Environmental Analysis Using Integrated GIS and Remotely Sensed Data: Some Research Needs and Priorities

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ABSTRACT: This paper discusses some basic scientific issues and research needs in the joint processing of remotely sensed and GIS data for environmental analysis. Two general topics are treated in detail: (1) scale dependence of geographic data and the analysis of multiscale remotely sensed and GIS data, and (2) data transformations and information flow during data processing. The discussion of scale dependence focuses on the theory and applications of spatial autocorrelation, geostatistics, and fractals for characterizing and modeling spatial variation. Research using these and related techniques is needed to identify characteristic space and time scales of surface variation, to help define the measurement scales of remotely sensed and GIS data, and to formulate strategies for acquiring and integrating multiscale geographic data to model Earth systems. Data transformations during processing are described within the larger framework of geographical analysis, encompassing sampling, cartography, remote sensing, and GIS. These transformations, which may introduce noise but may also involve more fundamental changes in the input data, have not been investigated in terms of overall processing flow and information development. Development of better user interfaces between image processing, GIS, database management, and statistical software is needed to expedite research on these and other impediments to integrated analysis of remotely sensed and GIS data.

INTRODUCTION

THE PURPOSE OF THIS PAPER is to discuss some basic scientific issues and research needs in the joint processing of remotely sensed and GIS data for environmental analysis. Over the past decade there has been an explosive increase in georeferenced data and computer systems for spatial data handling. Our perspective is that of scientists attempting to take advantage of these data and new technologies to investigate real world environments, their conditions, patterns, and dynamics. As noted by Curran (1987), remote sensing and GIS are tools not only for scientific research on how the world works, but also for technological applications in meeting human needs. The need for close coupling between research and application is especially important to the emergent programs for monitoring the environmental and social consequences of global change.

The type of spatial information system required for regional to continental scale environmental analyses is very large (e.g., 10^3–10^6 megabytes) and may include fundamentally different kinds of data, for example, (a) multi-temporal and multi-resolution digital images acquired from one or more satellite and aircraft platforms; (b) gridded elevation data; (c) digitized maps of land surface variables such as soils, hydrography, and vegetation cover; (d) socioeconomic data (e.g., population density, zoning district) aggregated by political reporting units; and (e) point measurements of subsurface, surface, and atmospheric variables at scattered locations. Queries of such databases can range from relatively simple (e.g., where? how much?) to extremely complex (e.g., what is the projected distribution of variable *A* at time *T* based on linked simulation models 1, 2, and 3?).

Much work has been devoted to overcoming technical obstacles to joint processing of image and GIS data, such as converting between vector and raster data structures and jointly displaying digital imagery and maps. Continued developments should lead to Integrated Geographic Information Systems (IGIS) for joint analysis of remotely sensed and GIS data, capable of handling multiple data structures and supporting complex spatial analyses and user queries (Ehlers *et al.*, 1989; Faust *et al.*, 1991, this issue). In contrast, scientific theory to guide modeling

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and analysis using the amalgamated data inputs and outputs of IGIS has been slow to develop. Several features of IGIS analysis make processing and interpretation of the outputs especially complex, for example:

- use of multiple data layers varying in their structure, level of preprocessing, and spatial consistency;
- multiple (and often poorly known) measurement scales, ranging from "points" to grids to irregular polygons;
- unknown measurement errors for most variables;
- unknown spatial dependencies in the data and their propagation through spatial models;
- limited ability to verify or validate IGIS model outputs; and
- limited capability for model sensitivity analysis.

These challenges or impediments to IGIS analysis have long been recognized (e.g., Everett and Simonett, 1976; Strahler *et al.*, 1980). Many important topics such as the integration of disparate data structures, analysis of large spatial databases, user-IGIS interfaces, and error analysis are the focus of other research initiatives by the National Center for Geographic Information and Analysis, and are treated elsewhere in this issue. Our purpose here is to expand on two general topics that we believe are high priority areas for research:

- Investigation of surface patterns and biophysical processes at multiple space and time scales to quantify scale dependence of IGIS inputs and outputs, and development of robust procedures to account for scale-dependence in IGIS modeling; and
- Development of principles, methods, and technical support for quantifying and tracking data transformations and information flow in IGIS processing.

In presenting our view of research needs and priorities, we hope to stimulate discussion and debate among IGIS users. We do not attempt a full review of the literature on remote sensing and GIS, and our perspective is somewhat narrow, reflecting our research specialties in terrestrial ecosystems and in the physical and biological sciences. We have tried to keep the discussion at a fairly high level of generalization, but we believe that continued focusing and prioritization of research needs must occur, both to coordinate research efforts and to guide the design of future hardware and software systems.

SCALING OF GEOGRAPHIC PHENOMENA

Research into the scaling properties of geographic phenomena, as represented by remotely sensed and digital cartographic data, must address three general and related questions:

- What are the characteristic spatial and temporal scales and scale dependencies of Earth system processes and phenomena (notably in those related to the electromagnetic variation measured by satellite sensors)?
- What are the measurement scales of GIS and remote sensing data and their derived products, and how do these scales vary depending on data processing algorithms and overall data processing flow?
- How can multiscale geographic data be integrated and linked in a statistically robust design to model Earth systems?

These questions are similar to those formulated in a recent workshop on predicting across scales in landscape ecology (Dale *et al.*, 1989), and have been recognized as central to geographic research for a long time (e.g., Harvey, 1969). In this section we hope to show that research on scaling of geographical data remains a very high priority in the context of IGIS analysis.

SCALE DEPENDENCE OF EARTH SURFACE VARIATION

By *scale* we mean the interval of space or time over which a measurement is made. Nearly all surface processes are highly *scale dependent*, that is, their magnitude or variability depends on the measurement scale. Thus, a phenomenon may appear homogeneous at one spatial scale but heterogeneous at another (e.g., Goodchild, 1980; Townshend and Justice, 1988; Nellis and Briggs, 1989). The practical consequences are familiar to anyone who has conducted geographical surveys. For example, the proportions of a region occupied by different land-cover types depend on the spatial resolution of the mapping system. The distribution and magnitude of slopes on a topographic surface depends on the density of elevation measurements.

Each of the disciplines in the Earth sciences seeks to recognize and link *characteristic scales* for the processes it investigates. For example, atmospheric scientists distinguish microscale versus mesoscale processes as those occurring at length scales of 0.01 to 1000 m versus 10 to 1000 km, respectively (Oke, 1987). A hurricane is a feature of atmospheric circulation associated with mesoscale pressure gradients over a characteristic time scale of a few days. Graetz (1990) has defined characteristic scales for environmental changes, biotic responses, and vegetation pattern. For example, climatic fluctuations occurring over short time periods (10^1 years) and large areas (10^6 m^2) are associated with biotic responses of phenology and population dynamics that produce pattern in plant communities. Characteristic scales thus define the space and time intervals with which a process can be detected and monitored as well as the characteristic dimensions of geographic phenomena. Many natural systems exhibit hierarchical organization, with nested patterns and processes occurring over a wide range of characteristic space/time scales. Often the links between different scales of processes or phenomena are not well understood (Allen and Starr, 1982).

In principle, scale dependencies or *scaling properties* of surface variables should be known and should guide the collection, processing, and interpretation of remotely sensed and GIS data. Scale dependence is especially significant in the context of IGIS analysis, which seeks to deduce or to exploit relationships among geographical variables, because those relationships change as the spatial scale is changed (Meentemeyer, 1989; Turner, 1990). In practice, the scaling properties of many surface processes are not well known, in part because these properties are frequently site- or region-specific and also time-dependent, making it difficult to generalize from isolated studies. For example, spatial variation of solar radiation over terrain exhibits different characteristic scales and scaling properties depending on topography, sun position, and atmospheric conditions (Dubayah *et al.*, 1989; 1990). Nelson (1989) found that estimates of forest cover for the continental United States based on AVHRR Global Area Coverage (GAC) data were not correlated with estimates based on Landsat MSS data, and that the relationship varied by region depending on the spatial pattern of forest cover.

A key consequence of scale dependence is the presence of spatial covariability (the degree of dependence between values of a spatial process at different locations) in most spatial datasets. Recently, there has been increased application of spatial statistical techniques in remote sensing and GIS research, aimed at characterizing and modeling spatial dependence (see, for example, Woodcock and Strahler (1988), Davis *et al.* (1989), and Webster *et al.* (1989)). Explicit modeling of spatial statistical structure should improve interpolation of point data, sampling designs for field studies, and estimation of the effects of spatial averaging, and should also contribute to our understanding of underlying processes. There are a number of related statistical approaches to modeling spatial variation based on covariance, the power spectrum, the variogram, or fractal analysis. What follows is a brief technical summary of the statistical models underlying these approaches, which is included to highlight some commonalities in the approaches and the general issue of non-stationarity in spatial data.

Formally, a set of spatial data can be considered as a sample realization of a stochastic process, $Z(\mathbf{x})$, where $\mathbf{x}$ is a two-dimensional position vector. The process is characterized by its cumulative distribution function,

$$F_{Z(x)}(z) = \text{Prob}(Z(\mathbf{x}) <= z), \quad (1)$$

or, equivalently, by its probability distribution function (PDF),

$$f_{Z(x)}(z) = dF/dz, \quad (2)$$

assuming the derivative exists. It is important to note that the distribution function characterizes random variations at each fixed location, x, over the ensemble of realizations of the stochastic process. Similarly, the dependence of the process at two different locations is characterized by the joint PDF, $f_{12}(x_1, x_2)$.

In practice, a stochastic process is usually characterized by its first and second moments, the mean

$$\mu(\mathbf{x}) = E[Z(\mathbf{x})], \quad (3)$$

and covariance

$$c(\mathbf{x}_1,\mathbf{x}_2) = E[(Z(\mathbf{x}_1) - \mu(\mathbf{x}_1))\,(Z(\mathbf{x}^2) - \mu(\mathbf{x}_2))]. \quad (4)$$

Note that

$$c(\mathbf{x}_1,\mathbf{x}_1) = \sigma^2(\mathbf{x}_1) \quad (5)$$

is the variance of $Z(\mathbf{x}_1)$. (Note also that the same information can be conveyed in the power spectrum (Jenkins and Watts, 1968), the Fourier transform of the covariance.) In this general formulation the moments are a function of absolute location, producing what is still a very complicated model.

A common assumption is that the stochastic process is stationary or spatially homogeneous, meaning that the moments are independent of absolute position. Under the assumption of weak, or second-order, stationarity, the mean and variance are constant; i.e.,

$$\mu(\mathbf{x}) = \mu \text{ and } \sigma^2(\mathbf{x}) = \sigma^2 \quad (6)$$

and the covariance is only a function of amount of separation,

$$c(\mathbf{x}_1,\mathbf{x}_2) = c(\mathbf{h}), \quad (7)$$

where $\mathbf{h} = \mathbf{x}_1 - \mathbf{x}_2$. Often it is assumed that the covariance is also independent of direction, depending only on the distance between locations.

Unless one assumes stationarity, it is impossible to estimate any of the moments without multiple realizations from the ensemble of the stochastic process or an explicit model of the non-stationarity. In some applications, such as meteorology and oceanography, one has repeated spatial samples over time and can reasonably invoke temporal stationarity to estimate ensemble means and variances at each location and ensemble covariances between each pair of locations. More commonly, however, one has to use some type of spatial averaging to estimate the moments, necessitating a model of the non-stationarity.

A process can be non-stationary in mean (often referred to as trend or drift), variance, or both. Non-stationarities in mean can usually be modeled fairly easily with a low order trend surface or some similar method. Alternatively, the increments, $Z(\mathbf{x} + \mathbf{h}) - Z(\mathbf{x})$, may be mean stationary with non-zero mean while the actual process is non-stationary (Woodcock *et al.*, 1988); however, this is only possible in one dimension. Non-stationarity in variance can be more difficult to correct. It is possible, though not easy, to develop a two-dimensional process that has a non-stationary variance while the increments of the process do not. When the mean is also non-stationary, variance may increase with the mean. A transformation such as a square root or log can help to make the variance more stationary.

If stationarity can be assumed or if the non-stationarity can be modeled and adjusted for, it is possible to estimate the ensemble covariance with spatial averages. The two most common approaches are to estimate the covariance (or power spectrum) directly or to estimate the variogram (Journel, 1989); i.e.,

$$2\gamma(\mathbf{h}) = E[(Z(\mathbf{x}+\mathbf{h}) - Z(\mathbf{x}))^2]. \quad (8)$$

If the process is stationary the two approaches are identical and

$$\gamma(\mathbf{h}) = \sigma^2 - c(\mathbf{h}) \quad (9)$$

If the process is non-stationary, the relationship is somewhat more complex because

$$2\gamma(\mathbf{h}) - \sigma^2_{x+h} + \sigma^2_x + (\mu_{x+h} - \mu_x)2 - 2c(\mathbf{x}+\mathbf{h},\mathbf{x}). \quad (10)$$

It has been suggested (e.g., Webster *et al.*, 1989) that the variogram is preferable in non-stationary situations because the variance will be infinite, increasing with increasing area. As noted by Journel (1989), however, using a spatial average to estimate the variogram is only appropriate if the process is stationary. Thus, working with the variogram is only preferable in situations where increments are stationary but the process is not. As noted above, this is possible for non-stationarity of variance. In general, though, there seems to be very little reason to prefer one statistic over the other.

The estimated covariance, power spectrum, or variogram can each be utilized to define a correlation length scale, which is a measure of the minimum distance between uncorrelated locations. This information can be useful for designing field surveys or obtaining rough estimates of the variance of spatial averages. For many purposes (e.g., interpolation using kriging), however, it is desirable to fit a model of spatial variation to the data. This typically involves estimating parameters of the model from the sample moments or from the data. An approach commonly used in kriging is to fit a curve of the appropriate shape to the sample covariance or variogram. Alternatives include selecting one of a family of models, such as autoregressive or fractal models, and estimating values of the key parameters.

No one modeling approach is best in all situations. The geostatistical model has been extensively utilized for interpolation because of the flexibility in choice of functions for fitting the covariance (Journel, 1989). This model is less useful, however, when one wants to derive expressions showing the effects on changing scales, in which case an explicit model such as an autoregressive or fractal might be preferable. The fractal model, for example, implies that changing scales only changes variances by a fixed constant related to the fractal dimension (Tel, 1988). In Euclidean geometry the dimensions of a curve and plane are one and two, respectively, whereas in fractal geometry the dimension of a curve lies between one and two, depending on its complexity (Lam, 1990). Fractal models have become popular recently, possibly because of the connection to chaos theory or because fractal models produce surfaces that "look like" natural features. Unfortunately, there is no consensus on the best way to estimate fractal dimension from geographic data. Under certain conditions (i.e., Brownian fractal process), the fractal dimension can be related to (or derived from) the variogram, covariance, or spectrum, where decreasing fractal dimension is equivalent to increasing autocorrelation. In general, however, this estimation problem has meant that fractal models have been most successfully utilized in simulations of natural features.

Recent spatial analyses of geographical data include the use of fractals to characterize the scale dependence of precipitation (e.g., Lovejoy and Schertzer, 1985; Gupta and Waymire, 1990), remotely sensed images (Lam, 1990; DeCola, 1989), topography (e.g., Mark and Aaronson, 1984), soil properties (Burrough, 1983a; 1983b), and land use (e.g., Milne, 1991). Semi-variograms have been used to characterize spatial variability in topography (e.g., Mulla, 1988; Dubayah *et al.*, 1989), solar radiation (Dubayah *et al.*, 1990), surface albedo (Webster *et al.*, 1989), satellite radiances (Ramstein and Raffy, 1989), spectral vegetation indices (Davis *et al.*, 1989), soil properties (Burrough, 1983a; 1983b; Oliver and Webster, 1986; Robertson *et al.*, 1988), and vegetation (Woodcock *et al.*, 1988; Townshend and Justice, 1988; Pastor *et al.*, 1990). Jupp *et al.* (1988, 1989) have shown how the semi-variogram of a scene composed of discrete objects is related to that of digital images of that scene as "regularized" to different pixel sizes. Much more research along this line is needed to improve our understanding of the relation between surface variation and the spatial properties of multi-resolution images, especially when one considers that remote sensing imagery is the main source of measurement data for analyzing the spatial dependence of surface and atmospheric phenomena at relatively large measurement scales and over large areas.

Related to the problem of non-stationarity in spatial processes is that of infrequent, extreme variability or intermittency (Lovejoy and Schertzer 1985). An approach that shows some promise for dealing with extreme variability is to model such fields as the expression of multiple scales of random processes (Schertzer and Lovejoy, 1987). Lovejoy and Schertzer (1985) have coined the term *Generalized Scale Invariance* to describe spatial variability in terms of a cascading process, in which a process is more concentrated or localized at finer scales but its average value remains constant across scales. This approach has shown promise in applications to hydrology (Gupta and Waymire, 1990) and atmospheric processes (Schertzer and Lovejoy, 1987).

Measurement and Sampling of Geographic Variation

There are significant challenges to both defining and changing the measurement scale of remote sensing and GIS data. Socioeconomic data are aggregated to reporting units that vary in size and shape. The spatial scale of many ground measurements is often only approximately known. Although most ground measurements are treated as points, they typically represent an area, often of indeterminate extent. The measurement scale of maps produced from point data or from survey and image data is even less well specified (Goodchild, 1980).

Extrapolation of point measurements and model estimates to large areas remains a major problem in geographical analysis, and continued research is needed to identify appropriate sampling and scaling strategies for sparse ground measurements, especially in the context of regional and global assessments. Interpolating point measurements to a surface creates variation that may or may not approximate the scaling properties of the actual surface. Only recently have Earth scientists made explicit use of spatial autocorrelation theory in designing sampling and interpolation schemes for surface variables (e.g., Dancy *et al.*, 1986; Oliver and Webster, 1986; Curran, 1988). Kriging, for example, uses the variogram in estimating a surface from point measurements (e.g., Estes *et al.*, 1987; Webster *et al.*, 1989). Co-kriging based on ground and image or GIS data may prove an even more powerful technique for some applications, for example, in generating precipitation maps from rain gauge and digital elevation data, or in mapping soil moisture using soil samples and remotely sensed microwave imagery. Such methods may need to be combined with traditional approaches such as stratified sampling in order to be applicable over heterogeneous regions, and there is continuing need to develop and refine methods for optimal stratification of surfaces for spatial sampling and distributed modeling (e.g., Band and Wood, 1988; Davis *et al.*, 1990).

The measurement scale of remotely sensed data is relatively well specified compared to many geographic data, but may still be quite uncertain. The resolution of a map produced from interpretation of aerial photography may be defined by the effective resolution element, that is, the size of the smallest object that can be reliably detected against a radiometrically contrasting background, but mapping is rarely done to that resolution. Resolution depends instead on the complex generalization process applied by the analyst. For this reason the effective scale of GIS data is sometimes described in terms of the minimum mapping unit (MMU), but the actual MMU may vary both within and between maps as a function of map classes, terrain type, and analyst.

The pixel size is generally taken to define the spatial resolution of digital remotely sensed data, although the term image resolution has various meanings (Forshaw *et al.*, 1983). However, the measurement scale is not fixed. Resolution varies not only as a function of the sensor's instantaneous field of view (IFOV) and altitude, but also because of many other factors including the sensor point spread function, surface-sensor geometry, atmospheric conditions, and data processing such as image rectification or enhancement (Billingsley, 1983; Duggin, 1985; Strahler *et al.*, 1986).

Given that surface processes and phenomena exhibit characteristic scale dependencies, then remote sensing data of multiple resolutions, either from multiple sensors or from degradation of high resolution imagery, can be used to study and exploit those dependencies for mapping and modeling (e.g., Woodcock and Strahler, 1987; Wharton, 1989, Ramstein and Raffy, 1989; Weiler and Stow, 1991). Each spatial resolution provides a somewhat different perspective, and the factors influencing surface patterns as measured at each spatial resolution may reflect different underlying processes. While such an approach, in which scaling property is treated as an explicit variable in an analysis, has been productive in some industrial applications of visual pattern recognition, it has still seen relatively little application in remote sensing and IGIS analysis (Wharton, 1989).

There are strong practical incentives for understanding the scale dependence of Earth surfaces and of IGIS data. Environmental scientists using remote sensing and GIS data usually operate at multiple space and time scales wherein data density is a technical consideration. As illustrated in Figure 1, data density depends jointly on spatial and temporal resolution (and the spectral dimensionality of the sensor), so that data density decreases from the lower left to upper right corners of the diagram. Continuous increases in computing capacity have shifted the data volume threshold towards the lower left hand corner, allowing the investigation of processes operating at relatively fine space and time scales over increasingly large areas and with finer spectral resolution. Nevertheless, there are still very real practical limits to the spatial and temporal domain of remote sensing for regional and global analysis, and to the volume of data that can be effectively archived, retrieved, and analyzed (Atkinson *et al.*, 1990). For global analysis, practical scales are still far more coarse than the measurement scales of many kinds of biophysical data (e.g., small plot measurements of biomass or trace gas fluxes, or high time frequency of measurements of rapidly varying atmospheric properties such as temperature, humidity, or cloud cover) (Rosswall *et al.*, 1988). According to Haber and Schaller (1988), field measurements are most appropriate for sampling ecosystem processes such as photosynthesis or mineral cycling, whereas remotely sensed data and GIS data can be used to measure or represent some of the spatial controls on those processes, such as radiation or soil moisture. Because not all controls on biophysical processes can be mapped directly from remotely sensed data or existing maps, an important role of IGIS will be the generation of such information by appropriate modeling using more than one information source (Risser, 1986).

A real challenge in combining remote sensing and GIS for Earth science studies is the proper nesting of observations at multiple space and time scales in order to link short-term, fine scale measurements and process models to long-term, broad scale measurement and modeling efforts. This is a key issue in monitoring and modeling global change (Rosswall *et al.*, 1988).

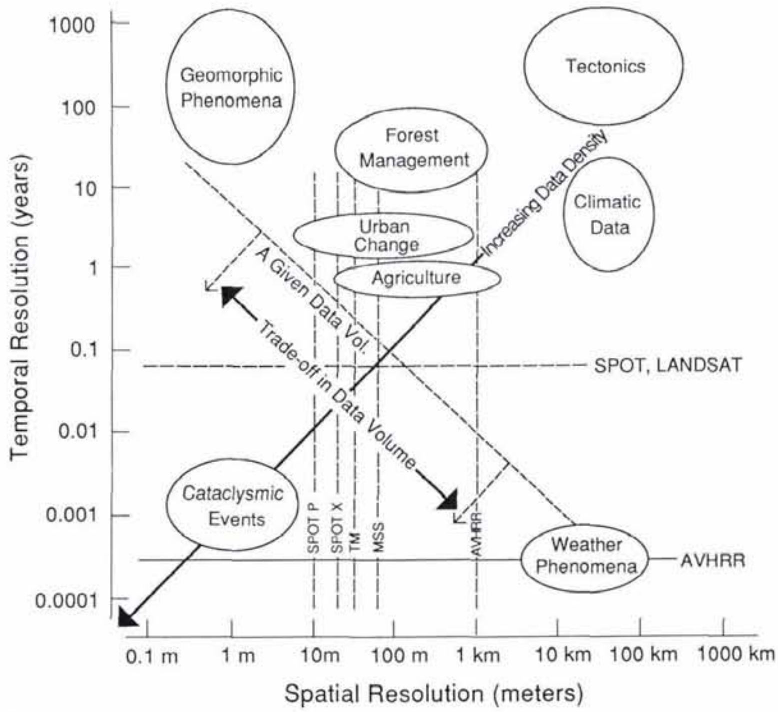

FIG. 1. Spatial and temporal measurement scales for ground samples (shaded region) and remote sensing data. Data density decreases from lower left to upper right.

One research effort of special relevance is the NASA FIFE (First ISLSCP (International Satellite Land Surface Climatology Project) Field Experiment) project, which was conducted between 1987 and 1989 over the Konza Prairie Long Term Ecological Research Site near Manhattan, Kansas. FIFE was designed to study regional land surface climatology and to develop methods for deriving quantitative information about surface climate variables from satellite observations (Sellers *et al.*, 1988). This is one of the first attempts to simultaneously acquire ground and remote sensing data over a range of measurement scales in order to explicitly examine how processes and patterns at small scales are related to those at larger scales. Preliminary data analyses have indicated the potential as well as the enormous complexity in scaling from ground to satellite measurements of surface biophysical properties (Sellers *et al.*, 1988; 1990).

Studies like those just cited are improving our understanding of scaling properties of geographic variation. However, in the context of IGIS analysis, the most pressing need is for coordinated research that considers spatial scale dependence of surface variation from the joint perspectives of process-oriented measurements, remote sensing, and cartography. In this section we have only discussed issues of scale in terms of absolute spatial scales of measurement and modeling. However, in joint processing of cartographic and remote sensing it is important to consider relative space and relative spatial scale as well. Absolute space is space as referenced to a Euclidean coordinate system. The topology of elements within this coordinate system is determined by location, distance, direction, shape, and geometry, as well as the size of the observation area (i.e., local, regional, global) (Meentemeyer, 1989). In relative space, distance, direction, and geometry are predicated on a functional relationship (Meentemeyer and Box, 1987; Meentemeyer, 1989). Remotely sensed measurements can be degraded from higher to lower resolution based on the size, shape, and location of those measurements in a Euclidean coordinate system (for example, an image of surface albedo can be transformed from higher to lower resolution by simple image filtering). This is very different from the kind of operation one would use to simplify or reduce the scale of a vector representation of a variable such as watershed boundaries, where aggregation of subbasins within a basin would be more appropriate and relative space is especially problematic.

MONITORING AND CHANGE DETECTION

Although satellite remote sensing has long been advocated for monitoring surface processes through time, there has been remarkably little progress in quantitative spatiotemporal analysis of multi-temporal imagery, particularly for land surface analysis. There is a pressing need for such research applied to sensors with low spatial resolution and short repeat intervals (e.g., AVHRR, GOES) as part of efforts to study global ecological changes (e.g., Townshend and Justice, 1990).

There are many uncertainties in detecting change with multitemporal satellite data. As noted by Townshend and Justice (1988), the ability to detect changes in a surface identified over time with remote sensing depends on the spatial (geometric registration, resolution), spectral (band location and width), radiometric (signal-to-noise and quantization levels), and temporal (imaging frequency) properties of the sensor system. Changes in instrument function such as gain or offset and factors related to atmospheric or sun angle conditions have a destabilizing influence on temporal data sets (Duggin and Robinove, 1990). High frequency variation in solar, atmospheric, and surface conditions during scene acquisition (e.g., illumination, rapid changes in physiological response of vegetation) contribute noise to the analysis. Comparisons based on more than one sensor convolve surface changes with instrument noise, atmospheric influences, and the varying IFOVs and spectral response characteristics of the sensors.

Integrating multitemporal remote sensing data into IGIS analysis obviously requires understanding of both the sensing systems used and the phenomena under observation. Often, surface change can only be detected with a high level of uncertainty, depending upon the radiometric contrast between successive surface states, the rate of change, and its spatial distribution (Townshend and Justice, 1989). However, the greatest source of uncertainty may be the data transformations imposed by image processing, rectification, and registration procedures used to build a multitemporal database (Walsh, 1989). We believe that research to improve our understanding of those transformations is essential and of high priority.

DATA PROCESSING AND INFORMATION FLOW

IGIS analysis can be conceptualized as a flow of geographic data through a series of transformations into geographic information (Figure 2). Data flow in geographic information systems ultimately begins with georeferenced measurements of the "real world," whether by sampling, survey, or remote sensing. These measurements take several fundamentally different pathways into a digital spatial database. Ground and survey measurements may be entered directly into the database, potentially carrying with them both measurement or categorization error and locational error, or they may be interpolated to make a map, in which case sampling and estimation errors must also be considered (Curran and Hay, 1986; Curran and Williamson, 1986).

Analog remote sensing imagery is usually converted to geographic information by human interpretation, whereas digital imagery is guided by human analysts but also depends on image processing and statistical algorithms (see Duggin and Robinove (1990) for a fuller treatment of information flow in remote

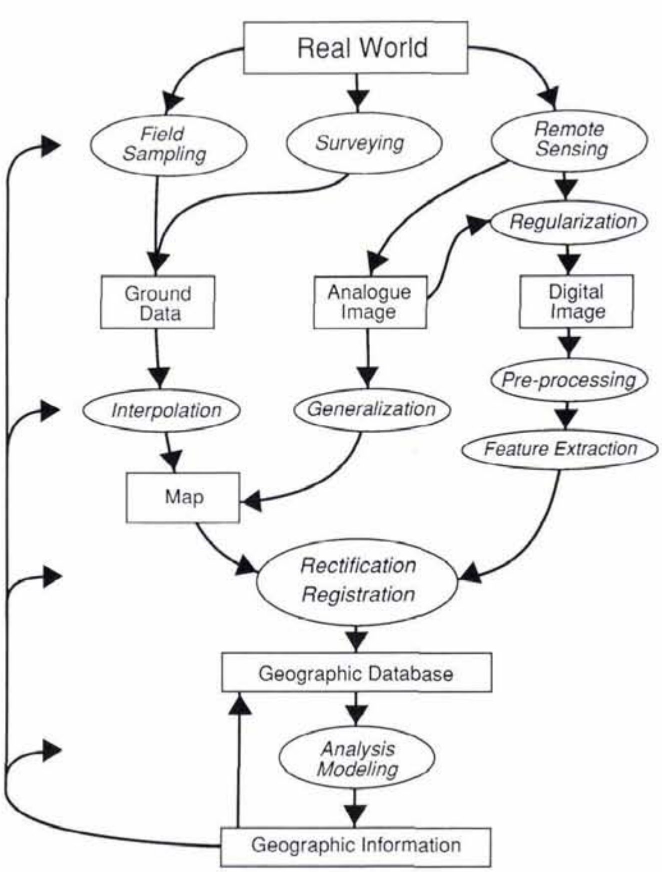

FIG. 2. Conceptual diagram of data processing and information flow during integrated analysis of GIS and remote sensing data. Processes are enclosed in ellipses and products in boxes.

sensing). Image interpretation is a complex interpreter-dependent process that involves both objective and subjective criteria (Estes *et al.*, 1983). Automated or semi-automated digital image analysis is also analyst dependent, and the main difference may lie in the more uniform application of rules for information extraction across an image or series of images (Duggin and Robinove, 1990).

Merging ground, map, and image data requires digitizing, geo-referencing, and registration, each entailing additional transformations of the original measurement data. These include introduction of noise (e.g., locational and thematic errors), but also may involve more fundamental changes in the input data. For example, conversion of gridded elevation data to a triangulated irregular network (TIN) for vector-based analysis changes the effective spatial scale of surface representation and the surface topology, with profound effects on modeling of topographic processes such as surface runoff or solar radiation.

Once compiled, the geographic database is used in analysis and modeling to derive new geographic information, which in turn may guide processing steps or serve as input to subsequent IGIS analyses. Efforts to relate processing flow to model output usually focus on this step, taking the form of an accuracy assessment or model sensitivity analysis. However, it is obvious that the quality of the new geographic information may depend as much on any of the preceding processing steps as on this last step, that is, the joint analysis of the remote sensing and GIS data. Often the original measurement data and steps taken in developing the geographic database are not documented in sufficient detail to relate them to model output. This renders model testing and validation an *ad hoc* process that, at its worst, can lead to misspecification of the model in order to compensate for errors introduced during database development. As the database and analytical products are used to guide the acquisition and processing of new data, potential error can become deeply embedded in the overall data processing flow.

Tracking the changes in geographic data during processing is a formidable task, in part because of the wide variety of changes that can occur, including

- datum value (i.e., category, level or magnitude)
- range of a variable
- data precision (higher -> lower)
- spatial or temporal resolution (higher -> lower)
- data type (e.g., numerical -> ordinal -> categorical)
- data structure (tabular <-> vector <-> raster)
- for GIS data, changes in polygon attribute information

For remotely sensed data, procedures such as radiometric rectification, edge enhancement, and feature extraction (e.g., image classification) that are used to process radiances into thematic information generally raise the information value of the data (Ehlers *et al.*, 1989; Duggin and Robinove, 1990). Additional transformations such as resampling to coregister imagery to other spatial data and processing of existing geographic data tend to lower their information content. Kerekes and Landgrebe (1987) provide a noise taxonomy for remote sensing systems subdivided into scene, sensor, and processing subsystems. An expanded taxonomy that includes both GIS and remote sensing would be valuable, especially if developed in a systems framework that accounts for both existing and future processing capabilities and information needs.

RESEARCH ISSUES

Many of the important research issues in IGIS data processing can be posed in terms of the following questions:

What are the appropriate mathematical and statistical models to describe the accuracy and scale dependence of IGIS data?

How do the accuracy, scale dependence, and predictive value of the information that flows from IGIS analysis depend upon the measurement and processing strategies used to derive that information?

What is the appropriate sampling and integration strategy for combining ground measurements, remote sensing measurements, and existing cartographic information to model a particular process?

What are the preferred processing strategies and algorithms for production and integration of digital geographic data?

What methods should be applied or developed to track changes in the content, spatial, and temporal properties of geographic data during data processing and analysis? What processing information and data attributes should be retained and/or transmitted to facilitate such tracking?

Research into integrated processing of remote sensing and GIS data must consider the origin and evolution of those data and, therefore, must be placed in the larger framework of geographic analysis, incorporating the theory and methods of mathematics and spatial statistics, cartography, remote sensing, and GIS (Fisher and Lindenberg, 1989). Relevant research issues range from those related to measurement and sampling of geographical variables to those concerned with geographic data storage, retrieval, and display to development of methods of spatial simulation modeling, verification, and validation.

In principle, the relationships among cartography, remote sensing, and GIS should be highly synergistic. Remote sensing allows the investigator to measure and monitor surface electromagnetic variation. GIS allows the organization and analysis of these measurements, and the cartographic database provides the context to improve the modeling of surface processes using spectral data. In practice, there are many poorly understood tradeoffs in coupling remote sensing data to existing thematic maps. Maps use points and lines to represent selected features of the environment in a highly abstracted and generalized fashion (Peucker and Chrisman, 1975). Map properties such as minimum mapping unit, degree of generalization, boundary accuracy, and thematic accuracy are typically unknown and may vary considerably from one part of a map to another. Satellite data differ from traditional cartographic data in their consistency, high positional accuracy, and high spatial resolution. These are complementary features, and there are many ways in which remote sensing and GIS data have been profitably merged, for example:

- use of remote sensing data to create, update, and/or improve the positional accuracy of thematic coverages (e.g., Hill and Kelly, 1987);
- use of GIS data in image classification (e.g., Strahler, 1981; Hutchinson, 1982; Richards *et al.*, 1982); and
- calibration of remote sensing data and overlay on thematic maps for disaggregated estimation of ecosystem parameters (e.g., Reiners *et al.*, 1989) and for spatially distributed process modeling (e.g., Running *et al.*, 1989).

On the other hand, joint analysis of remote sensing and map data such as topographic data or soils data carries many costs, including potential loss of precision and object-based representation of map information during vector to raster conversion, new cartographic error due to misregistration of image and map data, imposition of thematic map errors on remote sensing measurements, and error due to misspecification of the relationship between map classes and remote sensing data.

The literature is now well stocked with examples of integrated analysis of remote sensing and GIS data. None have systematically examined the suite of transformations, information gains, and losses inherent to this integration. Of special concern is the appropriate use and effective management of attribute data in IGIS processing and analysis. These data are often lost or transformed in deriving new GIS products, at the risk of inappropriate use of those products in subsequent analyses. Conversely, the ability to invest geographic features with multiple attributes means that information can be preserved or enhanced during processing. For example, multiple attributes of a polygon related to scaling could be explicitly stored (e.g., sub-pixel variance, polygon constituents, boundary characteristics).

CONCLUDING REMARKS

The trend in remote sensing over the past decade has been from empirically based image classification, mapping, and inventory to more deterministic modeling of scene characteristics based on physical laws of radiative transfer and energy balance (e.g., Sellers *et al.*, 1990), and to knowledge-based image interpretation systems (Goodenough *et al.*, 1987; Argialis and Harlau, 1990). Similarly, GIS analyses have grown increasingly sophisticated, moving from simple map overlay and relational models to spatially distributed simulation modeling (e.g., Costanza *et al.*, 1990). It is obvious that the progress made to this point and future developments in this area depend critically on hardware and software that facilitate the integration of remote sensing and GIS. As these technologies continue to improve, the power of IGIS analysis is increasingly limited by our understanding of the phenomena under investigation and their representation in spatial databases. At its worst, IGIS is a powerful technology that can be used to answer poorly posed questions by running misspecified models on improperly extrapolated data to generate output whose validity can never be tested. At best, the coupling of satellite measurements with other spatial data has tremendous potential for describing Earth surfaces, predicting future conditions, and validating biophysical representations produced solely through remote sensing or GIS data. The concerns that we have highlighted in this paper in terms such as inappropriate mixing of scales and degradation of information obviously must be weighed against the robustness of the analysis and the user's willingness to tolerate uncertainty in applying IGIS products to decision making.

We have argued that impediments to the integration of multiple spatio-temporal remote sensing data are not only technical but are, more importantly, conceptual in nature. Some of the difficult problems relate to defining appropriate strategies for data acquisition and spatial modeling. This will require research on scale dependence in surface features and the relationships of absolute and relative scale within a remote sensing context. Another set of problems relate to tracking and understanding the impact of data processing steps on output products. Tools are needed for measuring spatial properties of input data such as spatial autocorrelation, two-dimensional spectral analysis, and block variance analysis. What other analytical tools should be included in an Integrated Geographic Information System? What are appropriate statistical approaches for analyzing IGIS products? At present, it appears that the more complex modeling efforts cannot be validated except in a piecemeal fashion, and thus sensitivity analyses will be the best method for assessing the robustness of model outputs. Thus, user interfaces and analytical software need to be designed that facilitate sensitivity analysis of complex spatial models. Much can be gained simply from improved methods for the display and visualization of IGIS products (see Faust *et al.*, (1991) this issue). Development of better interfaces between image processing, GIS, database management, expert systems, and statistical software will go a long way in improving analysis capabilities.

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