifest significantly larger perimeters than do
Figure 9.2  Plots of fractal dimension versus classification methods and scaling algorithms tested on classified water regions.

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smaller features. As the water polygons become more complex, the perimeter becomes increasingly plane filling with the size of dominant water features increasing. Hence, within 90 m to 150 m, the ANN techniques results in higher fractal dimension.

Figure 9.2b shows the relationship between fractal dimension and Gaussian smoothing. The fractal dimension shows a progressive decrease for the maximum-likelihood method. The reverse trend is displayed by the neural network classifier. Within 0 to 1.0 sigma values, $D$ from maximum-likelihood drops off considerably from 1.268 to 1.205, while $D$ from neural network increases sharply from 1.21 to 1.24 before dropping off again at higher scaling constants. Thus, at sigma 1.0 (filter size = 7*7) land/water proportions classified using maximum-likelihood are visually delineated accurately, while at higher sigmas there are more water regions than land regions. At sigma = 2.0 and higher, most land boundaries classified by maximum-likelihood classifier that are smaller than filter size are blurred out, resulting in a stepped appearance of pixels, reduced complexity, and therefore lower $D$. Also, the perimeter fractal dimension increases when water polygons have very convoluted boundaries and decreases if the polygons have smooth edges, i.e., the measured fractal dimension changes at specified levels of scale.

Figure 9.2c shows the relationship between fractal dimension and local variance analysis. Both maximum-likelihood and neural network exhibit similar patterns with $D$ lying between 1.2 - 1.33.

We can therefore conclude that the relationship between water area and water perimeter changes with spatial resolution and sigmas. The number of water features observed decreases as resolution becomes coarser and small water bodies disappear. $D$ is sensitive to disappearance of these small water features with loose arrangements, and a break point occurs when $D$ is plotted against resolution (Figure 9.2a). The rate at which large area objects increase with decreasing resolution depends on their spatial arrangement. If a small water feature is highly aggregated, it
tends not to disappear or to diminish slowly; if it is well dispersed in small areas, it disappears rapidly. It can also be observed from Figures 6.27, 6.28, 7.18, 7.19, 8.11 and 8.12 that, while the distribution of holes or gaps in the water polygons increases, the perimeter of large water polygons increases and area decreases. This suggests that perimeter fractal dimension measured is affected by - the size of water features delineated and the degree of spatial detail (density distribution) within the water features observed in the study area.

9.4 Lacunarity analysis

From the results (NDVI, ANN, and M-L classifications) obtained it can be deduced that lacunarity analysis is a very general technique that can be easily applied to binary (classified) data. It allows the determination of scale-dependent changes in spatial structure between water regions that can give insight into the underlying process affecting them. Lacunarity analysis also reveals presence of a range of self-similarity as evidenced by the various charts of lacunarity index against resolution and scale constants.

From plots of lacunarity function and various scaling algorithms (Figures 6.29, 7.21, and 8.14), we can utilize the decay pattern of the lacunarity function to reveal information about the spatial structure of binary classified images (water regions). Specifically, the lacunarity index depends on the pattern of aggregation and box size. An image with self-similarity across ranges of resolution (30 m, 90 m, and 150 m) exhibits a linear decay. For images with an arrangement of land/water patterns at a particular resolution (210 m and 270 m), the lacunarity decay is slow until the box size exceeds the scale of the patterns and is rapidly declining thereafter (Figures 6.28a, 7.20a and 8.12a). But, under the effects of Gaussian smoothing and local variance analysis, the lacunarity function does not convey any significant information. The decay patterns are all gradual and linear indicating that the images exhibit self-similarity across all scales and
mask sizes. Therefore, we can conclude that the lacunarity function varies only under specific resolution levels (spatial structure) and box sizes.

9.5 Hypothesis validation

My first hypothesis is that ANN yields more accurate classification. While seemingly marginally inferior in overall percent classification accuracy with comparison to statistical classifiers such as maximum-likelihood, the ANN approach is still able to use the spatial association of objects at multiple resolutions to recognize land/water patterns as evidenced by the qualitative analysis of various sets of images. The results obtained from neural network analysis prove that there are advantages (such as classification speed, generalization capability and the ability to successfully recognize transitional areas between land and water) in using a multispectral neural network classifier.

My second hypothesis is that land/water boundaries are more clearly discernible at certain scales. Spatial scale is inherent in techniques that reveal patterns in the environment and in understanding the relationships between the observed patterns and the environmental or human processes affecting them. Specific environmental and human processes function at various ranges of scales. These ranges vary and might overlap and the spatial patterns are discernible clearly at certain spatial scales. The observed scales at which these patterns are delineated is referred to as 'characteristic' scale (Bian and Walsh, 1993). Bian and Walsh (1993) examined the effects of spatial scale on estimating the relationship between vegetation biomass and topography. The authors concluded that the effective range of spatial scales within which the two sets of variables were spatially dependent and the degree of spatial dependence, could be characterized through semivariance and fractal analysis. They defined the 'characteristic' scale, which marked the underlying dependence of spatial variation of topography and vegetation biomass. Similarly, in this research, the results demonstrate that there is a close relationship
between the 'characteristic' scale (definable, as occurring at 150 m) and internal variance of the classes when the best visual classification accuracies are achieved at each resolution level. For some cases a peak in fractal dimension and lacunarity analysis is obtained at 150 m spatial resolution, confirming the hypothesis that land/water boundaries are clearly discernible at certain spatial resolutions than at others. This concept of 'characteristic' scale can be very useful for selecting a scale (resolution level) at which remotely sensed data should be acquired or aggregated to satisfy research objectives and in identifying the physical or human processes shaping the observed spatial patterns.

The results show that hypothesis three is generally validated, as the percent overall classification accuracies obtained from all three classification methods (maximum-likelihood, neural network, and NDVI) decrease at coarser spatial resolutions. Proportions of smaller scale objects (land features) decrease and proportions of large scale objects (water features) were found to increase with coarser resolutions and higher sigmas. It was observed that at 210 m and 270 m spatial resolutions however, classification accuracies increase marginally for both ANN and maximum-likelihood classifiers. The slight increase in classification accuracy with decreasing resolution by the ANN and maximum-likelihood classifier indicates that this issue needs to be further investigated.
Chapter 10

Conclusions

In Chapters 6, 7 and 8, NDVI, neural network and maximum-likelihood analyses were respectively discussed and the classifications from various scaling algorithms presented. The results were compared both qualitatively and quantitatively. Qualitatively, the neural network produces more homogeneous regions than maximum-likelihood when using resampled, Gaussian smoothed, and local variance images. Quantitatively, maximum-likelihood classifier has a slightly higher overall classification accuracy. Much of the poorer performance of the maximum-likelihood classifier when compared to the ANN classifier for classifying Gaussian smoothed data can be attributed to the misclassification of land class. Many of the land pixels were misclassified as water. The results also indicate that the neural network has enough generalization capability to extend what it has learned about the training patterns to the rest of the images. From results obtained with previous experiments, it is evident that the maximum-likelihood classifier requires a lot of effort in selecting homogeneous training samples than ANN to perform classification. In other words, ANN is more tolerant with noise. The results from applying the NDVI technique to delineate land/water regions indicate that the method is reasonably accurate. A distinct grouping of water pixels and quite a sharp transition from water pixels to land pixels is obtainable by employing a thresholding approach. But, the adoption of a thresholding technique alone on NDVI data can result in ambiguity when classifying transitional areas between land and water pixels.

It is shown that the two land cover categories (land/water) can be delineated in a highly complex environment such as in this study. Overall classification accuracy of 75-85% has been achieved. Using neural networks for image classification gives results that are comparable to maximum-likelihood and NDVI classifiers. Although maximum-likelihood gives better results
quantitatively, the margin is only very small. The advantages of ANN is that it is not sensitive to
the form of the underlying probability density functions. Although the classification accuracies
of all three classification methods decrease at coarser resolutions as found out from this study, in
the case of Gaussian smoothing, ANN produced higher classification accuracy than maximum-
likelihood with increasing sigma. Within a particular sigma, ‘land’ class is better classified at
finer sigmas (0.5 and 1.0), while ‘water’ class can still be distinguished at higher sigmas (2.0 and
4.0).

More important, in neural network classification, the misclassifications are clearly
visible in the transition zone between the two cover types. The strength of class membership of
each pixel can be used to determine a third land cover category (mixed pixel), the transitional
zone between land and water. Thus, the ability of the ANN classifier to derive information on the
land cover composition of mixed pixels adjoining land and water classes using Gaussian
smoothed data presents an encouraging and convincing trend that needs to be further
investigated. Previous researchers (Foody, 1996; Moody et al., 1996; Civco and Wang, 1994;
Schouten and Gebbinck, 1994; Civco, 1993; Heermann and Khazenie (1992); McClellan, 1989)
have reached similar conclusions. However, classification of the transition region between land
and water boundaries have not been highlighted clearly in the literature before. This study shows
that the applicability of using scaling algorithms such as Gaussian smoothing (sigma = 0.5 and
1.0) produces very encouraging results in classifying the transition zone between land and water
(mixed pixels). Also, the ANN was able to effectively use the spatial association between objects
at multiple resolution levels to delineate land/water patterns much as a human does in image and
map recognition.

The neural network approach, being non-parametric, is more robust to training site
selection and class definition, and it can more easily accommodate a heterogeneous class such as
“mixed pixel” to produce a fairly accurate classification. On the other hand, the maximum-
likelihood algorithm is very sensitive to the homogeneity of the class signatures and performs poorly if they are not statistically homogeneous. The same conclusions had been reached by Paola and Schowengerdt (1995), but the authors noted that the maximum-likelihood procedure required more number of training samples than the ANN approach to perform the same classification. Also, the major benefits of employing the ANN approach compared with other techniques are that: (1) the method uses only the minimal information available; (2) is relatively easy to implement; (3) the classification produces relatively homogeneous regions, sharp transition boundaries and continuous connected features; and (4) as a dynamic medium capable of learning, the network can be updated through alternative network architectures, better training algorithms, and more efficient network topologies.

This dissertation has demonstrated the methodology of using area-perimeter relationships from classification of images to determine fractal dimensions. There is a general trend that the fractal dimension $D$ increases with a decrease in spatial resolution of images, indicating complexity of landscape increases with coarser spatial resolution. In general, maximum-likelihood method produces higher values of fractal dimension than other methods. This can be explained by the fact that maximum-likelihood produces less homogeneous regions resulting in higher values of $D$. While in this study fractal dimension was calculated by regressing area and perimeter of water bodies, the values of $D$ obtained must be validated with other fractal measurement techniques such as the isarithm, variogram and triangular prism methods.

It was determined that a single-valued index such as lacunarity index is inadequate for characterizing a heterogeneous landscape such as the one used in this study. In fact, it is the change of the value of lacunarity index over different box sizes and spatial resolution that yields the most information. The lacunarity analysis was found to be primarily related to the change in texture and distribution of mass (water bodies).
The concept of investigating the 'characteristic' scale and aggregation level on image information content is closely related to that of Marceau et al. (1992) who have concluded similar results that are described below. The results from this research demonstrate that the resolution 150 m defines the 'characteristic' scale and marks the spatial variation of land/water patterns for this study area. Land/water boundaries are spatially dependent at resolutions finer than the 'characteristic' scale and less dependent at coarser resolutions. These results are validated through fractal analysis, local variance analysis, and lacunarity analysis.

The results of this study are important to many issues involving remote sensing image classification accuracies and spatial analysis of land/water patterns. The concepts of overall classification accuracy and fractal dimension are useful for selecting a resolution at which data can be sampled or aggregated to meet research objectives. Changes in fractal dimension indicate the variation in processes that affect the spatial pattern of land/water boundaries. Therefore, information about the spatial dependence of land/water patterns as indicated by Gaussian smoothing, fractal analysis, and lacunarity analysis can help to optimize data sampling and interpolation techniques.

From this study, we can make the following five recommendations. First, the information content of remote sensing images varies with the spatial resolutions of the data. Therefore, neglecting the scale and aggregation level when classifying remote sensing images can produce results with little correspondence to the objects in the scene. Secondly, it is impossible to draw generally applicable conclusions from the analysis using only one image. The results reported here are subject to the type of environment, size of land/water bodies in the study area, and the aggregation method employed. Other aggregation techniques, such as those involving decimation, convolution, or replication, need to be investigated. Thirdly, no quantitative measure of the best resolution, best accuracy, best scale, or the optimum local variance mask size can be made without using more accurate ground truth data.
Fourthly, the minimum training sample size, number of spectral bands, and the homogeneity of training samples for a given expectation of classification accuracy needs to be analyzed more fully. Finally, in this research, the neural network was treated as a black-box tool. All of the various resampled, Gaussian smoothed and local variance analysis images were submitted to the neural network for classification. Although improved classification was achieved, the contribution of each individual cover type in the final decision region making process (assigning each pixel to a class type) was not observed. Therefore, by making graphical visualization of the behaviour of ANN classification in feature space and by comparing this behaviour to that of traditional parametric classifiers such as maximum-likelihood, the ANN approach to image classification can be better understood.
Bibliography


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Appendices
Appendix - A

Summary of neural network literature for application of back-propagation theory in remote sensing applications
<table>
<thead>
<tr>
<th>AUTHORS</th>
<th>IMAGERY</th>
<th>OBJECTIVE</th>
<th>LEARNING FUNCTION</th>
<th>INPUT LAYER</th>
<th>HIDDEN LAYER</th>
<th>OUTPUT LAYER</th>
</tr>
</thead>
<tbody>
<tr>
<td>Civco, 1992</td>
<td>LandSat TM (6 bands)</td>
<td>Classification of 15 land cover types</td>
<td>Backpropagation</td>
<td>6 nodes</td>
<td></td>
<td>1 node</td>
</tr>
<tr>
<td>Lee et al., 1990</td>
<td>LandSat MSS (3 bands)</td>
<td>Classification of 4 cloud cover types</td>
<td>Backpropagation</td>
<td>9 nodes</td>
<td>2 cases: 6 and 15 in two layer case</td>
<td>3 nodes</td>
</tr>
<tr>
<td>Benediktsson et al., 1990</td>
<td>LandSat MSS (4 bands), Elevation, Slope, Aspect</td>
<td>Compared NN and traditional Classification of 10 land cover classes with multisource data</td>
<td>Backpropagation</td>
<td>56 nodes</td>
<td>32 nodes</td>
<td>10 nodes</td>
</tr>
<tr>
<td>Hopner et al., 1990</td>
<td>LandSat TM (4 bands)</td>
<td>Land cover classification of 4 land cover categories</td>
<td>Backpropagation</td>
<td>Array of 3x3 pixels with 4 nodes: 36 nodes</td>
<td>10 nodes</td>
<td>4 nodes</td>
</tr>
<tr>
<td>Key et al., 1989</td>
<td>Merged data sets of AVHRR &amp; SMMR Arctic data</td>
<td>Classification of 4 surface classes and 8 cloud cover classes</td>
<td>Backpropagation</td>
<td>7 nodes</td>
<td>10 nodes</td>
<td>12 nodes</td>
</tr>
<tr>
<td>Downey et al., 1990</td>
<td>LandSat TM (4 bands)</td>
<td>Land cover classification</td>
<td>Std. Backpropagation</td>
<td>3 nodes</td>
<td>12 nodes</td>
<td>15 nodes</td>
</tr>
<tr>
<td>Hura et al., 1994</td>
<td>Polotometric SAR</td>
<td>Terrain cover imagery classification</td>
<td>Learning Vector Quantization (LVQ) training algorithm</td>
<td>6 nodes</td>
<td>2 layers: (18-34 nodes)</td>
<td>20 nodes</td>
</tr>
<tr>
<td>Kanellopoulous et al., 1992</td>
<td>2 Date SPOT-HRV</td>
<td>Land cover classification of 20 land cover types</td>
<td>Multilayer perceptron model with backpropagation</td>
<td>6 nodes</td>
<td>2 layers: (18-34 nodes)</td>
<td>20 nodes</td>
</tr>
<tr>
<td>Yoshida and Onishi, 1994</td>
<td>LandSat TM (3 bands)</td>
<td>Classification of land cover types.</td>
<td>Backpropagation. Training patterns are selected based on geographical information and Kuhonen's Self-Organizing Feature Map</td>
<td>3 nodes</td>
<td>varying from 4 - 14 nodes</td>
<td>9 nodes</td>
</tr>
<tr>
<td>Sadjadi et al., 1993</td>
<td>Polarized SAR</td>
<td>Classification of land cover types.</td>
<td>Backpropagation. Dimensionality of feature space is reduced prior to the application of the NN using PCA</td>
<td>64 nodes</td>
<td>2 layers: (27 - 9 nodes)</td>
<td>3 nodes</td>
</tr>
</tbody>
</table>

While there are a variety of different neural networks models, most remote sensing applications have used a supervised feed-forward structure employing a back-propagation algorithm that adjusts the weights to produce convergence between the network outputs and the training data.
<table>
<thead>
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<th>OUTPUT LAYER</th>
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</thead>
<tbody>
<tr>
<td>Bischof et al., 1992</td>
<td>Landsat TM</td>
<td>Land cover classification</td>
<td>Backpropagation</td>
<td>7 nodes each consisting of 13 units</td>
<td>varying from 3 - 15 nodes</td>
<td>4 nodes</td>
</tr>
<tr>
<td>Cosen, 1993</td>
<td>Landsat TM (6 bands)</td>
<td>Land use and land cover information derivation for input to an automated GIS</td>
<td>Several variants of the standard Backpropagation</td>
<td>6 nodes</td>
<td>2 cases: (15 nodes in case 1; 6 - 15 nodes in case 2)</td>
<td>1 node</td>
</tr>
<tr>
<td>Ritter and Hepner, 1990</td>
<td>Landsat TM (4 bands)</td>
<td>Land cover classification</td>
<td>Std. Backpropagation, with assimilation of spatially adjacent pixels in both training and classification</td>
<td>3x3x4 array of nodes</td>
<td>10 nodes</td>
<td>4 nodes</td>
</tr>
<tr>
<td>Fosdy and McCulloch, 1992</td>
<td>SAR imagery</td>
<td>Classification of land cover using 2 techniques: Discriminant analysis and NN</td>
<td>Variant of std. Backpropagation learning (Quickpropagation)</td>
<td>4 nodes with bias</td>
<td>3 nodes</td>
<td>7 nodes</td>
</tr>
<tr>
<td>Viscus et al., 1996</td>
<td>Landsat TM</td>
<td>Comparison and visualization of feature space behavior of statistical and NN classifiers</td>
<td>Backpropagation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sergi et al., 1995</td>
<td>Landsat TM (6 bands)</td>
<td>Multispectral land cover classification using dimensional vector of Multispectral measurements concerning different pixels, and reducing the Dimensionality of data with PCA</td>
<td>3 NN architectures: Multi layer perceptron (MLP), Self-Organizing Feature Map (SOFM), and Hybrid Encoding Vector Quantization (HEVQ).</td>
<td>6 nodes</td>
<td>3 nodes</td>
<td>9 nodes</td>
</tr>
<tr>
<td>Heermann and Kraneruel, 1992</td>
<td>Landsat TM (3 bands)</td>
<td>Classification of land cover</td>
<td>Backpropagation</td>
<td>24 nodes</td>
<td>3 nodes</td>
<td>9 nodes</td>
</tr>
<tr>
<td>Paud and Schwerederdt, 1995</td>
<td>Landsat TM (6 bands)</td>
<td>Urban land use classification using NN and Maximum Likelihood classifier. Concluded that NN was superior in suppression of mixed pixel classification errors</td>
<td>Backpropagation</td>
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</tr>
<tr>
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</tr>
<tr>
<td>Giveco and Wang, 1994</td>
<td>2 Date Landsat TM (14 bands), illumination data, DEM and Textual</td>
<td>Explored potential to derive information on land cover composition of mixed pixels</td>
<td>Quick-propagation learning</td>
<td>3 nodes</td>
<td>6 nodes</td>
<td>3 nodes</td>
</tr>
<tr>
<td>Moody et al., 1996</td>
<td>Landsat TM (6 bands)</td>
<td>To detect mixed pixel response in coarse resolution satellite data</td>
<td>Multi-layer perceptron using backpropagation</td>
<td>6 nodes</td>
<td>12 nodes</td>
<td>5 nodes</td>
</tr>
<tr>
<td>Gopal et al., 1994</td>
<td>MODIS Imagery</td>
<td>Highlight the utility of ART-based NN for MODIS land cover classification</td>
<td>Fuzzy ART classifier</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Moody et al., 1993</td>
<td>MODIS Imagery</td>
<td>To show that NN output vectors need not be interpreted categorically, but under some circumstances can be used as fuzzy predictors of class membership and to detect mixed pixels,</td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Schmutz and Gebbink, 1994</td>
<td>3 types (Modular Airborne Imaging spectrometer with 30 bands; Landsat TM with 6 bands; and AVIRIS data with 220 bands)</td>
<td>A Neural network approach to special mixture analysis showing the relation between the intensities of a pixel and the fractions of its ground cover categories is described.</td>
<td>Back-propagation</td>
<td>6 nodes</td>
<td>2 cases (24 nodes for Landsat and 16 nodes for other data sets)</td>
<td>2 nodes</td>
</tr>
<tr>
<td>Finlay, 1996</td>
<td>2 data sets (Airborne Thematic Mapper with 3 band; and Landsat MSS image with 1 band)</td>
<td>Investigates the potential to derive information on the land-cover composition of mixed pixels from an ANN classification by relating the activation level of the ANN output units (strength of class membership) to land cover composition</td>
<td>Quick-propagation</td>
<td>3 nodes</td>
<td>2 layers (6 - 6 nodes)</td>
<td>3 nodes</td>
</tr>
</tbody>
</table>
Appendix -B

C - program listing for Gaussian smoothing algorithm
void Gaussian Smoothing With Moving Mask Size
Using SIGMA As Input Parameter.

Raj (12/16/96)

# include <stdio.h>
# include <stdlib.h>
# include <string.h>
# include <fcntl.h>
# include <math.h>
# include "gaussian.h"

#define FILESIZE 30
#define PI 3.1415927

/* Global Variables */
char infilename[FILESIZE], outfilename[FILESIZE];
FILE *ifp, *ofp;
short ppn, nol;
struct ing

main(argc, argv)
int argc;
char *argv[];
{

/* Check for valid number of arguments */
if ((argc < 5) || (argc <= 1))
{
    printf("Usage: gaussian <input image> <output image> <mask> <sigma> \n");
    return(1);
}

/* Check for input filename */
if ((argc < 5) || (argc <= 1))
{
    printf("Enter Input Image: ");
    fscanf(stdin, "%s", infilename);
    ifp = fopen(infilename, "rb");
}
else
{
    strcpy(infilename, argv[1]);
    ifp = fopen(infilename, "rb");
}

/* Check for output filename */
if ((argc < 5) || (argc <= 1))
{
    printf("Enter Output Image: ");
    fscanf(stdin, "%s", outfilename);
    ofp = fopen(outfilename, "wb");
}
} else
{
    strcpy(outfile, argv[2]);
ofp = fopen(outfile, "wb");
}

/* Check for mask size */
if((argc < 5) || (argc <= 1))
{
    printf("Enter Mask size for Gaussian Filtering: ");
    scanf(stdin, "%d", &mask);
}
else
    mask = (int) atoi(argv[3]);

maskrows = (int) (mask/2.0);
maskcols = (int) (mask/2.0);
gauss_rows = (int) (mask-1.0)/2.0;
gauss_cols = (int) (mask-1.0)/2.0;

/* Check for Sigma Size */
if((argc < 5) || (argc <= 1))
{
    printf("Enter Sigma Size for Gaussian Filter: ");
    scanf(stdin, "%f", sigma);
}
else
    sigma = (double) atof(argv[4]);

/* If all input parameters are present, print them */
printf("\n");
printf("Input file selected is \"%s\", infile);
printf("Output file selected is \"%s\", outfile);
printf("Mask size selected is \"%d\", mask);
printf("Mask Rows selected is \"%d\", maskrows);
printf("Mask Columns selected is \"%d\", maskcols);
printf("Sigma selected is \"%f\", sigma);
printf("\n");

printf("\nReading Input File ....\n");
read_cot(&ifp, infile);

printf("\nCalculating Gaussian filter coefficients....\n");
printf("\nComputing Gaussian Template....\n");
printf("\nPrinting Gaussian Template....\n");

compute_gaussian(&inp);

printf("\nPerforming Convolution with input image : \n");
convolve_gaussian(&ifp, &ofp, &inp);

read_cot(&ofp, outfile);
printf("\n");
printf("\n => Successfully completed Gaussian Smoothing <= \n\n");
return(0);
}

/*
FUNCTION : compute_gaussian()
*/
/* PURPOSE : To compute mask coefficients for first order derivative of Gaussian Smoothing filter
*/
/* PARAMETERS: struct ingr inp
*/
/* CALLING : compute_gaussian(struct ingr inp)
*/
/* INPUTS : Structure for generic input raster image
*/
/* OUTPUTS : n*n mask coefficients for First derivative of Gaussian filter.
*/
/*.Normalize Gaussian Template values */
compute_gaussian(struct ingr inp)
{
double temp, temp1;
double temp2, temp3;
norm_sum = 0.0;
for (x=0; x<maskrows; x++) {
    for (y=0; y<maskcols; y++) {
        temp = (double) ( 1.0 / (2.0 * PI * sigma * sigma) );
        temp1 = (double) ((x-2.0)*(x-2.0)) + (y-2.0)*(y-2.0) ;
        temp2 = (double) ( 2.0 * sigma * sigma ) ;
        temp3 = (double) ( temp * exp(-temp1/temp2) ) ;
        norm_sum+= temp3;
        n = (maskcols * (maskrows - y - 1) + x);
        inp.template[n] = (double) temp3;
    }
}

/* Normalize Gaussian Template values */
for (x=0; x<maskrows; x++) {
    for (y=0; y<maskcols; y++) {
        n = (maskcols * (maskrows - y - 1) + x);
        temp3 = inp.template[n] / norm_sum;
        inp.template[n] = (double) temp3;
        fprintf(stdout, " %f\t", inp.template[n]);
    }
}
return(inp.template[n]);

convolve_gaussian(FILE *ifp, FILE *ofp, struct ingr inp)
{
  int  dtc, app, ver;
  int  scn, slo, dtm;
  short  htc, wtf;

  /* Open input file for reading */
  ifp = fopen(infile, "rb");
  if (ifp == NULL)
  {
    printf("Error in opening file %s to read \n", infile);
    exit(1);
  }

  /* Seek to end of file */
  byte = fseek(ifp, 0L, SEEK_END);
  filesize = ftell(ifp);
  rewind(ifp);

  /* allocate memory for input buffer */
  inp.data = (unsigned char *) malloc(filesize);
  if (!inp.data)
  {
    printf("Error: Insufficient Memory\n", filesize);
    exit(1);
  }

  /* Open output file for writing */
  ofp = fopen(outfile, "wb");
  if (ofp == NULL)
  {
    printf("Error in opening file %s to write \n", outfile);
    exit(1);
  }

  /* Do convolution */
  ...

  /* close the files */
  fclose(ifp);
  fclose(ofp);

  return(0);
}
/* set field for header type code */
htc = (short)0x0908;
ret = fseek(ofp, 0, SEEK_SET);
byte = putw((short)htc, ofp);

/* set field for words to follow */
wtf = (short)0x01FE;
position = (long int)2;
ret = fseek(ofp, position, SEEK_SET);
byte = putw((short)wtf, ofp);

/* set field for data type code */
position = (long int)4;
ret = fseek(ofp, position, SEEK_SET);
byte = fputc((short)2, ofp);

/* set field for application type */
position = (long int)6;
ret = fseek(ofp, position, SEEK_SET);
byte = fputc((short)0, ofp);

/* set field for PIXELS PER LINES (COLUMNS) */
position = (long int)184;
ret = fseek(ofp, position, SEEK_SET);
byte = putw((int)ppl, ofp);

/* set field for NUMBER OF LINES (ROWS) */
position = (long int)188;
ret = fseek(ofp, position, SEEK_SET);
byte = putw((int)nol, ofp);

/* set field for SCAN LINE ORIENTATION */
position = (long int)194;
ret = fseek(ofp, position, SEEK_SET);
byte = fputc((unsigned char)4, ofp);

/* set field for SCANNABLE FLAG */
position = (long int)195;
ret = fseek(ofp, position, SEEK_SET);
byte = fputc((unsigned char)0, ofp);

/* Set Field for DATA TYPE MODIFIER */
position = (long int)212;
ret = fseek(ofp, position, SEEK_SET);
byte = fputc((short)0, ofp);

/* set field for VERSION NUMBER */
position = (long int)511;
ret = fseek(ofp, position, SEEK_SET);
byte = fputc((unsigned char)3, ofp);

/* Seek to end of header : 1024 byte to write results */
position = (long int)1024;
ret = fseek(ofp, position, SEEK_SET);

/* Read infile into input buffer using Binary mode */
if (fread(inp.data, filesize, sizeof(unsigned char), ifp) != 1)
{
   printf("\nError: could not read data into inp buffer \n");
   exit(1);
}

/* set pointer to image data */
inp.image = inp.data + 1024;

printf(stderr, "\nPerforming Gaussian Kernel Smoothing......\n");

for (j=maskrows; j<(nrows-maskrows); j++) {
   for (i=maskcols; i<(ncols-maskcols); i++) {

      gauss = 0.0;

      for (y=-gauss_rows; y<=gauss_rows; y++) {
         for (x=-gauss_cols; x<=gauss_cols; x++) {

            gauss1 = (double) (* (inp.image + i + x + (long)j + y * (long)ncols));
            gauss += (double) (gauss1 * (*(inp.template + x + y * maskrows)));
         }
      }

      *(inp.image + (j * ncols) + i) = (unsigned char) (255 * (MAX-MIN) * (gauss - MIN));
   }
}

/* write results of variance calculation to output file */
if (fwrite(inp.image, filesize, sizeof(unsigned char), ofp) != 1)
{
   printf("\nError: Could not write image data to %s\n", outfile);
   exit(1);
}

free(inp.data);
free(inp.image);

rewind(ifp);
fclose(ifp);
rewind(ofp);
fclose(ofp);

return(0);
Appendix - C

C - program listing for resampling by aggregation algorithm
/* Resampling by aggregation using averaging method to sample every n*n pixel using moving window procedure
Raj (12/15/96) */

#include <stdio.h>
#include <stdlib.h>
#include <string.h>
#include <fcntl.h>
#include <math.h>
#include "aggregate.h"

#define FILESIZE 30

/* Global Variables */
char char infile[FILESIZE], outfile[FILESIZE];
FILE *ifp, *ofp;
int ppl, nol;
struct inp inp;

/* Declaration for main */
main(argc,argv)
in argc;
char *argv[];
{

    /* check for valid number of arguments */
    if ( (argc < 4) || (argc <= 1) )
    {
        printf("\n Aggregate <input image> <output image> <Mask size>: \n");
        return(1);
    }

    /* Check for input filename */
    if ( (argc < 4) || (argc <= 1) )
    {
        printf("\n %s", "Enter Input Image: ");
        fscanf(stdin,"%s", infile);
        ifp = fopen(infile, "rb");
    }
    else
    {
        strcpy(infile, argv[1]);
        ifp = fopen(argv[1], "rb");
    }

    /* check for output filename */
    if ( (argc < 4) || (argc <= 1) )
    {
        printf("\n %s", "Enter Output Image: ");
    }
```c
fscanf(stdin, "%s", outfile);
ofp = fopen(outfile, "wb");
}
else
{
    strcpy(outfile, argv[2]);
ofp = fopen(argv[2], "wb");
}

/* Check for window size */
if ((argc < 4) || (argc <= 1))
{
    printf("Enter Window (Mask) Size: ");
    scanf("%d", &mask);
}
else
{
    mask = (int) atoi(argv[3]);
}

Nx = Ny = mask;
maskrows = (int)(mask/2.0);
maskcols = (int)(mask/2.0);

/* if all input arguments are present, print them */
printf("\n");
printf("\n \%s\t\%s", "Input Image selected is: ", infile);
printf("\n \%s\t\%s", "Output Image selected is: ", outfile);
printf("\n \%s\t\%d", "Mask Size selected is: ", mask);
printf("\n");

printf("\n Reading input file....\n");
read_cot(&ipt, infile);
rewind(ifp);
fclose(ifp);

printf("\n\n Performing Aggregation Analysis....\n\n");
aggregation_calc(&ifp, &ofp);

printf("\n\n Printing Header for Output file....\n");
read_cot(&ofp, outfile);

printf("\n\n==> Completed Aggregation Procedure <=\n\n");
rewind(ifp);
fclose(ifp);
rewind(ofp);
fclose(ofp);
```
return(0);

FUNCTION : aggregation_calc()  
PURPOSE : To perform aggregation procedure using moving filter. The result is coarser resolution images degraded by a factor varying with mask size  
PARAMETERS: FILE *ifp, FILE *ofp  
CALLING : aggregation_calc(FILE *ifp, FILE *ofp)  
INPUTS : Input and Output raster image file pointers  
OUTPUTS : result of resampling input image file with the specified mask size.

aggregation_calc(FILE *ifp, FILE *ofp)
{
    int dtc, app, ver;
    int scn, slo, dtm;
    int htc, wtf;
    int sum, variance, std;
    short mean, smoment, var, total;
    int sindex, eindex;

    /* open input file for reading */
    ifp = fopen(infile, "rb");

    /* open output file for writing */
    ofp = fopen(outfile, "wb");

    /* seek to eof in input image */
    ret = fseek(ifp, 0L, SEEK_END);
    filesize = ftell(ifp);
    rewind(ifp);

    /* allocate memory For input buffer */
    inp.data = (unsigned char *) malloc(filesize);
    if (! (inp.data))
    {
        printf("Error: Insufficient Memory\n", filesize);
        exit(1);
    }

    put_header(&ofp);

    /* read infile using binary mode */
    if (fread(inp.data, filesize, sizeof(unsigned char), ifp) != 1)
    {
        printf("\n Error: Could not read %s file\n", infile);
    }
exit(1);
}

/* Set file pointer to image data in input image */
inp.image = inp.data + 1024;

fprintf(stderr, "\n Performing Aggregation Calculation......\n\n");

for (j=0; j<(nrows-maskrows); j++)
    for (i=0; i<(ncols-maskcols); i++)
        sindex = (j * ncols * maskrows + j*maskcols);
        sum = 0.0;

for (y=0; y<maskrows; y++)
    for (x=0; x<maskcols; x++)
        eindex = sindex +(y*ncols)+x;
        sum = sum + *(inp.image+eindex);

*(inp.image+(long)j*ncols+i) = (unsigned char)
    ( 255.0 / (MAX - MIN) * ((sum/(maskcols*maskrows)) - MIN) );

/* seek to end of header: 1024 bytes to write results */
position = (long int)1024;
ret = fseek(ofp, position, SEEK_SET);

/* Write results of aggregation to output file */
if (fwrite(inp.image, filesize, sizeof(unsigned char), ofp) != 1)
{
    printf("Error: Could not write image data to output.\n");
    exit(1);
}

free(inp.data);

rewind(ifp);
fclose(ifp);
rewind(ofp);
fclose(ofp);
return(0);
Appendix - D

C - program listing for pattern09
/* Converts Image Grey level from 0-255 range to 0.1 - 0.9 range (normalized input) for input to normalized data to neural network Raj (12/14/96) */

#include <stdio.h>
#include <stdlib.h>
#include <fcntl.h>
#include <string.h>
#include <math.h>
#include <malloc.h>

#define RAWNUM 8 /* Bit level of input image data */
#define Amax 0.9 /* Neural Network Upper Data limit */
#define Amin 0.1 /* Neural Network Lower Data limit */
#define Vmax 255.0 /* Maximum Gray level in i/p data */
#define Vmin 0.0 /* Minimum Gray level in o/p data */

main(argc, argv)
int argc;
char *argv[];
{
    int i;
    int filesize;
    double out_val;
    double r;
    long int ncols, nrows;
    unsigned char *buffer, *ptr, *limit;
    char infUe[30];
    FILE *ifp;

    if ( (argc < 4) || (argc < 1) )
    {
        printf("Usage: patternO9 <ncols> <nrows> <infile> <stdout> \n\n");
        return(1);
    }

    /* Request number of columns in input image */
    if ( (argc < 4) || (argc < 1) )
    {
        printf("Enter number of Columns :");
        scanf("%ld", &ncols);
    }
    else
    
    /* Request number of Rows in input image */
    if ( (argc < 4) || (argc < 1) )
{ 
  printf("\n Enter number of Rows : ");
  scanf("%ld", &nrows);
} 

else 
  nrows = (long int) atoi(argv[2]);

/* Request input image name */
if ((argc < 4) || (argc < 1))
{
  printf("\n Enter name of input image : ");
  fscanf(stdin, "%s", infile);
  ifp = fopen(infile, "rb");
} 
else 
{
  strcpy(infile, argv[3]);
  ifp = fopen(infile, "rb");
}

filesize = (int) (ncols * nrows);

if ((unsigned char *)malloc(filesize) == NULL) 
{
  fprintf(stderr, "ERROR: Insufficient Memory available : ");
  exit(-1);
}

if ((unsigned char *)fread(buffer, filesize, sizeof(unsigned char), ifp) == NULL) 
{
  fprintf(stderr, "ERROR: Could not read from %s\n", infile);
  exit(-1);
}

/* Scale input data from 0-255 to 0.1-0.9 */ 
/* Using Equation from Timothy Masters C++ */ 
/* A = r*V + (Amin - r*Vmin) */

r = (double) ( (Amax - Amin) / (Vmax - Vmin) );
i = 0;
limit = buffer + filesize;

for(ptr=buffer; ptr<limit; ptr++)
{

  out_val = (double) ( ((double)*ptr) * r ) + 0.1;

  if ((i % ncols == 0) || (i % RAWNUM == 0)) && (i != 0) 
    printf("\n");
  i++;
printf ("%.6f ", out_val);
}

printf ("\n");
free(buffer);
fclose(ifp);

return(0);
}
Appendix - E

Script for implementing Batch mode training and testing
SNNS BATCH Program to execute SNNS xgui calls in batch mode

Raj (01/23/97)

This execution run loads a network and pattern file with variable pattern format, initializes the network, trains it for 50000 cycles (or stops, if the error is less than 0.1), and finally computes the result file train.res

PerformActions:

NetworkFile: /scratch/raj/decatur.net
InitFunction: Randomize_Weights
NoOfInitParam: 2
InitParam: -1.0 1.0

LearnPatternFile: /scratch/raj/train.pat
NoOfVarDim: 2 2
SubPatternSize: 3 3
SubPatternOSize: 1 2
SubPatternOStep: 3 3
SubPatternOSStep: 3 3
NoOfLearnParam: 2
LearnParam: 0.25 0.1
MaxLearnCycles: 50000
MaxErrorToStop: 0.1
Shuffle: YES

TrainedNetworkFile: train.net
ResultFile: train.res
ResultMinMaxPattern: 1 4
ResultIncludeInput: NO
ResultIncludeOutput: NO

This execution run continues the training of the already loaded file for another 10000 cycles before creating a second result file.

PerformActions:

NetworkFile: /scratch/raj/decatur.net

LearnPatternFile: /scratch/raj/train.pat
NoOfLearnParam: 2
LearnParam: 0.2 0.1
MaxLearnCycles: 50000
MaxErrorToStop: 0.1
Shuffle: YES
#

ResultFile: decatur.res
ResultMinMaxPattern: 1 4
ResultIncludeInput: NO
ResultIncludeOutput: NO
TrainedNetworkFile: decaturl.net
#

#This execution run concludes the training of the already loaded file.
#After another 10000 cycles of the training with changed learning.
#Parameters of the final network is saved to a file and a third result
#file is created.
#
Appendix - F

C - program listing for pattern255
I* Converts Image Grey level range from 0.1-0.9 range to * /
I* range 0-255 range for displaying neural network * /
I* output results. * /
I* Raj (12/14/96) */
*******************************************************************************/
#include <stdio.h>
#include <stdlib.h>
#include <fcntl.h>
#include <malloc.h>
#include <math.h>

#define Amax 0.9
#define Amin 0.1
#define Vmax 255.0
#define Vmin 0.0

main(argc, argv)
int argc;
char *argv[];
{
  float r, temp;
  char infile[30], outfile[30];
  unsigned char out_val;
  FILE *ifp, *ofp;

  if ( (argc < 3) || (argc < 1) )
  { 
    printf (stderr, "Usage: Rescale Output Activation Values from SNNS to image format...\n");
    printf (stderr, "Usage: pattern255 <infile> <outfile> \n\n");
    return(1);
  }

  /* Prompt for input image file name */
  if ( (argc < 3) || (argc < 1) )
  { 
    printf("Enter Name of Input image : ");
    scanf(stdin, "%s", infile);
    ifp = fopen(infile, "r");
  } else
  { 
    strcpy(infile, argv[1]);
    ifp = fopen(infile, "r");
  }

  /* Prompt for Output image file name */
  if ( (argc < 3) || (argc < 1) )
```c
    printf ("Enter Name of Output image : ");
    fscanf(stdin, "%s", outfile);
    ofp = fopen(outfile, "w");
}
else
{
    strcpy(outfile, argv[2]);
    ofp = fopen(outfile, "w");
}

/* If all input arguments are present; print them */
printf ("n");
printf ("\n\n Input File = \%s\n", infile);
printf ("\n\n Output File = \%s\n", outfile);
printf ("\n");

/* Scale input data from 0-255 to 0.1-0.9 */
/* Using Equation from Timothy Masters C++ */
/* A = r*V + (Amin - r*Vmin) */

r = (double) ( (Amax - Amin) / (Vmax - Vmin) );

while (fscanf(ifp, "%f", &temp) != EOF )
{
    out_val = (unsigned char) ( (((double)temp/r)*r) + 0.5 );
    fprintf (ofp, "%d ", out_val);
}

return(0);
```

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Appendix - G

C - program listing for local variance analysis
/***************************************************************/
/* Determination of Second Order Texture Measure (VARIANCE). */
/* Adopted from Woodcock and Strahler. */
/* Raj (12/16/96) */
/***************************************************************/
#include <stdio.h>
#include <stdlib.h>
#include <string.h>
#include <fcntl.h>
#include <math.h>
#include "variance.h"

#define FILESIZE 30
#define ODD 0
#define EVEN 1

/* Global Variables */
char infIe[FILESIZE], outfile[FILESIZE];
FILE *ifp, *ofp;
int ppl, nol, temp;
struct ingr inp;

/* Declaration for main */
main(argc,argv)
int argc;
char *argv[];
{
    if ( (argc < 4) || (argc <= 1) )
    {
        printf("Usage is: variance <input image> <output image> <window size> \n\n");
        return(1);
    }

    /* Check for input filename */
    if ( (argc < 4) || (argc <= 1) )
    {
        printf("Enter Input Image: ");
        fscanf(stdin,"%s", infIe);
        ifp = fopen(infIe, "rb");
    }
    else
    {
        strcpy(infIe, argv[1]);
        ifp = fopen(argv[1], "rb");
    }

    /* check for output filename */
    if ( (argc < 4) || (argc <= 1) )
    {
        printf("Enter Output Image: ");
        fscanf(stdin,"%s", outfile);
    }
    else
    {
        strcpy(outfile, argv[2]);
        ofp = fopen(outfile, "wb");
    }

    while(1)
    {
        /* Read a Line */
        char line[200];
        int length = 0;
        ifp

        /* Parse Line */
        /* Do something with the line */
    }

    /* Close files */
    fclose(ifp);
    fclose(ofp);
}

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printf ("\n %s", "Enter Output Image: ");
 fscanf(stdin,"%s", outfile);
ofp = fopen(outfile, "wb");
}
else
{
    strcpy(outfile, argv[2]);
ofp = fopen(argv[2], "wb");
}

/* Check for window size */
if ( (argc < 4 ) || (argc <= 1 ) )
{
    printf ("\n Enter Window (Mask) Size: ");
scanf ("%d", &mask);
}
else
{
    mask = (int) atoi(argv[3]);
    maskrows = (int) (mask/2.0);
    maskcols = (int) (mask/2.0);
}

/* Determine Mask Dimensions */
if ( mask==2 || mask==4 || mask==6 || mask==8 || mask==10 )
mask_size = EVEN;
if ( mask==3 || mask==5 || mask==7 || mask==9 )
mask_size = ODD;

/* if all input arguments are present, print them */
printf ("\n");
printf ("\n %s\t\t %s", "Input Image selected is:", infile);
printf ("\n %s\t\t %s", "Output Image selected is:", outfile);
printf ("\n %s\t\t %d", "Mask Size selected is: ", mask);
printf ("\n");

printf ("\n Reading input file....\n");
read_cot(&ifp, infile);

rewind (ifp);
fclose (ifp);

printf ("\n Calculating Variance......\n");
variance_calc(&ifp, &ofp);

read_cot(&ofp, outfile);

printf ("\n\n==> Completed Calculating Texture (variance) Measures <=\n\n");
fclose (ifp);
fclose (ofp);

return(0);

/* FUNCTION : read_cot() */
/* PURPOSE : To read/write Header records from a Generic Intergraph Raster Image */
/* PARAMETERS: ifp, infile */
/* CALLING : read_cot(FILE *ifp, char *infile) */
/* INPUTS : Input file pointer and generic raster filename */
/* OUTPUTS : Header Information and min/max byte values */

read_cot (FILE *ifp, char *infile)
{
    int dte, app, ver;
    int scn, slo, dtm;
    short htc, wtf;

    /* Open Input image for reading */
    ifp = fopen(infile, "rb");
    if (ifp == NULL)
    {
        fprintf(stderr, "Error in opening file %s\n", infile);
        return(0);
    }

    get_header(&ifp);

    /* Seek to end of Header (1024) byte in input image */
    position = (long int)1024;
    ret = fseek(ifp, position, SEEK_SET);

    /* Initialize MIN and MAX */
    MIN = 255;
    MAX = 0;

    /* Open input file for reading */
    while ( (byte = getc(ifp)) != EOF )
    {
        if (byte < MIN)
            MIN = byte;

        if (byte > MAX)
            MAX = byte;
    }

    /* Continue processing... */
}

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/* Print Header Information for Input Image */
printf ("\n\n Printing Header for image => %s <= \n\n", infUe);
printf (stdout, "Pixel Per Line = %d", ppl);
printf (stdout, "Number Of Lines = %d", nol);
printf (stdout, "Minimum Gray Value = %d", MIN);
printf (stdout, "Maximum Gray Value = %d", MAX);
printf ("\n\n");

rewind (ifp);
close (ifp);
return(0);
}

/***********************************************************/
/* FUNCTION : variance_calc */
/* PURPOSE : To calculate second order texture measures    */
/* (variance) from input raster image using                */
/* varying mask size                                       */
/* PARAMETERS:FILE *ifp, FILE *ofp                         */
/* CALLING : variance_calc(FILE *ifp, FILE *ofp)           */
/* INPUTS : Input and Output file pointers                */
/* OUTPUTS : Mean Standard deviation for the specified mask*/
/***********************************************************/
variance_calc (FILE *ifp, FILE *ofp)
{
    int dtc, app, ver;
    int scn, slo, dtm;
    short htc, wtf;
    int variance, std;
    int mean, smoment, var, total;

    /* Open Input file for reading */
    ifp = fopen(infile, "rb");
    if (ifp == NULL)
    {
        fprintf(stderr, "\nError in opening file %s\n", infile);
        return(0);
    }

    /* Seek to EOF in input image */
    ret = fseek(ifp, OL, SEEK_END);
    filesize = ftell(ifp);
    rewind(ifp);

    /* allocate memory For input buffer */
inp.data = (unsigned char *) malloc (filesize);
if (!(inp.data))
    {
        printf("Error: Insufficient Memory\n", filesize);
        exit(1);
    }

/* Open output file for writing */
ofp = fopen(outfile, "wb");
if (ofp == NULL)
    {
        fprintf(stderr, "Error in opening file %s\n", outfile);
        return(0);
    }

put_header(&ofp);

/* read infile using Binary mode */
if (fread(inp.data, filesize, sizeof(unsigned char), ifp) != 1)
    {
        printf("Error: could not read %s file. \n", infile);
        exit(1);
    }

// set pointer to image data in input image */
inp.image = inp.data + 1024;

fprintf(stderr, "Performing Variance Calculation.....\n");
if ( mask.size = EVEN )
    {
        for (j=maskrows; j<(nrows-maskrows); j++) {
            for (i=maskcols; i<(ncols-maskcols); i++) {

                sum = 0.0;
                suml = 0.0;
                total = 0.0;

                for (y=0; y<=maskrows; y++) {
                    for (x=0; x<=maskcols; x++) {

                        sum = ( sum + (*(inp.image+i+x+(long)(i+y)*ncols)) );
                        suml = ( suml + (pow(*(inp.image+i+x+(long)(i+y)*ncols), 2)) );
                        total++;
                    }
                }

                mean = (int) (sum/total);
                smoment = (int) (suml/total);
                var = (int) (smoment-(mean*mean));
                variance+= var;
                std = (double) sqrt(var);
*(inp.image+(long)j*ncols+i) = (unsigned char) (std + 0.5);

} }
}

else if ( mask_size = ODD )
{

for (j=maskrows; j<(nrows-maskrows); j++) {
for (i=maskcols; i<(ncols-maskcols); i++) {

sum   = 0.0;
sum1  = 0.0;
total = 0.0;

for (y=-maskrows; y<=maskrows; y++) {
for (x=-maskcols; x<=maskcols; x++) {

sum = ( sum + (*(inp.image+i+x+(long)ncols)));
sum1 = ( sum1 + (pow(*(inp.image+i+x+(long)ncols), 2)));
total ++;

}

}

mean  = (int) (sum/total);
smoment = (int) (sum1/total);
var   = (int) (smoment-mean*mean);
variance+= var;
std    = (double) sqrt(var);

*(inp.image+(long)j*ncols+i) = (unsigned char) (std + 0.5);

}
}

else

fprintf (stderr, "An Error in Specifying Mask size !!!\n");

/* Seek to end of header : 1024 byte to write results */
position = (long int)1024;
ret = fseek (ofp, position, SEEK_SET);

/* write results of variance calculation to output file */
if (fwrite(inp.image, filesize, sizeof(unsigned char), ofp) != 1)
{
printf ("Error: Could not write image data to %s\n", outfile);
exit(1);

window = (int) ( (nrows-maskrows) * (ncols-maskcols) );

printf ("\n\n The Mean Standard Deviation for Mask Size %d*%d is %f\n\n", mask, mask, sqrt(variance/window) );

free(inp.data);
rewind (ifp);
fclose (ifp);
rewind (ofp);
fclose (ofp);

return(0);
}
Appendix - H

C - program listing for calculating total area / perimeter in classified raster imagery
Program to perform area calculation on Intergraph raster images

Raj (03/16/97)

#include <stdio.h>
#include <stdlib.h>
#include <fcntl.h>
#include <string.h>
#include <math.h>
#include "area.h"

#define FILESIZE 30

/* Global Variables */
char infile[FILESIZE], outfile[FILESIZE];
FILE *ifp, *ofp;
int ppl, nol, temp;
int unused;
int nx, ny;
struct ingr inp;

/* Declaration for main */
main(argc,argv)
int argc;
char *argv[];
char *argv[];
{
    /* check for valid number of arguments */
    if ( (argc > 4) || (argc <= 1) )
    {
        printf("Enter Input Image: ");
        scanf(stdin,"%s", infile);
        ifp = fopen(infile, "rb");
        return(0);
    }

    /* Check for input filename */
    if ( (argc > 4) || (argc <= 1) )
    {
        printf("Enter Input Image: ");
        fscanf(stdin,"%s", infile);
        ifp = fopen(infile, "rb");
    }
    else
    {
        strcpy(infile, argv[1]);
        ifp = fopen(argv[1], "rb");
    }

    /* check for pixel size in x-dimension */
    if ( (argc > 4) || (argc <= 1) )
    {
printf("\n %s", "Enter pixel size in x-dimension: ");
scanf("%d", &nx);
}
else
nx = (int) atoi(argv[2]);

/* check for pixel size in y-dimension */
if ( (argc > 4) || (argc <= 1) )
{
    printf("\n %s", "Enter pixel size in y-dimension: ");
    scanf("%d", &ny);
}
else
ny = (int) atoi(argv[3]);

/* if all input arguments are present, print them */
printf("\n");
printf("\n %s\t\t %s", "Input Image selected is: ", infile);
printf("\n %s\t\t %d", "Pixel size in x-dimension is: ", nx);
printf("\n %s\t\t %d", "Pixel size in y-dimension is: ", ny);
printf("\n");
read_cot(&ifp, infile);
rewind(ifp);
fclose(ifp);

(int) area_calc(&ifp);

rewind(ifp);
fclose(ifp);

return(0);
}

/*****************************/
/* FUNCTION : read_cot() */
/* PURPOSE : To read/write Header records from a Generic */
/* Intergraph Raster Image */
/* PARAMETERS:ifp, infile */
/* CALLING : read_cot(FILE *ifp, char *infile) */
/* INPUTS : Input file pointer and generic raster filename */
/* OUTPUTS : Header Information and min/max byte values */
/*****************************/
read_cot (FILE *ifp, char *infile)
{
    int dtc, app, ver;

int sen, slo, dtm;
short htc, wtf;
/* Open Input image for reading */
ifp = fopen(infile, "rb");
if (ifp == NULL)
{
    fprintf(stderr, "\nError in opening file %s\n", infile);
    return(0);
}
get_header(&ifp);

/* Seek to end of Header (1024) byte in input image */
position = (long int)1024;
ret = fseek(ifp, position, SEEK_SET);

/* Initialize MIN and MAX */
MIN = 255;
MAX = 0;

/* Open input file for reading */
while ( (byte = getc(ifp)) != EOF )
{
    if (byte < MIN)
        MIN = byte;
    if (byte > MAX)
        MAX = byte;
}

printf ("\n\n Printing Header for image == > %s <= = \n\n", infile);
fprintf (stdout," Pixel Per Line = %d\n", ppl);
fprintf (stdout," Number Of Lines = %d\n", nol);
fprintf (stdout," Minimum Gray Value = %d\n", MIN);
fprintf (stdout," Maximum Gray Value = %d\n", MAX);
printf ("\n\n");

rewind (ifp);
fclose (ifp);
return(0);
}
FUNCTION : area_calc

PURPOSE : To perform area mensuration on raster images

PARAMETERS: ifp, infile

CALLING : area_calc(&ifp)

INPUTS : Input file pointer and generic raster filename

OUTPUTS : Header Information and min/max byte values

area_calc (FILE *ifp)
{
    int land, water;
    int area;

    /* Open input file for reading */
    ifp = fopen(infile, "rb");
    if (ifp == NULL)
    {
        fprintf(stderr, "% Error in opening file %s\n", infile);
        return(0);
    }

    /* Seek to EOF in input image */
    ret = fseek(ifp, 0L, SEEK_END);
    filesize = ftell(ifp);
    rewind(ifp);

    /* Allocate memory for input buffer */
    inp.data = (unsigned char *) malloc (filesize);
    if(!(inp.data))
    {
        printf("Erron Insufficient Memory\n", filesize);
        exit(1);
    }

    /* Read input file using binary file mode */
    if (fread(inp.data, filesize, sizeof(unsigned char), ifp) != 1)
    {
        printf("\n Error in reading input file %s\n", infile);
        exit(1);
    }

    inp.image = inp.data + 1024;

    /* Do area calculations on selected input image */
    fprintf(stderr,"\n PERFORMING AREA CALCULATION.....\n");

    land = 0;
    water = 0;
unused = 0;

for (j = 0; j < nrows; j++) {
    for (i = 0; i < ncols; i++) {

        if (*inp.image+j*ncols+i) == 255 )
            land++;

        if (*inp.image+j*ncols+i) == 1 )
            water++;

        if ( (*(inp.image+j*ncols+i) > 1) && (*(inp.image+j*ncols+i) < 255) )
            unused++;

    }
}

printf ("\n The AREA (255) for image %s = %f
", infîle, (double)(land*nx*nx) );
printf (" The AREA (1) for image %s = infile, (double)(water*ny*ny) );
printf ("\n The number of land pixels = %d
", land);
printf (" The number of water pixels = %d
", water);
printf (" The number of unused pixels = %d
", unused);

fflush(ifp);
free((unsigned char *)inp.data);

return(0);
}
Appendix - I

C - program listing for calculating lacunarity function
#include <stdio.h>
#include <stdlib.h>
#include <string.h>
#include <fcntl.h>
#include <math.h>
#include "lacunar.h"

#define FILESIZE 30
#define ODD 0
#define EVEN 1

/* Global Variables */
char infile[FILESIZE], outfile[FILESIZE];
FILE *ifp;
int box, box_size;
int boxrows, boxcols;
int temp;
int nol, ppl;
struct ingr inp;

/* Declaration for main */
main(argc,argv)
int argc;
char *argv[];
{
    /* check for valid number of arguments */
    if ( (argc < 3) || (argc <= 1) )
    {
        fprintf(stdout,"\n Usage is: Lacunarity <input image> <Box size> \n\n");
        return(1);
    }

    /* Check for input filename */
    if ( (argc > 3) || (argc <= 1) )
    {
        printf("\n %s", "Enter Input filename: ");
        fscanf(stdin,"%s", infile);
        ifp = fopen(infile, "rb");
    }
    else
    {
        strcpy(infile, argv[1]);
        ifp = fopen(infile, "rb");
    }
I*
Check for Box size */
if ((argc > 3) || (argc <= 1))
{
    printf ("Enter Box Size: ");
    scanf ("%d", &box);
}
else
{
    box = (int) atoi(argv[2]);
    boxrows = (int) (box/2.0);
    boxcols = (int) (box/2.0);
}

/* Determine Box dimensions for convolution purposes */
if (box % 2 == 0) box_size = EVEN;
else box_size = ODD;

/* if all input arguments are present, print them */
printf ("\n");
printf ("\n %s\t %s", "Input Image selected is: ", infile);
printf ("\n %s\t %d", "Box Size selected is: ", box);
printf ("\n");

printf ("\n Reading input file....\n");
read_cot(&ifjp, infile);
rewind(ifp);

printf ("\n Calculating Lacunarity Didex....\n\n");
box_count(&ifp, box);

printf ("\n\n ==> Completed Calculating Lacunarity Index Measures < ==\n\n");
fclose(ifp);

return(0);

*******************************************************************************/
/* FUNCTION : box_count() */
/* PURPOSE : Uses Gliding Box algorithm by Allan & Cloitres */
/* to calculate box mass (number of occupied sites (land pixels) for varying box size */
/* PARAMETERS:FILE *ifp, int box */
/* CALLING : box_count(FILE *ifp, int box) */
/* INPUTS : Input file pointer and Box size */
/* OUTPUTS : Lacunarity Index (lacunarity) for entire image */
*******************************************************************************/
box_count(FILE *ifp, int box)
{
    int    dtc, app, ver;
    int    scn, slo, dtm;
    short  htc, wtf;
    int    s, scount;
    double sfreq[256], freqs[256];
    double sprob[256];
    double z1[256], z2[256], lacunar[256];
    double lacunarity, boxtotal;

    /* Open Input file for reading */
    ifp = fopen(infile, "rb");
    if (ifp == NULL)
    {
        fprintf(stderr, "Error in opening file %s\n", infile);
        return(0);
    }

    /* Seek to EOF in input image */
    ret = fseek(ifp, 0L, SEEK_END);
    filesize = ftell(ifp);
    rewind(ifp);

    /* Allocate Memory for input buffer */
    inp.data = (unsigned char *) malloc (filesize);
    if (!(inp.data))
    {
        printf ("Error Insufficient Memory\n", filesize);
        exit(1);
    }

    if (fread(inp.data, filesize, sizeof(unsigned char), ifp) != 1)
    {
        printf ("Error could not read %s file. \n", infile);
        exit(1);
    }

    position = (long int) 1024;
    ret = fseek(ifp, position, SEEK_SET);

    /* set pointer to image data in input image */
    inp.image = inp.data + 1024;
    boxtotal = ( (nrows-box+1) * (ncols-box+1) );
    if (box_size == ODD)
    {
        /* Loop over entire image by rows and columns */
        for (j = boxrows; j <= (nrows-boxrows); j++) {  

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for (i = boxcols; i <= (ncols-boxcols); i++) { 

/* Initialize counter for occupied sites */
scount = 0;

/* Convolve with box */
for (y = -boxrows; y <= boxrows; y++) {
    for (x = -boxcols; x <= boxcols; x++) {

/* Perform calculations only over water pixels */
if ( *(inp.image+i+x+(i+y)*ncols) == (unsigned char)255 )

/* Increment counter */
scount++;

/* Calculate frequency distribution for scount */
sfreq[scount] = (double) (sfreq[scount] + 1.0);

/* Copy frequency distribution to freqs array */
freqs[scount] = (double) (sfreq[scount]);
}

/* Divide frequency counts by total number of boxes */
sprob[scount] = (double) (freqs[scount] / boxtotal);

/* First Moment of distribution */
z1[scount] = (double) (scount * sprob[scount]);

/* Second Moment of distribution */
z2[scount] = (double) (scount * scount * sprob[scount]);

/* Calculate Lacunarity Index from First and Second Moments */
if ( (z1[scount] != 0.000000) && (z2[scount] != 0.000000) )
{
lacunar[scount] = (double) (z2[scount] / (z1[scount] * z1[scount]));
lacunarity += (double) (lacunar[scount]);
}
}
}

if (box_size == EVEN) {
/* Loop over entire image by rows and columns */
for (i = 0; j < nrows; j++) {
    for (i = 0; i < ncols; i++) {

/* Initialize counter for occupied sites */
scount = 0;

/* Convolve with box */
for (y = 0; y < box; y++) {
    for (x = 0; x < box; x++) {

        /* Perform calculations only over land pixels */
        if (* (inp.image+i+x+(j+y)*ncols) == (unsigned char)255 )

        /* Increment counter */
        scount++;

        /* Calculate frequency distribution for scount */
        sfreq[scount] = (double) (sfreq[scount] + 1.0);

        /* Copy frequency distribution to freqs array */
        freqs[scount] = (double) (sfreq[scount]);

        /* Divide frequency counts by total number of boxes */
        sprob[scount] = (double) (freqs[scount] / boxtotal);

        /* First Moment of distribution */
        z1[scount] = (double) (scount * sprob[scount]);

        /* Second Moment of distribution */
        z2[scount] = (double) (scount * scount * sprob[scount]);

        /* Calculate Lacunarity Index from First and Second Moments */
        if ( (z1[scount] != 0.000000) && (z2[scount] != 0.000000) )
        {
            lacunar[scount] = (double) ( z2[scount] / (z1[scount] * z1[scount]) );
            lacunarity += (double) (lacunar[scount]);
        }
    }
}

printf("\n The lacunarity index for box size %d is %f\n", box, lacunarity/boboxtotal);

free(inp.data);

rewind (ifp);
fclose (ifp);
return(lacunarity);
}
Appendix - J

Tabulation for Threshold values derived from Neural Network
<table>
<thead>
<tr>
<th>IMAGE</th>
<th>SPATIAL RESOLUTION</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>30m</td>
</tr>
<tr>
<td>THRESHOLD</td>
<td>0.421845</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>GAUSSIAN SMOOTHING</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>THRESHOLD</td>
<td>0.421845</td>
<td>0.500584</td>
<td>0.497725</td>
<td>0.361562</td>
<td>0.443512</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>LOCAL VARIANCE</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>THRESHOLD</td>
<td>N/A</td>
<td>0.159975</td>
<td>N/A</td>
<td>0.424732</td>
<td></td>
</tr>
</tbody>
</table>
Vita

The author was born on May 07, 1970 in Madras, India. He graduated in May, 1991, from Annamalai University, Madras, India, with a bachelor of science degree in Electronics and Instrumentation Engineering. He completed his master of science degree in Geography with an emphasis in Mapping Sciences on December, 1994. After a brief stint as a Graduate Assistant in the Remote Sensing and Image Processing Laboratory, Louisiana State University, LSU, working on research projects for his advisor, Dr. Nina Lam, he became interested in pursuing a doctor of philosophy degree in Geography. He is currently attending Louisiana State University in pursuit of his doctorate in Geography with emphasis in Mapping Sciences, which he will earn in December, 1997.
DOCTORAL EXAMINATION AND DISSERTATION REPORT

Candidate: Rajabhushanam Cherukuri

Major Field: Geography

Title of Dissertation: LAND/WATER INTERFACE DELINEATION USING NEURAL NETWORKS

Approved:

[Signatures]

Major Professor and Chairman

Dean of the Graduate School

EXAMINING COMMITTEE:

[Signatures]

Date of Examination: June 6, 1997