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CHAPTER 14

Image Characterization and Modeling System (ICAMS): A Geographic Information System for the Characterization and Modeling of Multiscale Remote Sensing Data

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MULTIPLE SCALING AND REMOTE SENSING: A TIMELY PROBLEM

The scale of observation and measurement is undoubtedly one of the most essential considerations to be made in the interpretation and analysis of remote sensing data. It is widely recognized that many environmental processes and patterns are scale-dependent, wherein they may appear homogeneous at one spatial scale and heterogeneous at another (Davis et al., 1991; Ehleringer and Field, 1993; Foody and Curran, 1994a). Because spatial heterogeneity constrains the ability to transform information from one scale to another, it is an important factor in the integration and analysis of remote sensing data obtained from different scales and sensors. For example, Turner et al. (1989a) have shown that landscape pattern has a significant influence on the response of measurements to changes in spatial scale. Scale, from a remote sensing perspective, can be defined as the integral (or interval) of space and time over which a measurement is made (Davis et al., 1991; Quattrochi, 1993). The element of scale, therefore, exists as a metric used to measure the space and time domains for a phenomenon or process under observation.

The use of remotely sensed data in global change and other environmental modeling has grown rapidly in the last decade, due largely to the increasing availability of remote sensing and other spatial data in digital form at local, regional, and global scales from many sources. The National Aeronautics and Space Administration's (NASA) Earth Observing System (EOS) program, with its suite of polar-orbiting remote sensing platforms to be launched late this century, will present many new challenges in efficiently analyzing data obtained at different spatial and spectral resolutions. Because these sensors will span a range of wavelengths from visible to microwave, their spatial resolutions will vary from tens of meters to tens of kilometers, as will their times of data acquisition. We call such data multiscale data. A fundamental problem will be to understand how to combine data with different spatial and temporal properties in a meaningful way. The fusion of data from different sensors for analysis of Earth surface and atmospheric parameters is a prime goal of the EOS program and thus, there is a critical need to address this multiscale analysis problem. Since the ultimate goal of EOS is to better understand the Earth as a system, the need to develop methods for characterizing, analyzing, and eventually displaying various types of multiscale remote sensing data is paramount.

We describe in this chapter the design and implementation of a GIS software module developed to measure, characterize, and model multiscale remotely sensed data. This Image Characterization and Modeling System (ICAMS) contains a number of spatial measurement methods that are not conveniently available to the general research community. These methods mainly include:

- fractal measurement
- spatial autocorrelation
- land/water and vegetated/nonvegetated boundary delineation
- textural measures
- spatial aggregation routines

We first provide a brief overview of the theoretical background of, and practical need for, ICAMS by outlining the interrelationships between scale, remote sensing, GIS, and fractal analysis. A description of the system design and functionality of ICAMS then follows, with some examples provided of its implementation and use. Our experience and challenges in developing such a system are summarized in the final section.

Scale, Remote Sensing, GIS, and Fractal Analysis

Multiscale data and the efficient modeling of these data have long been an issue in environmental research involving spatial data, particularly because of the scale-dependent nature of environmental or ecological phenomena. In addition to being scale-dependent, these phenomena and the attendant processes–responses that drive these phenomena are also problem-dependent, whereby the stability or variability of the phenomenon or process under observation, as manifested in remote sensing data, will directly influence its qualitative and quantitative interpretation using remote sensing. The scale issue has become more acute because of the need to integrate remote sensing and other spatial data collected at different scales and resolutions within the purview of studying Earth processes as "Earth System Science." For example, one of the basic goals of modeling land–atmosphere interactions is to enable the movement up and down spatial scales, within and across scientific disciplines so that results concluded at one scale can be inferred to another scale (Townshend and Justice, 1988; Turner et al., 1989a, 1989b; Kineman, 1993; Steyaert, 1993). Because of the scale-dependent nature of environmental phenomena, multiscale data and the efficient modeling of these data have long been an issue in research involving spatial data. The scale issue has become more acute as the need to integrate remote sensing and other spatial data collected at different scales and resolutions in studying Earth processes from an integrated perspective becomes more apparent. Extrapolation of results across broad spatial scales remains the most difficult problem in global environmental research. Geographic information systems (GIS) and quantitative models offer an attractive set of tools for environmental modeling of multiscaled data. Both nested modeling approaches and GIS techniques have been suggested as two possible routes to address the problems associated with extrapolating across spatial scales (Coulson et al., 1991; Jarvis, 1993; Foody and Curran, 1994b). Whichever approach is used, there is a need for basic characterization of image data, and the techniques used to measure scale effects must be developed and implemented to allow for a multiple-scaled assessment of these data before any useful process-oriented modeling involving scale-dependent data can be conducted.

Fractals and fractal analysis have been suggested as an innovative technique for characterizing remote sensing images as well as identifying the effects of scale changes on the properties of images (De Cola, 1989, 1993; Lam and Quattrochi, 1992; de Jong and Burrough, 1995). The key parameter in fractals is the fractal dimension, which is used to represent the spatial complexity of point patterns, lines, and surfaces. The higher the fractal dimension, the more complex the form. Recent additions to the fractal literature, such as the concepts of self-affinity, random fractals, and multifractals, have expanded fractal applications to many phenomena where pure fractals with strict self-similarity do not exist (see for example, Lovejoy and Schertzer, 1990; Evertsz and Mandelbrot, 1992; Lavallée et al., 1993; Davis et al., 1994).

Moreover, fractals are seen as a potentially robust method for understanding landscape complexity. Landscape units become fragmented or disaggregated (i.e., the landscape becomes heterogeneous) depending upon the scale of observation and measurement. This heterogeneity imbues a perception that the landscape consists of a patchwork of different, but interrelated, components that make the landscape complex in appearance, structure, and function. The complexity results from biotic interactions that generate patterns (e.g., an insect infestation that kills selected tree species in a forest), from physical processes that alter landscape structure (e.g., topographically controlled thunderstorms that affect precipitation patterns at local scales), or from cultural and human-induced activities (e.g., urbanization) (Milne, 1991). Ultimately, complexity modifies processes that regulate landscape structure. Understanding how the geometric shape and size of the land cover patterns (i.e., complexity) are related to natural and human-induced processes is critical to determining the appropriate spatial scales and the type of remote sensing data to use in analysis of landscape dynamics (Krummel et al., 1987). Fractals can be applied to a variety of landscape problems because they conveniently describe many of the irregular, fragmented patterns found in nature (Mandelbrot, 1983). While the applications and calculation of fractals vary, they are limited to describing the degree to which the area of a landscape patch (e.g., a continuous grouping of grid cells representing the same landscape feature) is related to its edge, and how this measure can be modified to address diversity. By determining the fractal relationship of patch area to patch edge for a given landscape, measures of the geometric heterogeneity of the landscape, and thus the complexity of patch interaction within it, can be determined (Olsen et al., 1993). Shape, however, is not the only factor that affects the extant biophysical processes across a landscape. The juxtaposition of a patch to other patches (i.e., patch arrangement) can have significant effects, as can the number of different patches in an area (i.e., patch "richness") and the evenness in distribution of patches across the landscape (Shannon and Weaver, 1962; Patton, 1975; Rex and Malanson, 1990; Olsen et al., 1993). Fractals as a method for calculating patch complexity, therefore, are most effective when combined with measures to compute richness and evenness of patches within a landscape. This application of fractals has been addressed using remote sensing data by Olsen et al. (1993) with considerable success.

Although there appears to be good potential in utilizing fractals as a spatial analytical technique, as a visualization tool, and as a scale measurement device, three important facts need to be stressed here as caveats to the use of fractals in the analysis of remote sensing data that has occurred up to the present. First, despite numerous potential applications, fractals in remote sensing have not been widely used as a spatial analytical technique, particularly in the analysis of multiscale data. It has been suggested that an expanded employment of fractals in remote sensing research is needed to yield a better understanding of the relationship between surface variation and spatial properties of remote sensing data (e.g., Krummel et al., 1987; MacLennan and Howarth, 1987; Lovejoy and Schertzer, 1988; Lam, 1990; Davis et al., 1991; Quattrochi and Lam, 1992). This is especially true when one considers that remote sensing is the main source of data that can be used for analyzing the spatial dependence of surface and atmospheric phenomena at relatively large scales and over large areas (Lovejoy and Schertzer, 1990; Davis et al., 1991). More research is necessary, however, to relate fractal dimensions with different biophysical, ecological, geological, and landscape phenomena and statistical parameters, as manifested in remote sensing data (Jaggi et al., 1993).

Second, although there are a number of fractal software algorithms available, either commercially or in the public domain, none addresses the measurement of environmental/geographical phenomena from remotely sensed data. Pieces of fractal software for this purpose are scattered in various journals and books; the disparate pieces appropriate to the analysis of multiscaled remote sensing data need to be integrated and tested systematically to be useful and reliable.

Third, while fractals are potentially a useful tool for characterizing spatial phenomena, there are also discrepancies in the results obtained from employing different fractal measurement algorithms (Jaggi et al., 1993; Lam and De Cola, 1993; de Jong and Burrough, 1995). A thorough evaluation of the various measurement techniques is needed to reliably characterize and compare various types of landscapes and their corresponding fractal dimensions to better understand the relationships of landscape type, pattern, and process at multiple space and time scales.

Thus, an integrated software package that contains a robust set of fractal measurement algorithms embedded within a GIS-type architecture would be a useful tool for characterizing multiscaled remote sensing and associated spatial data for Earth system science research. A software engine of this type would permit studying biophysical, ecological, and environmental phenomena using data integrated from different remote sensing systems. This software within a GIS-type structure would also enable the modeling of how these phenomena change through space and time. Lastly, through the employment of the ICAMS software package, it would be easier to test the suitability, reliability, and accuracy of fractals for the characterization and robust spatial and temporal modeling of multiscaled landscape phenomena as measured from remote sensing data.

Image Characterization and Modeling System (ICAMS): Developmental Objectives and System Design

The development of ICAMS has been driven by the need to provide scientists with software that can be used to visualize, characterize (i.e., measure or describe specific attributes, such as landscape pattern), and analyze remote sensing images within the EOS era. An efficient set of spatial analytical techniques that are integrated and user-friendly, whereby researchers can perform basic, as well as advanced, spatial analysis tasks to characterize and model multiscaled remote sensing images, will be highly useful to NASA's EOS program. ICAMS is designed to read data from many different sensors with different data formats, co-register the images, manipulate and perform a variety of measurement operations on the images, and display them. The software has also been designed so that it is compatible with two state-of-the-art GIS/remote sensing software systems: Arc/Info™ and Intergraph™.* A PC-based stand-alone platform is also being developed. We believe that ICAMS will serve as a fundamental building block for process-oriented research and modeling using multiscaled remote sensing data.

ICAMS has four subsystems (Plate 7** upper left): (1) *Image Input:* This subsystem includes basic image processing functions, such as format transformation, georeferencing and co-registration, noise removal, and filtering functions. (2) *Image Characterization:* This subsystem will provide users with an array of non-spatial as well as spatial measures for characterizing an image. The non-spatial measures include mean, mode, median, variance, and histogram. The spatial measures include fractal analysis, variogram analysis, spatial autocorrelation statistics, and textural measures. (3) *Specialized Functions:* This subsystem calculates the Normalized Difference Vegetation Index (NDVI) and provides the user with easy-to-use routines to locate and delineate two major types of boundaries; i.e., land/water and vegetated/non-vegetated. Additionally, this subsystem provides aggregation routines for aggregating pixels to simulate multiscale data for scale effect studies; and (4) *Image Display and Output:* This subsystem includes the display and output of images in two-dimensional or three-dimensional form, outputs analytical results and statistics, and creates digital output of intermediate or derived images.

* Mention of a specific commercial product does not imply any endorsement of this product by NASA.
** Color plates follow numbered page 168.

Integral to this GIS software package is the capability for selecting and applying several different spatial analysis techniques for use in analyzing multiscaled remote sensing data. In addition to the fractal analysis, another important attribute of ICAMS is the development and implementation of specialized functions for image characterization that are not easily available in any existing GIS/remote sensing software, such as variogram analysis, multiscale analysis, and boundary delineation. The image input and display subsystems use existing commercially available GIS software as a foundation, while the image characterization and specialized function subsystems have been developed as entirely new software modules. Thus, ICAMS uses the basic GIS functions of existing available software as a framework; the image characterization and specialized function subsystems are integrated with these basic GIS functions to complete the ICAMS software. This appeared to be a prudent approach in developing ICAMS, since there was no need to expend time, effort, and money in developing basic GIS functionalities, such as data input/output, formatting procedures, or digital image display, when a number of excellent commercially available software packages that perform these operations already exist.

ICAMS uses the Arc/Info and Intergraph software engines as a foundation. Arc/Info incorporates a live-link with Erdas/IMAGINE, an advanced image processing software package. These three systems are considered state-of-the-art GIS/remote sensing software, and are used extensively in the private, public, and university sectors for production, research, and teaching activities. Hence, we have used these image processing/GIS packages as a basic engine for ICAMS to ensure that the image characterization and spatial statistical operations unique to ICAMS can be easily accessible and serve a large user community.

While the input and output subsystems may be dependent to one of the two specific GIS software platforms (i.e., Arc/Info or Intergraph), the image characterization and specialized functions subsystems are designed to be platform-independent, portable modules for both workstation and PC-based environments. This module is coded in C for transportability to both workstation and PC-based environments. A limited Fortran module is also in development. User-friendliness and simplicity, with hierarchical menus, are important design criteria in the development of the software. Distribution of ICAMS to the user community will be through requests made to a home page that will be established on the World Wide Web and through a network of contacts made via inquiries at professional meetings and conferences. We also are facilitating the use of ICAMS by offering it as a network based routine on the Internet using the JAVA programming language, that will permit access and use of ICAMS on virtually any type of computer platform.

Functions and Example Applications of ICAMS

We have developed ICAMS by bundling a number of techniques to permit ease of use, thereby allowing researchers from multiple disciplines to examine the utility of fractals and other geospatial techniques in analyzing multiscaled remote sensing data within the pre-EOS and EOS era of sensing systems. Moreover, ICAMS can be used to address a number of significant issues related to scale and fractal analysis utilizing remote sensing and GIS. These include, for example:

- Do different environmental/ecological processes (e.g., coastlines, vegetation boundaries, wetlands) have their own fractal dimension? How is the fractal dimension of an image affected by the resolution of the sensor?
- How does the fractal dimension compare with the more conventional spatial techniques (e.g., indices of dispersion and aggregation) in the effectiveness in characterizing image and multiscale remote sensing data?
- Can we identify areas with different properties (e.g., vegetation vs. bare ground) by measuring the corresponding fractal dimensions? What is the significance of changes in fractal dimension, either in space or time, over multiscaled remote sensing data?
- How can we use fractal analysis to identify specific patterns of land cover, terrain, and others?
- How will the land/water or vegetation/non-vegetated boundaries, NDVI, and temperature change with scale as manifested in remote sensing imagery?

In the following, we describe the major functions in the image characterization and specialized functions subsystems. A 201 × 201 pixel subset of a 1984 Landsat-TM image from Lake Charles, Louisiana was used to demonstrate some of the functions in the Arc/Info platform, namely the fractal and scaling functions. This data set was used as a standard data set to test the accuracy of all the modules in both Intergraph and Arc/Info platforms, and will be used to test the PC platform version. The same data set was used in Lam (1990). Therefore, the calculations made by ICAMS can be used for comparison with that of Lam's study, providing a convenient mechanism for checking the accuracy of all modules.

Image Characterization Methods

The image characterization subsystem of ICAMS computes basic descriptive statistics as well as spatial statistics of remote sensing images. Basic descriptive statistics include mean, mode, median, standard deviation, minimum and maximum values, and histograms. Spatial statistics include fractal analysis, variogram analysis (Lam et al., 1993), spatial autocorrelation statistics, namely the Geary and Moran ratios (Fan et al., 1993), and selected textural measures, such as the local variance method (Woodcock and Strahler, 1987). These methods have been applied to the analysis of spatial data and have proven useful in analysis of remote sensing data. References to these spatial techniques, however, are scattered in the scientific literature and their computer programs are not readily available in a systematic and easy-to-use manner. Once the ICAMS command is executed in Arc/Info, the system opens with a logo (Plate 7*, upper right) and then a menu for the user to select the various subsystems. Plate 7*, bottom, shows the Lake Charles image in a window, and in the other window its basic descriptive statistics.

Three different fractal surface measurement algorithms have been implemented in ICAMS, including the isarithm, variogram, and triangular prism methods. The implementation and operation of these methods, which are programmed in C, along with some initial tests using multiscaled remote sensing data, are described in Jaggi

* Color plates follow numbered page 168.

et al. (1993). The Fortran version of these algorithms is described in Lam and De Cola (1993). Lam and De Cola (1993) also describe in detail how these methods work in theory. These methods have been selected for inclusion in ICAMS based on their potential applicability to analyses of multiple-scaled remote sensing imagery.

Although the isarithm, variogram, and triangular prism methods have preliminarily been tested using multiscaled remote sensing data with promising results (Jaggi et al., 1993), these methods must be tested in a more robust manner using more extensive multiple-scaled remote sensing data from a variety of sensors (e.g., Landsat TM, AVHRR). Hence, these fractal analysis methods are offered as a part of ICAMS for further exploitation by the scientific community to assess their effectiveness in characterizing different spatial phenomena as manifested in different remote sensing data. Plate 8* compares the results from applying two different fractal measurement methods, the variogram and the isarithm methods, to the same Lake Charles image.

To demonstrate the variogram method, we picked 1007 points from the study area containing 201 × 201 pixels using the stratified random sampling routine implemented in the variogram method (Plate 8, top). The 1007 points were used to construct a variogram, from which the fractal dimension was subsequently determined using its slope. The variogram method is sensitive to the range of points included in the regression. For example, using a range including point 2 to point 29 (breakpoints specified as 1 to 30 in Plate 8, top), the fractal dimension for band 1 equals 2.97 ($r^2 = 0.54$). This value is likely to change if a different range of points is used to determine the regression slope and hence the fractal dimension. At present, the original version of the variogram method requires the user to view the variogram and input the breakpoints manually so that a range of points that yields higher r^2 can be found (Mark and Aronson, 1984; Lam and De Cola, 1993; Jaggi et al., 1993). To minimize the arbitrariness and make the variogram method useful, we suggest here that a routine should be added to automatically find the range of points yielding the highest r^2. Improvements to the existing method are in progress.

For the isarithm method (Plate 8, bottom), if all the isarithms (excluding 0's and including those having $r^2 < 0.9$) are included in the averaging process, the resultant D value becomes 2.69 (with $r^2 = 0.85$), a result similar to those yielded in Lam (1990). However, if only those isarithms that yield an $r^2 \geq 0.9$ are included in the averaging process, the approach adopted in Jaggi et al. (1993), then the resultant D is higher (D = 2.9). As outlined in Lam and De Cola (1993), a number of factors will affect the D values resulting from the isarithm method. These factors, designed as parameter inputs in the algorithm, include the isarithmic interval, the number of walks and the directions for these walks (i.e., either row, column, or row and column directions). Again, these measurement methods must be tested further to provide a better understanding of the behavior of the various algorithms and their relationship with the characteristics of the images.

* Color plates follow numbered page 168.

Specialized Functions

ICAMS has three specialized image characterization functions: (1) the calculation of the NDVI and temperature; (2) the delineation of land/water interface and vegetated/non-vegetated boundaries; and (3) the generation of multiscale, multiresolution data through an aggregation routine. For function (1), NDVI and temperature are two widely used indices in global environmental modeling and, therefore, it is important to have them available as analysis tools (Ehleringer and Field, 1993; Foody and Curran, 1994a). For function (2), a number of methods for land/water interface delineation could be programmed and tested, including the near-infrared analysis, thermal-infrared analysis, NDVI analysis, principal component analysis, image filtering, and image classification (Rajabhushanam, 1994; Cihlar et al., 1990; Barton and Bathols, 1989; Loveland et al., 1991; McGarry et al., 1989; Simpson, 1990, 1992; Lee, 1990). Currently implemented is the NDVI method for delineating land/water interface boundaries. Plate 9*, top, displays the NDVI values computed for the Lake Charles study area, with green color for higher NDVI and blue for lower NDVI. By using the same NDVI values but a different delimiting interval, the same study area can be delineated into water and land, as shown in Plate 9, bottom. The implementation of other land/water interface boundary delineation methods is in progress.

Function (3) provides some basic aggregation routines, including simple averaging, nearest neighbor method, and cubic convolution method (Lillesand and Kiefer, 1993) to generate multiscaled (i.e., multiresolution) data. Once multiscaled data are generated, they can be analyzed within the image characterization subsystem to recompute the fractal dimension, NDVI, or to derive surface temperatures, or redefine land/water, vegetated/non-vegetated interface boundaries. The changes in these index values with scale should provide information, heretofore unavailable in a single spatial analysis software package, on the basic structure of landscape phenomena as manifested in multiscaled remote sensing data.

To demonstrate the use of ICAMS for scale analysis of remotely sensed data, we aggregate the Lake Charles image using a 2×2 window via a simple averaging aggregation routine and recompute the basic statistics and the fractal dimensions from the isarithm method. Plate 10* displays four levels of aggregation using Bands 2 (Blue), 3 (Green), and 4 (Red). Table 1 compares the descriptive statistics for the original image and the resampled 2×2 image. Table 2 lists their fractal dimension values for all seven bands. It is interesting to note that the resampled image generally has lower standard deviations but higher fractal dimension values compared with those of the original image. The discrepancy in behavior between the non-spatial (standard deviation) vs. spatial (fractal dimension) statistics and their relationships with the scale effect is an area that we intend to research more intensively in the near future.

* Color plates follow numbered page 168.

Table 1 Summary Statistics of the Original (201 × 201) and the Resampled (101 × 101) Image

	Original image				Resampled 2 × 2 image			
Band	Min	Max	Mean	S.D.	Min	Max	Mean	S.D.
1	40	255	70.37	12.95	54.50	170.75	70.39	11.51
2	13	126	27.40	7.57	17.50	83.50	27.41	6.76
3	8	158	30.95	11.20	15.25	108.50	30.97	10.10
4	4	138	45.98	11.82	6.25	89.00	45.95	10.61
5	0	232	52.07	17.28	2.25	147.50	52.07	16.06
6	116	146	132.37	3.61	116.25	145.50	132.37	3.57
7	0	148	22.37	9.96	0.25	82.00	22.38	9.25

Table 2 Fractal Dimension and r^2 Values (in Parentheses) Computed for the Original and the Resampled 2 × 2 Image Using the Isarithm Method*

Band	Original image	Resampled 2 × 2 image
1	2.77(0.86)	2.90(0.97)
2	2.84(0.92)	2.92(0.98)
3	2.85(0.92)	2.89(0.99)
4	2.67(0.93)	2.76(0.97)
5	2.68(0.98)	2.72(0.94)
6	2.39(0.93)	2.56(0.96)
7	2.89(0.98)	2.89(0.96)

* Parameter inputs are: isarithmic interval = 10; number of walks = 6; direction = both row and column.

Conclusions and Future Research

We have described here the rationale, design, and major functions of ICAMS, which we expect will be a useful tool for application to multiscaled analysis of landscape characteristics within the EOS era, and to environmental research in general. Results based on a simple aggregation of the image using the averaging method and a 2 × 2 window have shown that fractal dimension values increase, indicating an obvious scale effect. It is not known, however, whether the scale effect is augmented or reduced by the resampling method, the fractal dimension method, and the image band characteristics. The interplay among these various factors is the subject for intensive research in the near future.

We have also identified that a major difficulty in applying fractals to geosciences is that different algorithms return different dimension values. Even within a single method ambiguity exists, as there are various parameter inputs that may affect the final fractal dimension values. Thus, researchers need to have a systematic and thorough understanding of what is being measured using fractals, and the meaning of the values derived by different fractal methods, before they can be used reliably and robustly to characterize various spatial phenomena from remote sensing data. We see ICAMS as a valuable tool in assisting researchers in this endeavor.

We are applying the spatial analysis tools available within the image characterization subsystem of ICAMS to various test data sets of remote sensing data, to evaluate the veracity of the software, and to analyze what differences in fractal dimension mean at different spatial and temporal scales. In particular, we want to know if there are certain fractal properties that correspond to different conditions on the Earth's surface, and whether fractals can be used to identify certain kinds of features or processes (i.e., are there thresholds or phenomenological breakpoints in fractals that are indicative of specific landscape processes or characteristics). Additionally, it is necessary to compare fractal results with the results from selected spatial statistics to assess whether fractals are providing any truly new or useful information and whether, or how, fractals correlate with these geostatistical measures. For example, does a high fractal dimension correspond with a high spatial autocorrelation? These are important questions to which we wish to provide answers, and with the assistance of ICAMS, we believe research can be performed more easily with better and more reliable evaluation in a variety of landscape and biophysical scientific applications.

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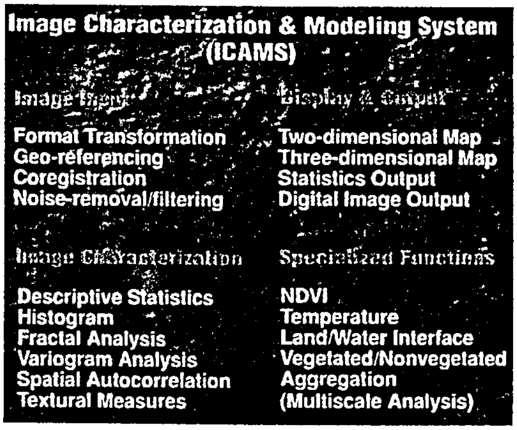
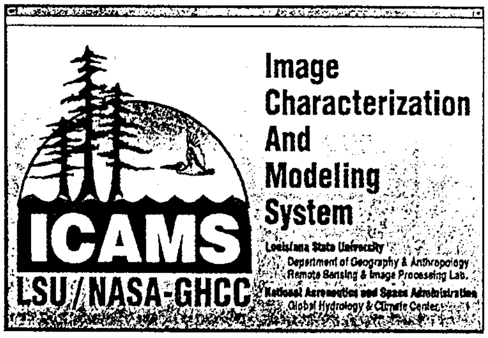




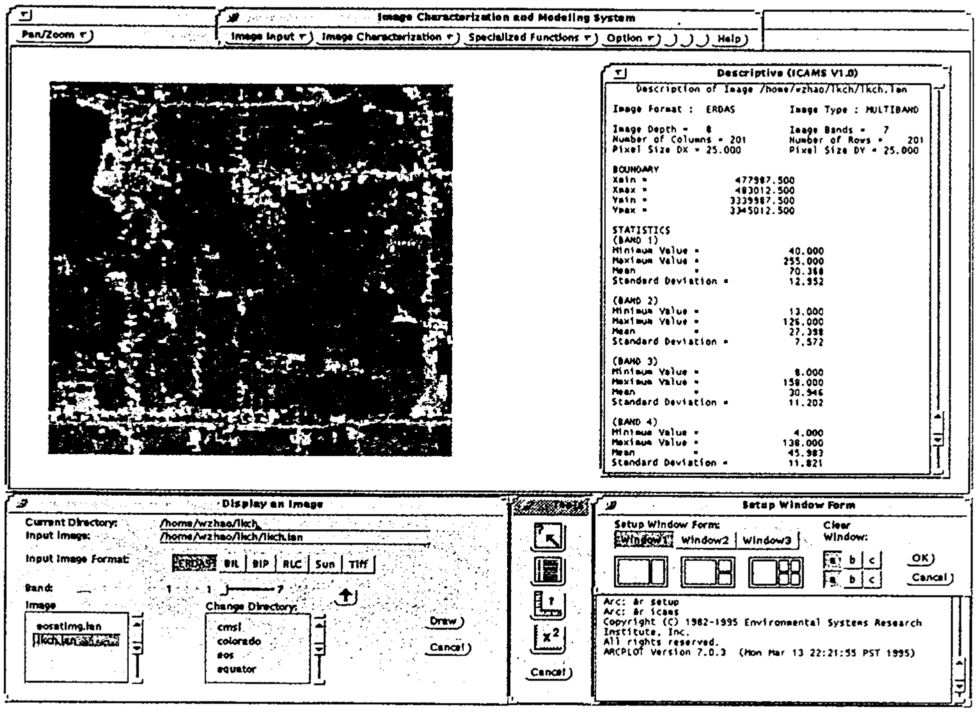
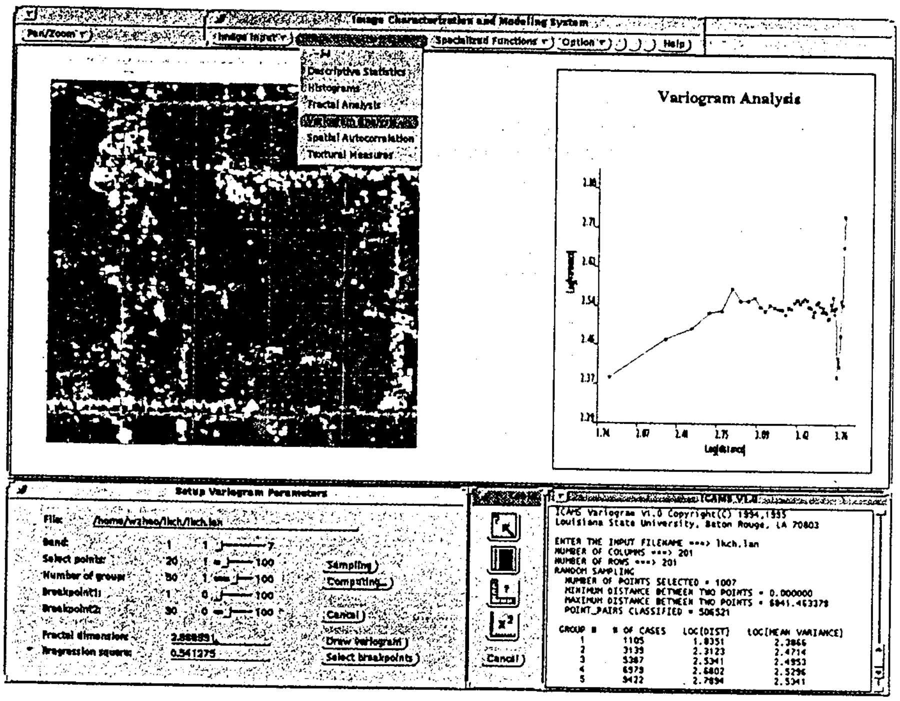


Plate 7 (Chapter 14)

Upper left. Image display of ICAMS subsystem processing functions.

Upper right. ICAMS opening logo.

Bottom. Display of Lake Charles, Louisiana TM image and basic descriptive statistics.



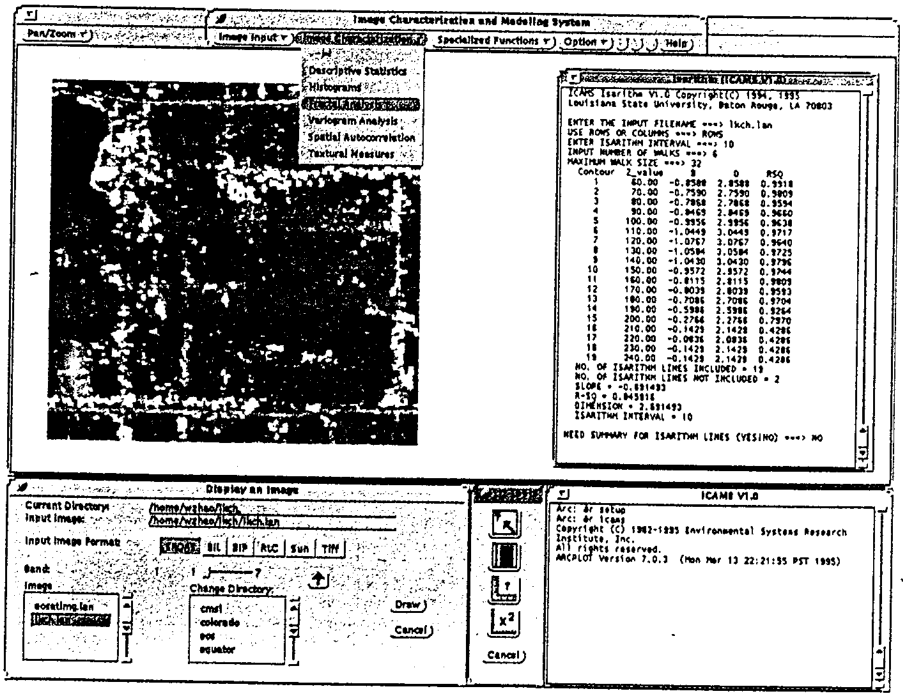
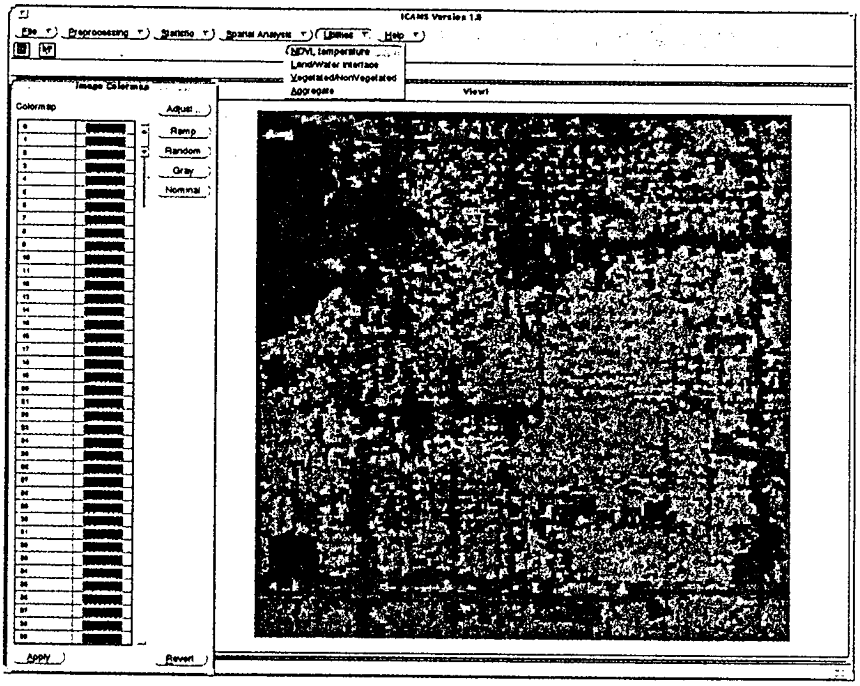


Plate 8 (Chapter 14)

Top. ICAMS variogram fractal analysis of Lake Charles, Louisiana TM image.

Bottom. ICAMS isarithm fractal analysis of Lake Charles, Louisiana TM image.



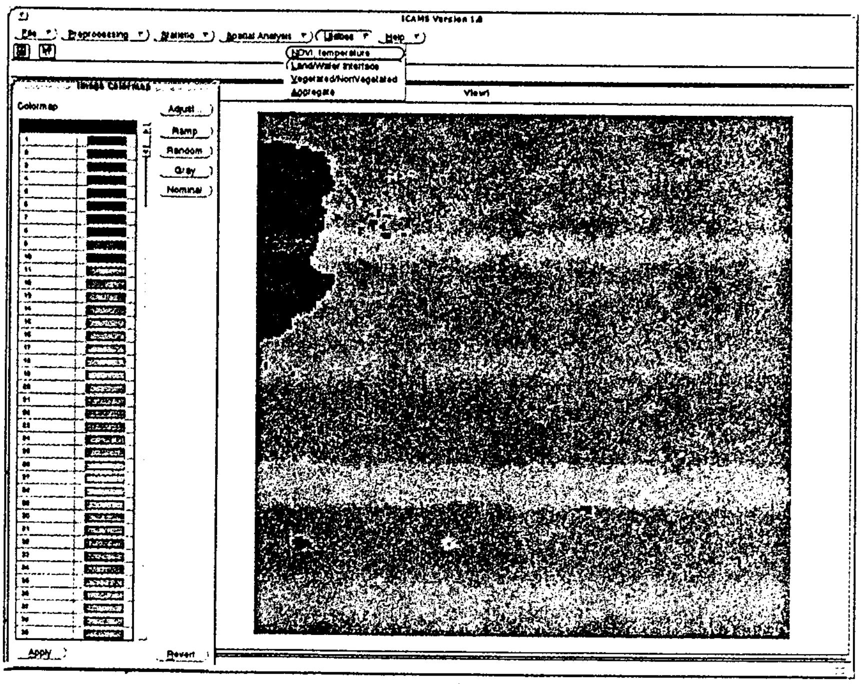


Plate 9 (Chapter 14)

Top. ICAMS NDVI computation of Lake Charles, Louisiana TM image. Green indicates higher NDVI values; blue indicates lower NDVI values.

Bottom. ICAMS land versus water delineation of Lake Charles, Louisiana TM image. Blue is water; green is land.

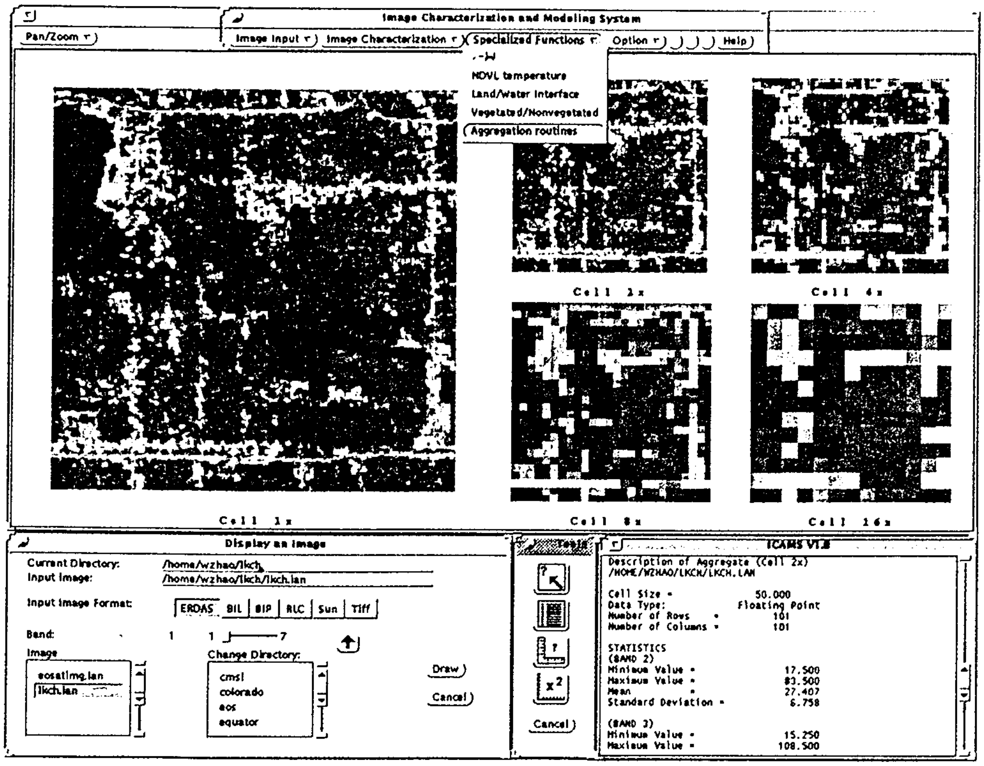


Plate 10 (Chapter 14) ICAMS aggregation of Lake Charles, Louisiana TM image from 2 x 2 to 16 x 16 aggregation.